POLITECNICO DI MILANO

SCHOOL OF INDUSTRIAL AND INFORMATION ENGINEERING

MASTER OF SCIENCE IN ELECTRICAL ENGINEERING

A Data-Driven Distributionally Robust Optimal Scheduling of Battery Storage Systems in Joint Electricity Market

Supervisor:

Prof. Marco Merlo
(Politecnico di Milano)

Co-Supervisor:

Prof. Hamidreza Nazaripouya
(University of California at Riverside)

Graduation Thesis by:

Seyed Shahin Parvar
(884045)

ACADEMIC YEAR 2018-2019

Abstract

The battery energy storage systems (BESS), as a promising solution to deal with variability and uncertainty of intermittent renewable energy sources (RES) and loads, could play a pivotal role in the power grid. The high capital expenditure of these assets leads to deploying batteries not only for storing the surplus energy of renewable sources but also to provide different services to the grid. In general, behind the meter batteries are a good candidate to participate in the electricity market either as a flexible load or generator along with improving the RES performance for demand-side management (DSM). To this end, optimal and comprehensive scheduling for BESS which considers different types of uncertainties variables is vital. This research presents the optimal scheduling solution for BESS to DSM along with the electricity market based on California Independent System Operator (CAISO) regulations. BESS can be deployed in a power grid to optimize the operation of the system. However, due to the high initial cost of BESS, the efficient operation of this asset is imperative. In addition, to deal with the stochastic nature of load and generation as well as uncertainties in the electricity market, stochastic optimization methods should be deployed. This study introduces the data-driven distributionally robust optimization (DRO) model to address the uncertainties by defining an ambiguity set, i.e., Wasserstein ball over historical data. Participation in energy, spinning reserve, regulation up and down markets, both in day-ahead and real-time markets, beside the DSM are considered in this paper. Finally, the proposed method is tested and verified using real market data by comparing different optimization methods such as deterministic and robust with DRO.

Keywords: Battery Energy Storage, California ISO energy market, data-driven decision making, distributionally robust optimization, Wasserstein metric

Sommario

I sistemi di accumulo dell'energia a batteria (BESS), rappresentano una soluzione promettente per affrontare la variabilità e l'incertezza delle fonti di energia rinnovabile intermittente (RES) e dei carichi, essi potrebbero quindi svolgere un ruolo fondamentale nella rete elettrica. L'elevata spesa in conto capitale di queste attività porta a distribuire batterie non solo per immagazzinare l'energia in eccesso di fonti rinnovabili, ma anche per fornire diversi servizi alla rete. In generale, le batterie installate presso gli impianti degli utenti finali sono un buon candidato per partecipare al mercato dell'elettricità sia come carico flessibile che come generatore, oltre a migliorare le prestazioni FER per la gestione della domanda (DSM). A tal fine, la pianificazione ottimale e completa per BESS che considera diversi tipi di incertezze variabili è vitale. Questa ricerca presenta la soluzione di pianificazione ottimale per BESS (Battery Energy Storage Systems) per partecipare a Demand Side Management (DSM) insieme al mercato dell'elettricità basato sulla normativa California Independent System Operator (CAISO). I BESS possono essere implementati essere implementato nella rete elettrica per ottimizzare il funzionamento del Sistema, tuttavia, a causa dell'elevato costo iniziale, il funzionamento efficiente di questa risorsa è indispensabile. Inoltre, per gestire la natura stocastica del carico e della generazione, nonché le incertezze nel mercato dell'elettricità, dovrebbero essere impiegati metodi di ottimizzazione stocastica. Questo studio introduce il modello di ottimizzazione distributiva robusta (DRO) basata sui dati per affrontare le incertezze definendo un insieme di ambiguità, ovvero la sfera di Wasserstein sui dati storici. Nell'ambito del lavoro di tesi si è investigata la fornitura di servizio di energia, si riserva rotante, di regolazione a salire e a scendere, la partecipazione a servizi di DSM. Infine, il metodo proposto viene testato e verificato utilizzando dati di mercato reali confrontando diversi metodi di ottimizzazione come deterministico e robusto con DRO.

Parole chiave: accumulo di energia, mercato energetico ISO della California, processo decisionale basato sui dati, ottimizzazione distributiva solida, metrica di Wasserstein

Acknowledgements

I wish to thank many individuals who offered their support, help, and valuable suggestions during my graduate studies. Without these people, completion of this work would not have been possible.

I would like to express my very great appreciation to my supervisor, Professor Hamidreza Nazaripouya, for his patient guidance, encouragement, insightful suggestions in the past one year. I was so lucky to have been given the chance to be a part of his research group. He taught me how to be critical of my work, how to explain it clearly, and how to prepare myself for my future career and academic life.

I would also like to extend my deepest gratitude to my internal supervisor, Professor Marco Merlo who not only offered their professional support in completing my research project, but also his deep advices during this research opened new doors toward the improvement of whole the research.

My special words of thanks should also go to my dear Professor Alessandro Ferrero who played as my academic father and he has always been there whenever I needed feedback on my academic carrier and someone to consult with.

Lastly, I am forever grateful to my parents and my grandparents, Hashem Parvar and Shahrzad Ebadat, Karim Ebadat and Homa Khansari and my dear sister Dr. Yasamin Parvar for all their unconditional love, patience and sacrifice while I have been far away from home and my dear love and my best friend Dr. Yasaman Yeganeh who I am so thankful for the trust and all the support she has kindly offered in every single decision that I have made in this journey.

Without your inspiration and love, I would not be where I am today.

Extended Summery

NOMENCLATURE

A. Indices and Sets

t	Time index.
$Spin$	Subscribe for Spinning Reserve.
$RegU$	Subscribe for Regulation Up.
$RegD$	Subscribe for Regulation Down.
E	Subscribe for Energy Market.
D	Subscribe for Demand.
PV	Subscribe for Photovoltaic.
$\mathbb{V}$	Set of decision variables.
v	Subscribe for decision variables.
π	Subscribe for uncertain variables (price).
T	Set of time.
L	Subscribe for Load.
ch	Subscribe for Charge.
dch	Subscribe for Discharge.
$Perf$	Superscript for regulation performance.
$mile$	Superscript for regulation mileage.
t_{end}	Last time interval
$PV2L$	Subscribe for delivered from PV to Load.
$PV2Bat$	Subscribe for delivered from PV to battery.
$Bat2L$	Subscribe for delivered from battery to Load.
$Bat2G$	Subscribe for delivered from battery to grid.
$G2Bat$	Subscribe for delivered from grid to battery.
$G2L$	Subscribe for delivered from grid to Load.
DA	Subscribe for day-ahead market.
RT	Subscribe for real-time market.
Op	Subscribe for Operational cost.
Im	Subscribe for Import energy from grid.
Ex	Subscribe for Import energy to grid.
ξ	Subscribe for uncertainty.
Ξ	Uncertainty set.
N	Number of training data set.
$\hat{\mathcal{P}}_N$	Ambiguity set.
$\mathbb{Q}$	Probability distribution.
$\hat{()}$	Index for training data-set.

B. Parameters and Constants

$\pi_t^{(.)}$	Market price at time t [\$/kWh].
ρ_t	Energy price at time t [\$/kWh].
$\eta^{(.)}$	Charging/discharging efficiency of battery.
P_{Max}	Nominal capacity of inverter
$Cap_t^{(.)}$	Nominal capacity at time t [kW]
$l^{(.)}$	Penalty rate for energy deviation [\$/kWh]
$\vartheta^{(.)}$	Energy deviation threshold.
ε	Confidence level of Wasserstein ball
α	Confidence level of CVaR.
ζ	Investor's risk-aversion.

C. Variables

$R_t^{(.)}$	Market Revenue at time t.
C_t^{Op}	Operational Cost at time t.

C_t^D	Demand Cost at time t.
SoC_t	State of Charge of Battery at time t.
$P_t^{(.)}$	Capacity offered in market [kW].
$Perf_t^{Reg}$	Performance Payment for regulation market [$].
m_t	Regulation Mileage Multiplier at time t.
acc_t	accuracy of Performance response at time t.
M_t	Binary variable for Charging/Discharging mode.
$E_t^{(.)}$	Total energy exchange at time t [kWh].
$\Delta E_t^{(.)}$	Energy deviation from day-ahead at time t [kWh].
$U_t^{(.)}$	Penalty for energy deviation [$].

INTRODUCTION

THE battery energy storage systems (BESS), as a promising solution to deal with variability and uncertainty of intermittent renewable energy sources (RES) and loads, could play a pivotal role in the power grid. The high capital expenditure of these assets leads to deploy batteries not only for storing the surplus energy of renewable sources but also to provide different services to the grid [1, 2]. In general, behind the meter batteries are a good candidate to participate in the electricity market either as a flexible load or generator along with improving the RES performance for demand-side management (DSM). To this end, optimal and comprehensive scheduling for BESS which considers different types of uncertainties variables is vital.

The literature on the scheduling of storage systems can be predominantly categorized into three main groups. In the first group, the main aim is to provide services directly for ISO/RTO. These services are including energy arbitrage [3, 4, 5, 6, 7], frequency regulation [4, 5, 7], spinning reserve [3, 5, 7] and black start. These storages can either connect to transmission system stand alone [3] or join with other distributed generators such as wind farms [8]. In [3], independent storage units in the day-ahead and hour-ahead energy and reserve markets bidding have been studied where a significant portion of the power generated in the grid is from wind and other intermittent renewable energy resources. Authors in [4] have been investigating different revenue stream such as energy frequency regulation market both in DA and RT market by considering the grid limitation in the presence of PV generators in different locations in network. Reference [5] focused on stand-alone battery participating in DA ancillary services. Authors in [7] included the battery cycle life model into a revenue maximization model to find the optimal bidding for participating in DA energy, spinning reserve and regulation market.

Second group focused on utility serves such as resource adequacy, transmission congestion relief, distribution and transmission deferral [9]. Reference [9] suggests a possible investment saving using ESS to defer investment in distribution network elements that are near to their technical limits. It avoids economical and focuses on technical analysis and suggests required ESS size based on load curve shape and loading growth rates compared with allowed loadings. In [10], authors looked for optimal installation place of a predefined number of BESS, Wind plant and capacitors. The objective function is the minimize of investment and reactive power costs. In the last set of articles, the problem of ESS scheduling has been solved from costumer perspective who installed ESS behind meters. Traditionally, behind the meter batteries had been used for time of use (TOU) management [11], demand charge reduction

[12, 11, 13], backup power [14, 15] and finally improving roof top PV self-consumption [16]. In [11] net present value (NPV) performed for hybrid PV-ESS system for optimized energy dispatch schedule by considering TOU pricing and reduction of peak demand minimization. Optimal scheduling of PV-ESS system in presence of incentives such as feed-in tariffs to maximize the daily operational saving through demand charge reduction has been presented in [12]. Authors in [16] developed closed loop controller with model predictive control (MPC) method to improve the performance of residential PV-ESS system and enhance the cost saving. The present paper is categorized in the first and third group in line with [17, 18] and model a battery energy storage system jointly with PV panels. It performs optimal scheduling by considering both an electricity market including energy, spinning reserve, regulation services in line with [7, 5, 4] as well as demand-side management in line with [16, 12] cooperatively.

Behind the meter BESS joint with RES scheduling problem to participate in market and demand side management suffer from three kinds of uncertainties including market clearing price, demand fluctuation, and adverse weather conditions. To accommodate these uncertainties in the power system problems, two major techniques are stochastic optimization (SO) [19, 20] and robust optimization [21, 22, 23]. H. Alharbi and K. Bhattacharya [24] formulate SO for the uncertainty of solar and wind along with power demand with separate probability distribution (PD) to find optimal power and energy size of BESS. Akhavan-Hejazi and Mohsenian-Rad [3] applied SO for dealing with market price fluctuation to choose optimal offering bids. Authors in [4] used SO for three types of uncertainties to determine optimal scheduling plan for joint PV-BESS. Mohsenian-Rad in [6] proposed a novel two stage SO for bulk battery system considering different design factors such as day-ahead and real-time market prices and the location, size, efficiency, lifetime, and charge/discharge rates of the batteries. In [25], a two-stage SO for grid connected battery developed and uncertainties such as wind, solar plugin vehicles had been covered. In general, in stochastic optimization, the PD of uncertain values assumed to be known or can be estimated based on historical data and aims to minimize the expected value of cost function by generating scenarios as many as possible.

Stochastic optimization suffers from two main drawbacks. First, usually enough historical data are not available which makes PD inaccurate. Second, high number of scenarios cause burdensome calculation time [21]. The second possible approach, which has been used in literature, is robust optimization (RO). RO does not require the exact knowledge about PD, and minimize the cost function under worth-case realization. Kazemi et al. [5] proposed the confidence gap around uncertainties to deal with market signal and price. In [22], authors used the combination of stochastic and robust optimization for day-ahead and real-time market, respectively. However, the worst-case scenario is always the extreme case with relatively low probability, therefore, the solution could be conservative and thus not the most economical solution. To deal with this problem few methods such as adoptive robust optimization [26] has been introduced.

The alternative solution to deal with uncertainties is data-driven distributionally robust optimization (DRO). In conventional stochastic optimization, the probability distribution is tuned based on the specific data set, however, it is quite often that PD performs poorly when confronted with a different data set, even if it is drawn from the same distribution [27]. Thus, the main feature in DRO is to immunize the optimal solution by finding the worst-case expected value over a family of uncertainty sets (ambiguity sets) instead of worst-case observations (robust optimization). The ambiguity set must be rich enough to cover all possible distributions with high confidence, meantime, it must be small enough to prevent the over-conservative results [27]. Two main approaches to construct the ambiguity sets for DRO are a moment-based and statistical-distance. In the moment-based approach, all distributions, which are applicable with certain known moments (mean and covariance matrix), are considered as ambiguity sets [28, 29]. In literature, this approach has been deployed widely since only the moment condition is required [30, 31, 18], however, by considering specific mean-variance based on historical data some important information might be discarded [32]. On the other hand, the statistical-distance approach constructs all distributions that are close enough to the target distribution with predefined probability specification. In this way, the degree of conservatism can be controlled by adjusting the radius (distance) of ambiguity set. To implement statistical-distance several methods such as the Prohorov metric [33], the Kullback–Leibler divergence [34], or the Wasserstein metric [27, 35] has been introduced. This research focuses on data-driven distributionally robust optimization over Wasserstein ball in line with [27, 36, 37], since it has a tractable reformulation and out-of-sample performance has been guaranteed [27, 38].

This paper presents a novel solution for scheduling of the behind the meter battery energy storage system joint with PV-cells. The main objective is to minimize the electricity cost of demand-side by participating in multiple electricity markets in Day-Ahead (DA) and Real-Time (RT) interval. In this way, the feasible markets such as spinning reserve, frequency regulation up, regulation down, and energy market as well as demand profile in both DA and RT have been investigated. Moreover, to deal with market uncertainty data-driven distributionally robust optimization (DDRO) have been developed and for RT both model predictive control (MPC) with the rolling time horizon and DDRO have been deployed. The main contributions of this paper include:

- Simultaneous participation model in electricity market and demand side management for PV-BESS by considering the market price uncertainties in both DA and RT.
- Developing the distributionally robust optimization for scheduling of BESS.

The rest of this paper is laid out as follow. In Section II, the market structure is described, and battery model is provided. Based on this model, problem reformulation for distributionally data-driven robust optimization is developed in Section III. In Section IV, the case study based on California wholesale energy market and Time-of-Use is studied and finally in Section V, the conclusion is discussed.

Problem formulation

The main scope of this research is to maximize the total revenue of battery energy storage systems installed behind the meter by participating in energy, spinning reserve and regulation market as well as simultaneous management of the demand side usage. However, due to uncertain nature of the market price, demand and PV production, the main challenge would be developing the proper optimization method for BESS scheduling. The problem formulation consists of two stages. In first stage, day-ahead optimization is developed to determine preliminary charging and discharging strategy of the battery and commitments for day-ahead market. The second stage would be in real-time interval (intra-hour) to update the initial scheduling based on updated values of the demand and real-time markets. In this section, first the market modeling formulation for both DA and RT has been presented and then in second part the reformulation based on DRO is provided.

A. Day-Ahead Scheduling

According to the Federal Energy Regulatory Commission (FERC) order 841 [39] in 2018, by removing participation barriers for electric energy storage, it is expected to have BESS with higher capacity in the market. BESS participation in market is promoted by different Independent System Operators (ISO) regulations such as NYISO [40], PJM [41] and CAISO [42]. In this research, CAISO Day-Ahead (DA) and Real-Time (RT) market structure is considered. CAISO wholesale energy markets provides the opportunity to buy and sell both power and energy which is comprised of energy market and Spinning reserve, regulation up and down market through DA and RT interval. Based on this market structure, the total cost and revenue of PV-BESS participating in DA multiple market and demand side can be formulated as (1):

$$\mathbf{J_T}(\boldsymbol{v_t}) := \min_{v_t} \sum_{t=1}^{T} \begin{Bmatrix} (\boldsymbol{C_t^D} + \boldsymbol{C_t^{Op}}) \\ -(\boldsymbol{R_t^{Spin}} + \boldsymbol{R_t^{Reg}} + \boldsymbol{R_t^E}) \end{Bmatrix} \quad (1)$$

Where C_t^D and C_t^{Op} are the demand and operational cost and $R_t^{(.)}$ is the revenue of different markets at each time interval. C_t^D in equation (2) depends on time of use ρ_t^{DA} price and the total energy that delivered from grid to procure demand P_t^{G2L}, charge the battery P_t^{G2Bat} and regulation down market P_t^{RegD} usage. The operational cost C_t^{Op} is proportional to the total exchange energy in storage for charging and discharging of battery, as derived in (3).

$$C_t^D = \rho_t^{DA}.\left(P_t^{G2L} + P_t^{G2Bat} + P_t^{RegD}\right) \ ;\forall t \in T \quad (2)$$

$$C_t^{Op} = c_{op}.\left(\left[P_t^{RegD} + P_t^{G2Bat} + P_t^{PV2Bat}\right] + \left[P_t^{Bat2L} + P_t^{Spin} + P_t^{RegU} + P_t^E\right]\right).h \quad ;\forall t \in T \quad (3)$$

The revenue of spinning reserve R_t^{Spin} is determined by spinning reserve capacity P_t^{Spin} and spinning price at each moment π_t^{Spin} in (4). The regulation market revenue R_t^{Reg} is structured as capacity payment and performance payment based on FERC order 755 [43]. The capacity payment is related to committed capacity for regulation market P_t^{Reg} and its price π_t^{Reg}, first part in (5), and performance payment is paid based on participants' accuracy acc_t and mileage price π_t^{Mile} by calculating how accurately service provider can follow the automated generation control (AGC) signal as shown in in second part of (5), where m_t is regulation multiplier estimated by CAISO and is the amount of total expected resource movement (up or down), or Mileage, for 1 MW of Regulation Up or Down capacity.

$$R_t^{Spin} = P_t^{Spin}.\pi_t^{Spin}.h \qquad ;\forall t \in T \quad (4)$$

$$R_t^{Reg} = P_t^{Reg}\pi_t^{Reg}.h + P_t^{Reg}.m_t.\pi_t^{Mile}.acc_t \quad (5)$$
$$;\forall t \in T$$

And finally, the energy revenue R_t^E comes from all energy sectors delivered to grid including regulation up P_t^{RegU}, spinning reserve P_t^{Spin}capacity and extra energy from battery to the grid P_t^E and energy price at time t $\pi_t^{E,DA}$ as illustrated in (6).

$$R_t^E = \pi_t^{E,DA}.\left(P_t^{RegU} + P_t^{Spin} + P_t^E\right).h \ ;\forall t \in T \quad (6)$$

In objective function (1), the optimization variables are participation capacities $P_t^{(.)}$, and market prices are uncertain parameters. Total charging and discharging powers are defined as (7) and (8) respectively. Equations (9) – (15) are the problem constraints. The constraints (9) and (10) are power limits of battery storage in charging and discharging mode respectively as well as complementary charging and discharging constraints for the battery which prevent battery to simultaneous charge and discharge.

$$\mathbf{P_t^{ch}} = \mathbf{P_t^{RegD}} + \mathbf{P_t^{G2Bat}} + \mathbf{P_t^{PV2Bat}} \quad ; \forall \mathbf{t} \in \mathbf{T} \tag{7}$$

$$P_t^{dch} = P_t^{RegU} + P_t^{Spin} + P_t^{E} + P_t^{Bat2L} \quad ; \forall t \in T \tag{8}$$

$$0 \leq P_t^{ch} \leq P_{Max}.M_t \quad ; \forall t \in T \tag{9}$$

$$0 \leq P_t^{dch} \leq P_{Max}.(1 - M_t) \quad ; \forall t \in T \tag{10}$$

State of charge of battery is defined as equation (11), which depends on previous SoC_{t-1} and the charging and discharging capacity at that moment. SoC must be kept in certain limit as shown in (74). Equation (13) forces the final values of SoC to be more than or equal to initial value of the SoC at the beginning to prepare the battery for the next day.

$$SoC_t = SoC_{t-1} + \eta^{ch} P_t^{ch}.h - \frac{1}{\eta^{dch}} P_t^{dch}.h \quad ; \forall t \in T \tag{11}$$

$$SoC_{Min} \leq SoC_t \leq SoC_{Max} \quad ; \forall t \in T \tag{12}$$

$$SoC_{t=0} \leq SoC_{t_{end}} \tag{13}$$

Constraint (14) provides the demand side management where the total demand power request Cap_t^D is procured by PV P_t^{PV2L} , battery P_t^{Bat2L} and grid P_t^{G2L}. Finally, constraint (15) shows the PV production Cap_t^{PV} at each moment.

$$P_t^{PV2L} + P_t^{Bat2L} + P_t^{G2L} = Cap_t^D \tag{14}$$

$$P_t^{PV2L} + P_t^{PV2Bat} + P_t^{PV2G} \leq Cap_t^{PV} \tag{15}$$

B. Real Time Scheduling

In context of RT scheduling, not only RT markets and demands but also the committed values in DA must consider. Specifically cost function (1) will modify as (16).

$$\mathrm{J_T^{RT}}(v_t) := \min_{v_t} \sum_{t=1}^{T} \left\{ \begin{array}{c} (C_t^{RT,D} + C_t^{Op}) \\ -(R_t^{Spin} + R_t^{Reg} + R_t^{RT,E}) \\ +U_t^D + U_t^E \end{array} \right\} \tag{16}$$

$$C_t^{RT,D} = \rho_t^{DA}.E_t^{DA,Im} + \rho_t^{RT}.\Delta E_t^{RT,Im} \tag{17}$$

$$R_t^{RT,E} = \pi_t^{E,DA}.E_t^{DA,Ex} + \pi_t^{E,RT}.\Delta E_t^{RT,Ex} \tag{18}$$

subject to

$$U_t^D \geq l^{Im}.(\Delta E_t^{RT,Im} - \vartheta^{Im}.E_t^{DA,Im}) \tag{19}$$

$$U_t^E \geq l^{Ex}.(\Delta E_t^{RT,Ex} - \vartheta^{Ex}.E_t^{DA,Im}) \tag{20}$$

Where C_t^{Op}, R_t^{Spin} and R_t^{Reg} are following equations (3), (4) and (5) respectively. However, demand cost and energy income have been updated as (17) and (18) where $E_t^{DA,Im}$ is total energy import from grid in DA including grid to battery, grid to load and regulation down and $\Delta E_t^{RT,Im}$ is its deviation from day-ahead amount which must calculate based on real-time price ρ_t^{RT} instead of day-ahead. In the same way, energy income must update based on value committed to export to grid in DA $E_t^{DA,Ex}$, including spinning reserve, regulation up and committed energy which must calculated in DA energy price $\pi_t^{E,DA}$ and second part that is deviation from DA values $\Delta E_t^{RT,Ex}$. Two last terms in RT cost function (16) is penalty for deviation from DA commitments. Accordingly, U_t^D and U_t^E are introduced to, respectively, present the penalties for deviation form committed values in RT at hour t in \$. l^{Im} and l^{Ex} are, respectively, the price penalties for energy import and export, in \$/kWh. ϑ^{Im} and ϑ^{Ex} are, respectively, ϑ^{Im} threshold which can be used for RT markets and uncertainties fluctuations, expressed as the percentage of the DA quantity, above which energy deviations are penalized.

In order to update general problem (16) with last estimation of demand power request and PV power production, model predictive control (MPC) algorithm over planning horizon $\mathcal{H}_t$ is developed. In this term, $Cap_t^{PV} = \bar{P}_t^{PV} + \tilde{P}_t^{PV}$ has been redefined as a summation of nominal value $\bar{P}_t^{PV}$ and forecasted error $\tilde{P}_t^{PV}$ in RT. Likewise, for $Cap_t^D = \bar{P}_t^D + \tilde{P}_t^D$.

$$\mathrm{J}_{\mathrm{T}}^*(v_t) = \min_{v_t} \sum_{t=1}^{T} \sum_{\tau=t}^{t+\mathcal{H}_t} \mathrm{J}_{\mathrm{T}}^{\mathrm{RT}}(v_t, \xi_\tau) \tag{21}$$

Only the immediate control decisions for time t till $\mathcal{H}_t$ are considered as BESS plan. Then time shifts forward one step, new forecast errors are realized, the optimization problem (21) is re-solved at time $t + 1$ hour, and the process repeats. This approach allows any forecasting methodology to be utilized to predict uncertainties over the planning horizon and recalculate intra hour decisions based on short term and more accurate forecasting.

C. Proposed distributionally robust optimization formulation

In Equation (21), described in preceding section, the mean value of historical data is assumed instead of uncertain parameters such as market prices. In order to consider the risk of different uncertainties, data-driven distributionally robust optimization method is introduced in this section. The conventional approach to optimize the objective function is the stochastic approach where the different scenarios based on assumed PD will be defined and the main aim is to minimize the expected cost expressed in (22).

$$J^* = \inf_{v \in \mathbb{V}} \left\{ \mathbb{E}^{\mathbb{P}}[h(v,\xi)] := \int_{\Xi} h(v,\xi)\mathbb{P}(d\xi) \right\} \tag{22}$$

with decision variable $v \in \mathbb{V} \subseteq \mathbb{R}_n$, random vector ξ with probability distribution $\mathbb{P}$ supported on uncertainty set $\Xi \subseteq \mathbb{R}_m$ and cost function $h: \mathbb{R}_n \times \mathbb{R}_m \to \overline{\mathbb{R}}$. A common approach to find $\mathbb{P}$ is to estimate the distribution from limited available data which lead to a poor out-of-sample performance since it is not precise. Moreover, more accurate results require more scenarios to be generated which increases the computational burden and time. The possible approach to guaranty out-of-sample performance is to define an ambiguity set $\hat{\mathcal{P}}_N$ which contains all possible distributions from training data [27]. In this way, the distributionally robust optimization (58) defines as the minimum worst-case expected cost over $\hat{\mathcal{P}}_N$.

$$\hat{J}_N := \inf_{v \in V} \sup_{\mathbb{Q} \in \hat{\mathcal{P}}_N} \mathbb{E}^{\mathbb{Q}}[h(v,\xi)] \tag{23}$$

To instruct the ambiguity set, in this research, we focus on the Wasserstain metric since it has a tractable reformulation and out-of-sample performance guarantees [27], [38]. We construct $\hat{P}_N$ as a ball around empirical distribution with radius based on Wasserstain metric to measure the distance between true PD and estimated one.

Definition [Wasserstein metric]. The Wasserstein metric is defined as a distance function between two probability distributions on a given supporting space $\mathcal{M}(\Xi)$. More specifically, given two probability distributions $\mathbb{Q}_1$ and $\mathbb{Q}_2$ on the supporting space $\mathcal{M}(\Xi)$, the Wasserstein metric is defined as (63):

$$dw(\mathbb{Q}_1, \mathbb{Q}_2) := \inf_{\Xi} \{\mathbb{E}_{\Xi}[\rho(X,Y)]: X \sim \mathbb{Q}_1, Y \sim \mathbb{Q}_2 \tag{24}$$

Where $\rho(X,Y)$ is distance between to random variable X and Y from $\mathbb{Q}_1$ and $\mathbb{Q}_2$. The Wasserstein metric quantifies the minimum “transportation” cost to move mass from one distribution to another.

The ambiguity set $\mathbb{B}_\varepsilon(\widehat{\mathbb{P}}_N)$ can be formulated as Wasserstein ball centered at a uniform empirical distribution $\widehat{\mathbb{P}}_N$ on training dataset Ξ_N and within ε as confidence level (25). The ε is a control variable for conservativeness and robustness of optimization compare to specific features of dataset.

$$\hat{\mathcal{P}}_N = \mathbb{B}_\varepsilon(\widehat{\mathbb{P}}_N) := \left\{ \mathbb{Q} \in \mathcal{M}(\Xi_N) : dw(\widehat{\mathbb{P}}_N, \mathbb{Q}) \le \varepsilon \right\} \tag{25}$$

In this research, the mean-risk portfolio for our problem structure in Equation (1) has been developed to solve single stage stochastic optimization which minimizes a weighted sum of the mean and the conditional value-at-risk (CvaR) of the portfolio revenue amount $\langle v, \pi \rangle$. Consider a total capacity of battery is divided between multiple services at each time interval and is encoded by a vector of percentage weights $v = [v_1, \dots, v_m]^T$ ranging over probability simplex $\mathbb{V} = \{v \in \mathbb{R}_+^m : \sum_{i=1}^m v_i = 1\}$. Uncertain price for each service is shown by the vector $\pi = [\pi_1, \dots, \pi_m]^T$ (26).

$$\mathrm{J}_{\mathrm{T}}^*(v_t) = \inf_{v_t \in \mathbb{V}} \{\mathbb{E}^{\mathbb{Q}}[-\langle v_t, \pi \rangle] + \zeta . \mathbb{Q}\_CVaR_\varepsilon(-\langle v_t, \pi \rangle \quad (26)$$

Here $CVaR_\varepsilon$ is conditional value at risk with confidence level of $\alpha \in (0,1]$ (Wasserstein radius) and $\zeta \in \mathbb{R}_+$ quantifies the investor's risk-aversion. The formula (26) can be reduced to piecewise affine form such as (116) by replacing CvaR in with its formal definition [44].

$$J^* = \inf_{v \in \mathbb{V}} \left\{ \begin{matrix} \mathbb{E}^{\mathbb{Q}}[-\langle v, \pi \rangle] + \\ \zeta \inf_{\tau \in \mathbb{R}} \mathbb{E}^{\mathbb{Q}}[\tau + \frac{1}{\alpha} \max_{v \in \mathbb{V}} \{-\langle v, \pi \rangle - \tau, 0\}] \end{matrix} \right\} \quad (27)$$
$$= \inf_{v \in \mathbb{V}, \tau \in \mathbb{R}} \mathbb{E}^{\mathbb{Q}}[\max_{k=1,2} a_k \langle v, \pi \rangle + b_k \tau]$$

where $k = 2$, $a_1 = -1$, $a_2 = -1 - \frac{\zeta}{\alpha}$, $b_1 = \zeta$, and $b_2 = \zeta(1 - \frac{1}{\alpha})$. Supposed that uncertainty $\Xi := \{\pi \in \mathbb{R}^m : C\pi \leq d\}$ and a polytope, then the stochastic formula of (116) can be solve in distributionally robust form counterpart of (58) with respect to the Wasserstein ambiguity set $\mathbb{B}_\varepsilon(\widehat{\mathbb{P}}_N)$ such as:

$$\hat{\mathrm{J}}_{\mathrm{N}} := \inf_{v \in \mathbb{V}, \tau \in \mathbb{R}} \sup_{\mathbb{Q} \in \mathbb{B}_\varepsilon(\widehat{\mathbb{P}}_{\mathrm{N}})} \mathbb{E}^{\mathbb{Q}}[\max_{k \leq 2} \mathrm{a_k} \langle v, \pi \rangle + \mathrm{b_k} \tau] \quad (28)$$

It is shown in [27] that the affine function (28) can be reformulated as linear programming such as (29) equivalently.

$$\hat{J}_{N,t}(\varepsilon) = \left\{ \begin{array}{c} \inf_{v_t, \tau_t, \lambda_t, s_{t,i}, \gamma_{t,i,k}} \lambda_t \varepsilon + \frac{1}{N} \sum_{i=1}^N s_{t,i} \\ s.t. \quad v_t \in V \\ b_k \tau_t + a_k \langle v_t, \hat{\pi}_{i,t} \rangle + \langle \gamma_{t,i,k}, d - C\hat{\pi}_{i,t} \rangle \leq s_{t,i} \\ \|C^T \gamma_{t,i,k} - a_k v_t\|_\infty \leq \lambda_t \\ \gamma_{t,i,k} \geq 0 \qquad ; \forall i \in N_s, k \leq 1,2 \end{array} \right. \quad (29)$$

Where τ_t is a CvaR auxiliary variable and $s_{t,i}$, $\gamma_{t,i,k}$ and λ_t are auxiliary variables associated with the distributionally robust Wasserstein ball reformulation. In formula (117), the optimum cost $\hat{J}_{N,t}$ for each time interval t and N training samples is calculated. Subsequently, the final objective function for our problem will be formulated as (30) in DRO form with the constraints (9) – (14) and (117).

$$\hat{\mathrm{J}}_{\mathrm{T}} = \min_{v_t, \tau_t, \lambda_t, s_{t,i}, \gamma_{t,i,k}} \sum_{t=1}^T \hat{J}_{N,t}(\varepsilon) \quad (30)$$

Case studies

In this section, after introducing the data used for these studies (i.e. PV and BESS ratings, market prices in DA and RT, load and PV profile and their uncertainties), we compare the effectiveness of different optimization methods (i.e. deterministic, robust and DRO) for both winter and summer.

A. Parameter Settings

In this study the main aim is to manage behind the meter battery join with rooftop PV. The nominal characteristic of battery and installed PV is described in Table 1. For market price, this study focused on CAISO wholesale energy market and market data is collected from [45]. We assume that each participant called for all ancillary services simultaneously and just for 8 times/day. On the other hand, as we are dealing with low capacity, system can participate in energy market in all day long. We select 30 random working days for winter (January 1 to May 30) and summer (June 1- September 30) in 2016 for the training data (Fig. 1) full winter and summer data of 2017 used for test. Solar irradiance data for Los Angeles area has been collected from Photovoltaic Geographical Information System (PVGIS) [46]. Mean value of PV generation and Load profile has been shown separately for winter and summer in Fig. 2. In RT cost function (16), penalty rate for import l^{Im} and export l^{Ex} both assumed as 0.15 \$/kWh and the threshold for deviation (i.e., $\vartheta^{Im}$and ϑ^{Ex}) are all set as 20% [48].

Table 1

Parameters of PV-battery system

Nominal Battery Capacity	30 kWh
Battery Charge Efficiency	85%
Battery Discharge Efficiency	95%
Initial State of Charge	16 kWh
Minimum SoC	15%
Maximum SoC	90%
PV array's and inverter nominal capacity	5 kW

The optimization is conducted with CVX integrated in MATLAB. MOSEK [47] has been chosen as solver for mixed-integer linear optimization problem. The environment is a desktop with Intel Core™ i5-2430 M, 2.4 GHz CPU and 8 GB RAM.

In this study, three optimization method including conventional deterministic, robust and DRO performed. Stochastic programming method neglected due to limitation of data and unavailability of accurate probability distribution. For deterministic solution, mean value of collected data has been used as reference value for markets. In robust programming, in line with ref [5], robustness gap $\pm 20\%$ is assumed as confidence gap in each hour both in DA and RT interval

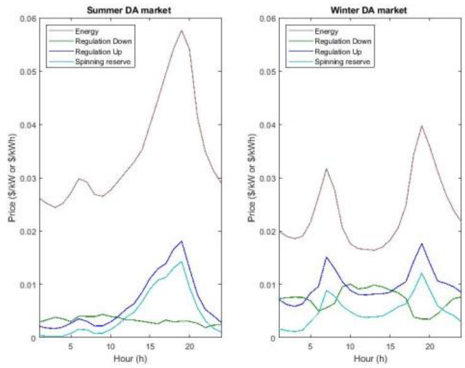


Fig. 1. Mean value of CAISO market in 2016 for Winter (left) and Summer (right) season.

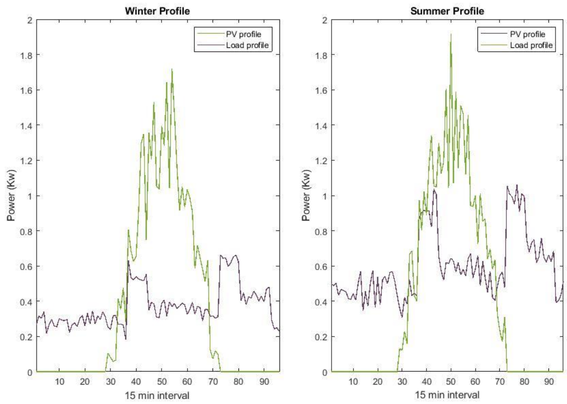


Fig. 2. Load and PV profile including forecasted uncertainties in RT interval, in left for winter period and in right for summer.

In final DRO formulation (29), the number of samples for each season including data set Ξ is limited to 30. The polytope parameter for each uncertainty sets C and d is assumed as one and the maximum of collected data respectively. In DRO, there is tradeoffs between final cost and robustness to price error. The conservativeness of the optimization is controlled by adjusting confidence level of CVaR α, the radius of Wasserstein ball ε and risk aversion value ζ. Here α and ε are assumed as 0.001 and ζ = 0.9.

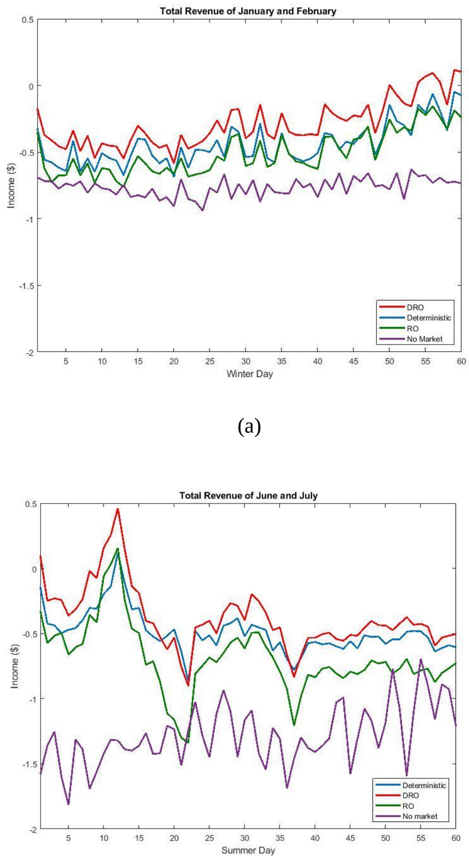
B. Numerical Results

The main aim of this research is to study the influence of the participation of battery in electricity market simultaneously with demand side management. In this regard, the feasible markets for participation in CAISO wholesale market are energy market, spinning reserve, regulation up and down both in day-ahead and real-time market. It is also important to consider different types uncertainties such as price, load and solar. In this way, first the conventional PV joint battery without participating in any market has been studied. Then we scheduled the battery for two different scenarios in winter and summer based on three different approach. In the first stage in DA, preliminary values for each power flow determined then MPC design to update the values due to updated values of load and PV production and RT market in each hour. Finally, the total revenue is calculated for two months in winter (January and February) and summer (June and July) based on real data of following year. The summery of test results for selected period of test is illustrated in Table 2. Moreover, daily revenue of these period has been shown in Fig2 and Fig3. These figures show that in all days, DRO method has a better result compare to others. However, RO lowest income compared with deterministic specially in summer due to conservativeness of this method. Consequently, the total result in all approaches shows higher revenue in case of participating in market instead only managing the demand load.

Table 2

Total Revenue in two months in winter and summer with different optimization approach

	No market	Deterministic	RO	DRO
Winter	-$45.85	-$26.41	-$30.41	-$17.35
Summer	-$77.13	-$29.41	-$41.52	-$22.72



(a)

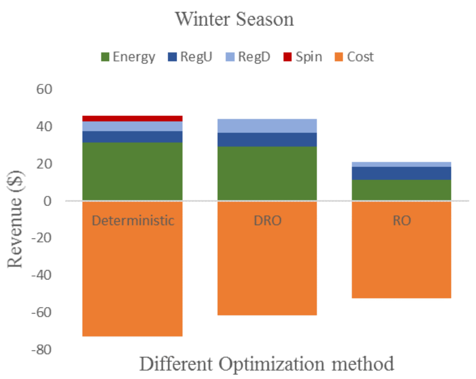
(b)

Fig. 3. Daily revenue of hybrid PV-battery system with and without participation in markets with different optimization approach in (a) Winter and (b) Summer.

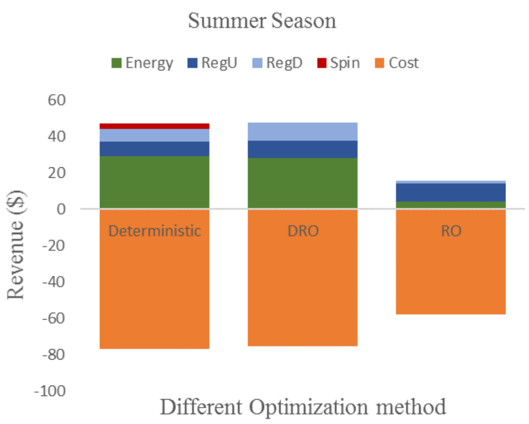
In the second part, we studied the influence of different market in total revenue. As we expected the maximum profit comes from energy market since in real market, each participant calls for ancillary services for limited time. The interesting point is that in DRO method it almost doesn't contribute in spinning reserve markets since it has high fluctuation and low price which is not considered in deterministic method. The other conclusion is that in general due to higher cost of energy in summer and higher load consumption, whole system participates less in energy market and more in regulation services since these markets have double payment both for power commitment and real-time dispatch.

conclusion

This paper proposed new approach for a short-term scheduling of PV-battery system in joint day-ahead and real-time energy, spinning and regulation markets along with demand side management. Date-driven distributionally robust optimization based on Wasserstein metric developed to deal with market uncertainties. This method has been compared with other conventional methods such as deterministic and robust optimization. The numerical results show the improvement of general performance in proposed solution both in winter and summer season. Moreover, it proved that in unpredictable area with limited data a degree of conservativeness is required. One remained challenge for future work would be design adoptive method for tuning of DRO parameters based on sample data.



(a)



(b)

Fig. 4. Segmented total revenue based on different market profit and importing energy costs for (a) winter and (b) summer season.

References

[1] Rocky Mountain Institue, "The conomics of battery energy storage," October 2015. [Online]. Available: http://bit.ly/2PdP1pm.

[2] D. Frankel and A. Wagner, "Battery storage: The next disruptive technology in the power sector," mckinsey & company, June 2017.

[3] H. Akhavan-Hejazi and H. Mohsenian-Rad, "Optimal Operation of Independent Storage Systems in Energy and Reserve Markets With High Wind Penetration," *IEEE Transactions on Smart Grid,* vol. 5, no. 2, March 2014 .

[4] Z. Wang, A. Negash and D. S. Kirschen, "Optimal scheduling of energy storage under forecast uncertainties," *IET Generation, Transmission & Distribution,* vol. 11, no. 17, p. 4220 – 4226, 30 November 2017.

[5] M. Kazemi, H. Zareipour, N. Amjady, W. D. Rosehart and M. Ehsan, "Operation Scheduling of Battery Storage Systems in Joint Energy and Ancillary Services Markets," *IEEE Transactions on Sustainable Energy* , vol. 8, no. 4, pp. 1726 - 1735, Oct. 2017.

[6] H. Mohsenian-Rad, "Optimal Bidding, Scheduling, and Deployment of Battery Systems in California Day-Ahead Energy Market," *IEEE Transactions on Power Systems,* vol. 31, no. 1, Jan. 2016.

[7] G. He, Q. Chen, C. Kang, P. Pinson and Q. Xia, "Optimal Bidding Strategy of Battery Storage in Power Markets Considering Performance-Based Regulation and Battery Cycle Life," *IEEE Transactions on Smart Grid,* vol. 7, no. 5, pp. 2359 - 2367, Sept. 2016.

[8] T. Zhao and Z. Ding, "Cooperative Optimal Control of Battery Energy Storage System Under Wind Uncertainties in a Microgrid," *IEEE Transactions on Power Systems,* vol. 33, no. 2, March 2018.

[9] J. M. Eyer, P. C. Butler and J. J. Iannucci, "Estimating electricity storage power rating and discharge duration for utility transmission and distribution deferral :a study for the DOE energy storage program.," U.S. Department of Energy Office of Scientific and Technical Information, November 2005.

[10] G. Carpinelli, F. Mottola, D. Proto and A. Russo, "Optimal allocation of dispersed generators, capacitors and distributed energy storage systems in distribution networks," in *Modern Electric Power Systems*, Wroclaw, Poland, 2010 .

[11] A. Nottrott, J. Kleissl and B. Washom, "Energy dispatch schedule optimization and cost benefit analysis for grid-connected, photovoltaic-battery storage systems," *Renewable Energy,* vol. 55, p. 2013, 230-240..

[12] E. L.Ratnam, S. R.Weller and C. M.Kellett, "An optimization-based approach to scheduling residential battery storage with solar PV: Assessing customer benefit," *Renewable Energy,* vol. 75, pp. 123-134, March 2015.

[13] V. Pradhan, V. S. K. M. Balijepalli and S. A. Khaparde, "An Effective Model for Demand Response Management Systems

of Residential Electricity Consumers," *IEEE Systems Journal,* vol. 10, no. 2, June 2016.

[14] J. Mitra and M. R. Vallem, "Determination of Storage Required to Meet Reliability Guarantees on Island-Capable Microgrids With Intermittent Sources," *IEEE Transactions on Power Systems,* vol. 27, no. 4, pp. 2360-2367, Nov. 2012.

[15] J. Mitra, "Reliability-Based Sizing of Backup Storage," *IEEE Transactions on Power Systems,* vol. 25, no. 2, pp. 1198 - 1199, May 2010.

[16] Z. Wu, H. Tazvinga and X. Xia, "Demand side management of photovoltaic-battery hybrid system," *Applied Energy,* vol. 148, pp. 294-304, 15 June 2015.

[17] M. Fisher, J. Apt and J. F.Whitacre, "Can flow batteries scale in the behind-the-meter commercial and industrial market? A techno-economic comparison of storage technologies in California," *Journal of Power Sources,* vol. 420, pp. 1-8, April 2019.

[18] Z. Wang, Q. Bian, H. Xin and D. Gan, "A Distributionally Robust Co-Ordinated Reserve Scheduling Model Considering CVaR-Based Wind Power Reserve Requirements," *IEEE Transactions on Sustainable Energy* , vol. 7, no. 2, April 2016.

[19] A. Alqurashi, A. H.Etemadi and A. Khodaei, "Treatment of uncertainty for next generation power systems: State-of-the-art in stochastic optimization," *Electric Power Systems Research,* pp. 233-245, December 2016.

[20] Q. P. Zheng, J. Wang and A. L. Liu, "Stochastic Optimization for Unit Commitment—A Review," *: IEEE Transactions on Power Systems* , vol. 30, no. 4, July 2015.

[21] Z. Chen, L. Wu and Y. Fu, "Real-Time Price-Based Demand Response Management for Residential Appliances via Stochastic Optimization and Robust Optimization," *IEEE Transactions on Smart Grid,* vol. 3, no. 4, Dec. 2012.

[22] G. Liu, Y. Xu and K. Tomsovic, "Bidding Strategy for Microgrid in Day-Ahead Market Based on Hybrid Stochastic/Robust Optimization," *IEEE Transactions on Smart Grid,* vol. 7, no. 1, Jan. 2016.

[23] P. Malysz, S. Sirouspour and A. Emadi, "An Optimal Energy Storage Control Strategy for Grid-connected Microgrids," *IEEE Transactions on Smart Grid,* vol. 5, no. 4, pp. 1785 - 1796, July 2014.

[24] H. Alharbi and K. Bhattacharya, "Stochastic Optimal Planning of Battery Energy Storage Systems for Isolated Microgrids," *IEEE Transactions on Sustainable Energy* , vol. 9, no. 1, Jan. 2018.

[25] W. Su, J. Wang and J. Roh, "Stochastic Energy Scheduling in Microgrids With Intermittent Renewable Energy Resources," *IEEE Transactions on Smart Grid,* vol. 5, no. 4, pp. 1876 - 1883, July 2014.

[26] D. Bertsimas, E. Litvinov, X. A. Sun, J. Zhao and T. Zheng, "Adaptive Robust Optimization for the Security Constrained Unit Commitment Problem," *IEEE Transactions on Power Systems,* vol. 28, no. 1, Feb. 2013.

[27] P. Mohajerin-Esfahani and D. Kuhn, "Data-driven distributionally robust optimization using the Wasserstein metric: performance guarantees and tractable reformulations," *Mathematical Programming,* vol. 171, no. 1-2, Sep 2018.

[28] E. Delage and Y. Ye, "Distributionally Robust Optimization Under Moment Uncertainty with Application to Data-Driven Problems," *Operations Research,* vol. 58, no. 3, Jan 2010.

[29] W. Wiesemann, D. Kuhn and M. Sim, "Distributionally Robust Convex Optimization," *Operations Research,* vol. 62, no. 6, Oct 2014.

[30] W. Wei, F. Liu and S. Mei, "Distributionally Robust Co-Optimization of Energy and Reserve Dispatch," *IEEE Transactions on Sustainable Energy,* vol. 7, no. 1, Jan. 2016.

[31] Y. Zhang, S. Shen and J. L. Mathieu, "Distributionally Robust Chance-Constrained Optimal Power Flow With Uncertain Renewables and Uncertain Reserves Provided by Loads," *IEEE Transactions on Power Systems* , vol. 32, no. 2, March 2017.

[32] Z. Wang, P. W. Glynn and Y. Ye, "Likelihood robust optimization for data-driven," *Computational Management Science,* vol. 13, no. 2, April 2016.

[33] E. Erdoğan and G. Iyengar, "Ambiguous chance constrained problems and robust optimization," *Mathematical Programming,* vol. 107, no. 1-2, p. 37–61, June 2006.

[34] Z. Hu and L. J. Hong, "Kullback-Leibler divergence constrained distributionally robust optimization," *Optimization Online,* 2013.

[35] D. Wozabal, "A framework for optimization under ambiguity," *Annals of Operations Research,* vol. 193, no. 1, p. 21–47, March 2012.

[36] Y. Guo, K. Baker, E. Dall'Anese, Z. Hu and T. H. Summers, "Data-Based Distributionally Robust Stochastic Optimal Power Flow—Part I: Methodologies," *IEEE Transactions on Power Systems* , vol. 34, no. 2, March 2019 .

[37] L. Yao, X. Wang, C. Duan, J. Guo, X. Wu and Y. Zhang, "Data-driven distributionally robust reserve and energy scheduling over Wasserstein balls," *IET Generation, Transmission & Distribution,* vol. 12, no. 1, Jan 2018.

[38] A. Shapiro, "Distributionally Robust Stochastic Programming," *SIAM Journal on Optimization,* vol. 27, no. 4, Oct 2017.

[39] Federal Energy Regualtory Commission, "Order No. 841 - Federal Energy Regulatory Commission," 15 February 2018. [Online]. Available: http://bit.ly/2JByncW.

[40] N. Y. I. S. Operator, "Market Participants User's Guide," 2018. [Online]. Available: https://www.nyiso.com/documents/20142/3625950/mpug.pdf/. [Accessed 2019].

[41] "PJM Manual 11: Energy & Ancillary Services Market Operations, Revision: 87," March 23 2017. [Online]. Available: http://bit.ly/2EV6Cu7.

[42] "Tariff - Fifth Replacement FERC," California Independent System Operator Corporation Electric,, 2019. [Online]. Available: http://www.caiso.com/Documents/ConformedTariff-asof-Mar1-2019.pdf.

[43] Federal Energy Regualtory Commission, "FERC order 755," 20 October 2011. [Online]. Available: http://bit.ly/2QhOhvz.

[44] R. T. Rockafellar and S. Uryasev, "Optimization of conditional value-at-risk," *Journal of risk,* vol. 2, pp. 21-42, April 2000.

[45] "California ISO Open Access Same-time Information System (OASIS)," CAISO, [Online]. Available: http://oasis.caiso.com/mrioasis/logon.do.

[46] "PHOTOVOLTAIC GEOGRAPHICAL INFORMATION SYSTEM," European Commission, July 2019. [Online]. Available: https://re.jrc.ec.europa.eu/pvg_tools/en/tools.html.

[47] "MOSEK Optimization Toolbox for MATLAB. Version 9.0.104," MOSEK ApS, Agu 2019.

[48] S. I. Vagropoulos and A. G. Bakirtzis, "Optimal Bidding Strategy for Electric Vehicle Aggregators in Electricity Markets," *IEEE Transactions on Power Systems*, vol. 28, no. 4, Nov. 2013.

[49] H. Oh, "Optimal Planning to Include Storage Devices in Power Systems," *IEEE Transactions on Power Systems* , vol. 26, no. 3, pp. 1118 - 1128, Aug. 2011.

[50] Y. Levron, J. M. Guerrero and Y. Beck, "Optimal Power Flow in Microgrids With Energy Storage," *IEEE Transactions on Power Systems*, vol. 28, no. 3, Aug. 2013.

Contents

Introduction

In the last decade, PV cell installation has experienced an average annual growth rate of 50%. At the meantime, in the U.S. the average cost of PV system drops to its lowest level in history in Q1 2019. An average-sized residential system has dropped from a pre-incentive price of $40,000 in 2010 to roughly $18,000 today, while recent utility-scale prices range from $28/MWh - $45/MWh, competitive with all other forms of generation [1]. On the other hand, the grid-scale battery storage systems are expected to grow to 12 GW by year the 2024 [2]. Two main factors slowed down grid-connected battery systems' development in the past decade, high capital cost and lack of regulatory initiatives. By recent development in battery technologies, they have reached to a point that their costs have become more attractive. It is also estimated that the installation cost of battery storage systems will drop by 25% by 2017, compared to 2015 [3]. Accordingly, in some developed markets such as California, U.S., the revision of the market regulation is already started. In the road map of CAISO on BESS [4], the necessity of clarifying the existing ISO requirements, rules and market products for participation of energy storage in the market as well as defining and developing models for multi-contribution of storage systems are mentioned as two important factors toward the maximum participation of BESS in the market. Consequently, there has been a growing interest in finding new and efficient applications for batteries in power systems.

The main aim of this research is to investigate the possible additional revenues for behind the meter's (BTM) battery storage system joint with rooftop PV in well-developed grid and regulations such as California wholesale energy market. Traditionally, BTM batteries just had been used for improving PV cell self-consumption and back-up usage. In such condition, these assets remained intact for most of the hours of day and they couldn't show their maximum performance. In the recent year, by new changes in market regulations, these assets are allowed to participate in various electricity markets such as spinning reserve and frequency regulation.

This research conduct between Winston Chung Global Energy Centre (WCGEC) in the University of California in Riverside and Politecnico di Milano to propose a practical solution for BTM batteries for joint participation in the electricity market and manage demand side load. In this way, different electricity market had been reviewed and CAISO market has been chosen as a reference due to it is recent regulatory development toward battery participation in the market and highly installation of rooftop PV in this region. The main challenge toward finding the most accurate and feasible solution in this problem is the stochastic nature of the problem and different types of uncertainties. Mainly, these uncertainties come from intermittency of PV production, load fluctuation, and the most challenging which the market price instabilities. To deal with these parameters different optimization approaches had been reviewed and finally, novel data-driven distributionally robust optimization (DRO) had been developed for proposed problem.

This thesis is organized as follows, in **Chapter 1** a comprehensive comparison between different electricity market has been done. In this chapter first different regional markets in North America introduced and the market process has been described and then the European market and specifically Italian market studied for further global comparison. In **Chapter 2** different possible usage for battery energy storages based on deployment location studied. In **Chapter 3**, different proposed optimization methods in the literature studied and the proposed DRO method described. In **Chapter 4**, the fundamental problem model formulation and different optimization approaches to solve the problem have been described. In **Chapter 5** and **Chapter 6**, the feasibility proposed methodology has been tested with respect to real demand and market data in different scenarios as well as simulation results and finally in **Chapter 7** the conclusion discussed.

1 Electricity Market

In an ideal world, the required energy could be traded in a real-time and nodal based price. In fact, the energy value changes in each node of the network because of the location of load which shows the loss and delivery cost and uncertainty of production and requested energy. However, this kind of ideal market design is not possible in the real world and some standardizations must be introduced. The standardization can be on:

- Temporal basis: markets do not refer to instants of time but to time intervals (from 1 hour until 5 minutes time steps);
- Spatial basis: some markets refer to grid nodes (US markets in general), others to market zones, which are market areas where there should not be congestions (like the Italian market), others still to the whole country (like the German energy market). The larger is the zone area, the more probable is that some congestions inside the area itself will occur.

If nodal market is adopted, further interventions - like re-dispatch - to ensure the line constraints respect are not needed and a reduction of the system costs is more probable. However, zonal markets are simpler to manage (also as regard to computational efforts) and, hence, more adopted in the European Union. For these reasons, the European electricity system is administrated in two essential phases separated by the so-called gate closure, as shown in Figure 1-1.

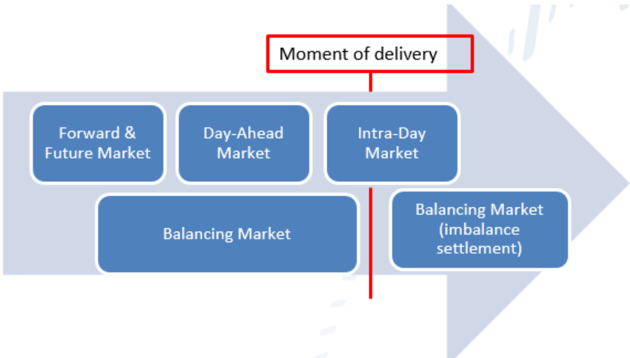


Figure 1-1- Temporal ordering of the different electricity market

The first phase before gate closure is characterized by electricity market transactions (decentralized decisions) and system operations (central coordination) prevails in real-time. Meanwhile, there is also a preliminary phase, known as a forward and future markets that runs years to days ahead of delivery time. Forwards and futures are contracts to deliver/consume a certain amount of electricity at a certain time in the future for a price agreed upon today, reducing the vulnerability to possible energy price decrease/increase to those generators and large consumers which choose these forms of negotiation. The difference between these markets is that futures are standardized contracts that can be further traded on power exchanges, whereas forwards are mainly traded by means of bilateral over-the-counter (OVC) non-standardized contracts, giving more flexibility to the involved parties.

In general, developed electricity markets have been designed based on two phases, these phases of the electricity market are subdivided into two different markets: The Day-Ahead spot Market (DAM) and the intra-day market. In DAM, each participant submits its bid for specific amount of energy which can be delivered to grid for following day. At the end of the DAM, each operator submits a balanced portfolio to the TSO, the so-called nominations, which give the planned generation or consumption for the following day. In general, DAM has important role in providing foreseen demand and the system-wide dispatching decisions of the various generators. However, DAM cannot ensure the reliability and security of service. These advantages can be enhanced by means of an Intra-day Market (IM), which allows market participants to correct their energy bids near the gate closure. In this second market, indeed, electricity is traded on the delivery day itself, enabling market participants to correct for shifts in their day-ahead nominations due to better forecasts and unexpected plant outages. The intra-day nominations are added to the day-ahead nominations. After the real-time, the unbalance discipline, that is the difference between the scheduled and the real energy exchanges, occurs. Such operations assume a role (and a cost) as much important as the previous markets do not consider the real actual conditions.

Currently, the electricity market in Europe is mainly an energy-only market, meaning that generators are remunerated for generated electric energy. The alternative is a capacity market in which power units are remunerated for the capacity commitment which is already using in CAISO is explained in following sub-section. The remuneration price can be formed according with two different mechanisms, as shown in Figure 1-2:

1. *System Marginal Price* (SMP): In this method, there is a uniform price which is the market clearing price and obtained by the intersection between the demand and the supply curves. This intersection identifies the equilibrium situation of the market. Awarded bids/offers are those having a selling price not higher than the clearing price and a purchasing price not lower than the equilibrium price.
2. *Pay as Bid* (PAB); is a discriminatory price mechanism. The awarded bids are valued at the offered price, so the operator is induced to present its offer betting on the maximum price of the last accepted bid. In this way, it is more probable that

the offered bids are higher than the marginal costs of the generation units where the offered price would be the variable cost plus a mark-up arbitrarily defined to recover the fixed costs.

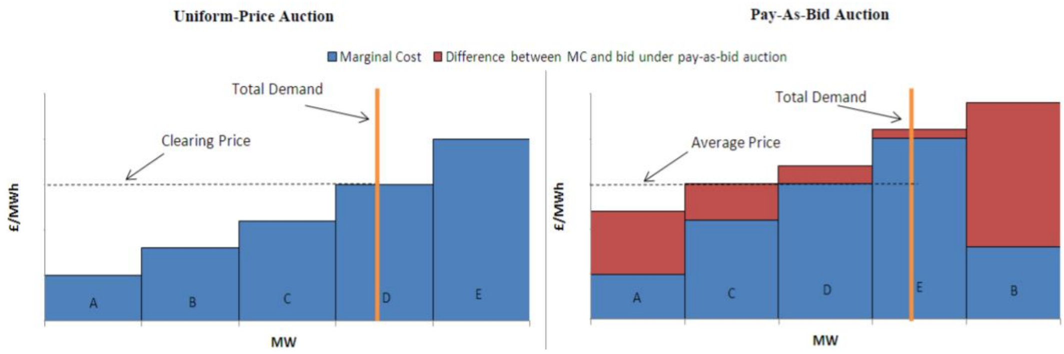


Figure 1-2- Comparison of System Marginal Price and Pay as Bid

Both SMP and PAB method has their own advantages. In SMP, there is more transparent market and in average and less competitive market the total cost would decrease. On the other hand, PAB gives more chance to different participants to influence on market and in highly compatible market it can ensure more reliable and cheaper energy.

In this research, the main focus is on California electricity market based on California Independent System Operator (CAISO) regulation. The wholesale energy and ancillary service market for BESS reviewed and the most updated regulations have been used for modelling. In the rest of this chapter, first north America electricity market and CAISO described in section 1.1 and then in second section (1.2) EU and Italian market studied for further comparison of results.

1.1 Energy and Ancillary Services Market Design in North America

The US electric power system is widely understood to be complex but is rarely represented in its entirety with appropriate regional and industry segment variations; nor is the control structure of what is commonly referred to as “the grid” available in a single depiction. Certain aspects are widely depicted, however, as illustrated in the two figures below. The US power grid is divided geographically at many levels, the top three of which are interconnections, reliability regions, and balancing authority areas. Each interconnection is a single synchronous machine, and the three interconnections in the contiguous states are controlled separately, although power exchanges between interconnections are provided via inter-tie stations [5]

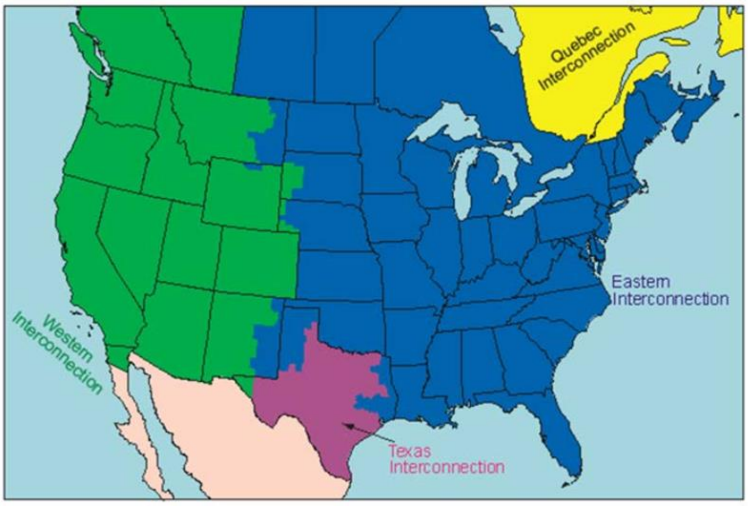


Figure 1-3- US Interconnections

Within interconnections, grids are divided into reliability regions, with reliability coordinators overseeing each. Reliability coordinators have an event-driven kind of control function, in which they continuously monitor grid state within their regions, and perform various operational and contingency analyses, issuing alerts and directives when certain reliability issues occur or are forecasted to occur. Within the reliability regions, grids are further broken into Balancing Authority Areas, each with a Balancing Authority (BA) that performs certain control functions, including generation dispatch and balance, interchange scheduling with neighbouring balancing authority areas, and load frequency control. Various changes to BA structure have been investigated.

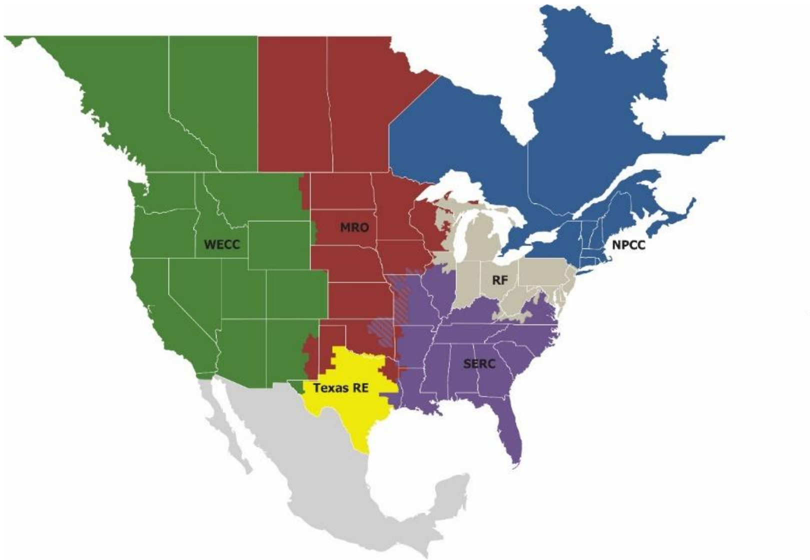


Figure 1-4- Reliability Regions and Balancing Authorities [6]

On the other hand, there are seven distinct power markets in the United States (Figure 1-5). In addition, there are three similar markets located within Canada. These markets are each operated by an Independent System Operator (ISO) or Regional Transmission Organization (RTO), hereafter jointly referred to as an ISO/RTO, which manages the transmission infrastructure in its service territory, administers markets for energy and ancillary services, and is responsible for ensuring that system reliability requirements that are established by North American Electric Reliability Corporation (NERC) are met. With the exception of the Electric Reliability Council of Texas (ERCOT) system in Texas, each ISO/RTO is subject to the jurisdiction of the Federal Energy Regulatory Commission (FERC). As the ERCOT system is wholly contained within a single state, it does not participate in interstate commerce and is therefore not subject to FERC jurisdiction. Roughly two-thirds of all energy demand in the United States falls in territory served by an ISO/RTO; however, large portions of the Western and South-eastern United States are not served by an ISO/RTO. Generators and utilities in these regions do not participate in wholesale power markets, but rather fulfil service obligations through power purchase agreements, bilateral trades, and as vertically integrated utilities. Each ISO/RTO operates markets for ancillary services. While these services typically fall into the three general categories outlined previously, Regulation, Spinning Reserves, and Non-spinning Reserves, the names and details of each service can differ from market to market. Table 3 summarizes the services offered in each ISO/RTO.

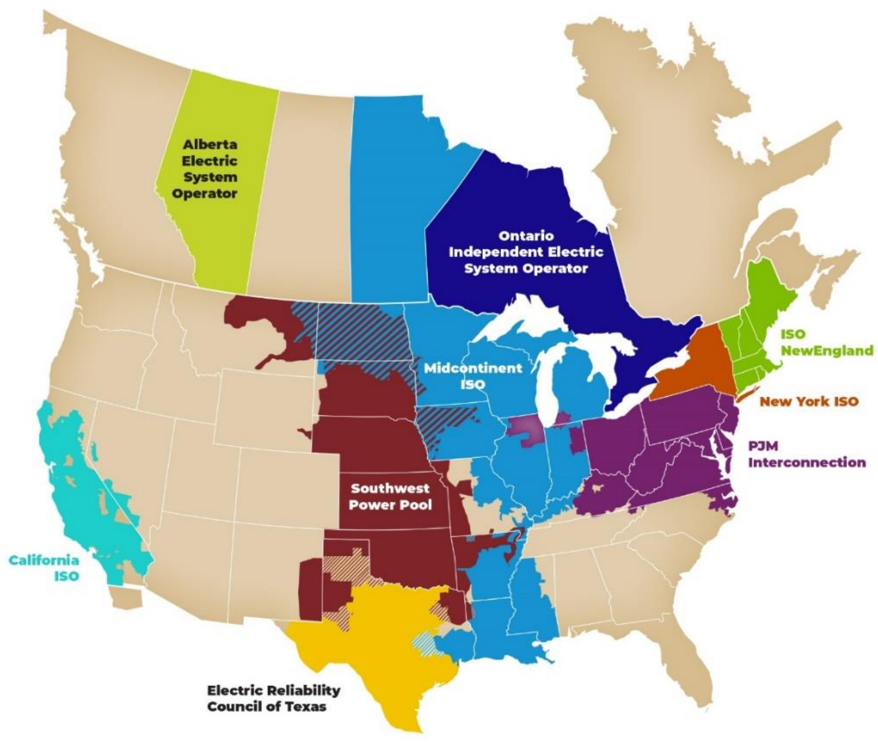


Figure 1-5 - Map of the transmission operators that serve the United States

ISO/TSO	Spinning Reserves	Non-Spinning Reserves	Frequency Regulation
CAISO	Spinning	Non- Spinning	Regulation-up Regulation-down Regulation Mileage-up Regulation Mileage-down
ERCOT	Responsive	Non- Spinning	Regulation-up Regulation-down
ISO-NE	Ten-minute Synchronized	Ten-minute Non-synchronized Thirty-minute Operating	Regulation
MISO	Spinning	Supplemental	Regulation
NYISO	Ten-minute Spinning Thirty-minute Spinning	Ten-minute Non-synchronized Thirty-minute Non-synchronized	Regulation
PJM	Synchronized	Primary	Regulation
SPP	Spinning	Supplemental	Regulation-up Regulation-down

Table 3- Overview of the ancillary services offered by each ISO/RTO

It is also worth to introducing North America institutions and agreements before covering each regional market. The most important and critical institutions and agreements are listed below:

- **North American Electric Reliability Corporation (NERC)**: A not-for-profit international regulatory authority that seeks to assure the reliability of the bulk power system in North America, including the continental United States, Canada, and the northern portion of Mexico in Baja, California. NERC is the official electric reliability organization for North America, and receives oversight from FERC as well as Canadian government authorities. NERC's responsibilities include the development and enforcement of reliability standards, annual assessment of seasonal and long-term reliability, monitoring of the bulk power system, and the education, training, and certification of industry workers [7]. The NERC Reliability Regions are shown in Figure 1-4.
- **North American Free Trade Agreement (NAFTA)**: In effect since January 1, 1994, NAFTA is a trilateral free trade agreement between Canada, the United States, and Mexico, which sets the rules of trade and investment in the three countries. NAFTA limited tariffs on a majority of goods traded trilaterally, and called for the gradual elimination (over 15 years) of most remaining barriers to

cross-border investment, as well as the movement of goods and services. While the agreement was, and continues to be highly controversial in all three countries, it is credited with modest economic gains and labor market restructuring [8]. Mexico, due to constitutional restrictions at the time, took exception to opening the oil and gas drilling sector to foreign competition, but trade in crude oil and natural gas was covered by the agreement, and did increase over the following two decades. Electricity trade was also included under tariff elimination rules under NAFTA, though its classification can become complicated as different elements of the power sector (generation, transmission, and distribution) defy simple definitions as "goods" or "services." There are, however, a number of conditions where NAFTA members may restrict or prohibit electricity flows, including cases where the energy is being resold to a non-NAFTA member, or where restricting trade will relieve critical shortages. Mexico – which entered NAFTA before the recent energy reforms -- also filed "reservations" on strategic activities to reserve the right to supply electricity within Mexico and exclude foreign parties from entering the sector, except under excepted circumstances [9].

- **Open Access non-discriminatory Transmission Tariff (OATT)**: On April 24, 1966, FERC issues Order No. 888 [10], which required public utilities to "provide open access transmission service on a comparable basis to the transmission service they provide themselves". This includes a requirement that public utilities that own transmission infrastructure file open access transmission tariffs that contain minimum terms and conditions for non-discriminatory service; and allows public and transmitting utilities to seek recovery of "legitimate, prudent, and verifiable stranded costs associated with providing open access". Order No. 888 was reformed slightly in 2007 to reflect recent changes in the utility industry, which were adopted in Order No.890 [11, 12].

1.1.1 Electricity Reliability Council of Texas (ERCOT)

The Electricity Reliability Council of Texas (ERCOT) was established in its current form as a power market operator in 2001. ERCOT currently serves approximately 85% of the electrical load in Texas and, as its service territory is entirely within the state of Texas, is the only ISO/RTO in the United States that is not regulated by FERC. ERCOT operates a DAM for four ancillary services, Responsive Reserves, Regulation-up, Regulation-down, and Non-spinning Reserves. These services are co-optimized along with energy provisions in the DAM. In addition, ERCOT implemented a real-time Operating Reserve Demand Curve (ORDC) methodology in 2014. Through this process, price adders are generated to reflect the value of available reserves in the market in real time. These price adders are based on the administratively determined value of lost load in the system and the probability that load would have to be shed, given the realized reserve levels. Price adders are calculated for both online (synchronized) and offline (unsynchronized) reserves and are added to the real-time locational marginal price (LMP) to determine settlement price points. This process is intended to approximate the co-optimization of energy and reserves in real-time. ERCOT is subject to reliability standards that are developed by the Texas Reliability Entity, Inc. (Texas RE) through FERC approved processes. According to Texas RE, its standards “go beyond, add detail to, or implement NERC Reliability Standards.” ERCOT also updated their procedure for determining reserve requirements on June 1, 2015. The following discussion reflects these updated procedures.

There is only a single ERCOT region related to ancillary services, which spans the entire ERCOT service territory (Figure 1-6). The real-time ORDC price adders for Spinning and Non-spinning Reserves are added to the real-time energy LMPs that are calculated for each energy settlement point. A single system-wide price adder is calculated for both Spinning and Non-spinning Reserves. These are then each added to energy prices at each node throughout the ERCOT system. [13, 14, 15]

Figure 1-6- Map of the ERCOT service territory

1.1.1.1 ERCOT Market Process

In the DAM, ERCOT establishes an Ancillary Services Plan and publishes relevant system information each day by 0600 hours Central time. This Ancillary Services Plan identifies the ancillary service obligations of all Qualified Scheduling Entities3 (QSEs) during each hour of the following day. QSEs can meet their obligations either through self-supply, bilateral trades with other QSEs, or purchases from ERCOT through the DAM. QSEs must submit their bids and offers for ancillary services by 1000 hours Central time. The day-ahead market is executed between 10:00 and 13:30 hours Central time, at which point results are posted. QSEs then have the opportunity to make bilateral trades with other QSEs based upon the results of the day-ahead market; any such trades must be reported to ERCOT by 14:30 hours Central time. In real-time operations security constrained economic dispatch (SCED) is conducted every five minutes and two price-adders are calculated based on the reserve levels that are realized during each settlement period—currently every 15-minute interval. One adder is calculated based on the realized level of online reserves and the other is calculated on the basis of the sum of the realized levels of online and offline reserves. These adders are then added to the LMP-based energy price that is paid to generating entities and charged to load-serving entities in each settlement period. If the Responsive Reserve level falls below a 2000 MW minimum contingency in any period, ERCOT will set the price adder to the administratively determined value of lost load (VOLL) in the system, which is currently $9000/MWh.

1.1.2 ISO New England (ISO-NE)

ISO New England (ISO-NE) was established in 1997 and began operating a wholesale power market in 1999. It currently operates a forward reserve market and a real-time reserve pricing market, as well as a regulation market.

The forward reserve market secures commitments for Ten-minute Non-synchronized Reserves (TMNSR) and Thirty-minute Operating Reserves (TMOR) in the system during peak hours. A real-time reserve pricing market is also conducted throughout the operating day for both TMNSR and TMOR, as well as for an additional product, Ten-minute Synchronized Reserves (TMSR). This market is designed to offset the opportunity cost a resource faces when it is selected to provide reserves instead of energy in real-time. It also provides additional revenues that are consistent with the increased value of reserves and energy when the system is short.

1.1.2.1 ISO-NE Market Process

A forward market auction for reserve (non-energy) capacity occurs twice per year, prior to the beginning of each seasonal capability period. These periods run from June through September (summer) and October through May (winter). Forward reserve resources are assigned hourly schedules one day in advance of the operating day. The market is designed to set threshold prices at approximately the marginal cost of a peaking plant with a 2–3% capacity factor.

In real-time operations, ISO-NE co-optimizes energy and reserves, finding the least-cost means of serving energy demand and meeting reserve requirements for TMSR (whole-system), TMNSR (whole system) and TMOR (whole-system and the three specified zones). If necessary, the system will redispatch resources to increase the amount of reserves that are available. This typically involves reducing the output of fast-response resources, which may increase the real-time energy LMP. There are administratively defined limits on these potential LMP increases, known as Reserve Constraint Penalty Factors. In addition to these real-time reserve prices, a regulation clearing price is also calculated on the basis of the offer of the highest marginal cost resource providing regulation capacity in each 5-minute settlement period [16, 17].

1.1.3 Midcontinent Independent System Operator (MISO)

The Midcontinent Independent System Operator (MISO) operates an Ancillary Services Market for Regulation and Contingency Reserves, which began operation in 2009. Currently, MISO operates both a DAM and RTM for ancillary services, which are simultaneously co-optimized with its Day-ahead and Real-time energy market. MISO's contingency reserve consists of two separate products for Spinning Reserves and Supplemental (Non-spinning) Reserves.

MISO manages the transmission network and energy markets throughout a geographic area from Montana to Michigan, and Manitoba, Canada. In late 2013, MISO expanded to include the new MISO South sub-region, which spans portions of Texas, Louisiana, Mississippi, and Arkansas. MISO determines the ancillary service requirements on both a system-wide level and a zonal level. Figure 1-7 illustrates the MISO reserve zones, also known as MCP zones. Separate MCPs are calculated for Regulating, Spinning and Supplemental Reserves in each zone. There are seven such zones in MISO related to ancillary services provision.

1.1.3.1 MISO Market Process

In the MISO market, resource owners who wish to participate in the DAM must submit offers no later than 11:00 hours EST on the day prior to the operating day for use in clearing the market. At 15:00 hours EST, the results for the DAM are posted. From 15:00 to 16:00 hours EST, participants can revise offers for RAC Post Day-Ahead (with knowledge of DAM results).

MISO calculates ex-ante and ex-post MCPs for Regulation Reserves, Spinning Reserves and Supplemental Reserves at all Resource nodes in the system. These ancillary service prices are determined through co-optimization with the energy market using a SCED-pricing algorithm, in both Day-ahead and Real-time operations. In the Day-ahead Operating Reserve Market, ex-ante MCPs and expost MCPs are calculated on an hourly basis. In the Real-time Operating Reserve Markets, MCPs are calculated for each five-minute dispatch interval on both an ex-ante and ex-post basis.

Figure 1-7 – MISO reginal map [18]

When the market is short of one or more of its ancillary service products, MISO uses an administratively defined demand curve to set prices. This price of each ancillary service is also included in the price of all higher-valued reserves and the energy price because of co-optimized market clearing. The demand curves are designed such that first, under abundant conditions, the supply curve sets the price and the demand curve determines the amount supplied, and second, under scarcity conditions, the demand curve sets the price and the supply curve determines the amount supplied. Separate demand curves are applied both to the entire market (Market-Wide Operating Reserve, etc.) and to each Reserve Zone (Zonal Operating Reserve, etc.) [19, 20].

1.1.4 New York ISO (NYISO)

In December 1999, New York ISO (NYISO) took over responsibility for the electric grid in New York. NYISO operates DAMs for both ancillary services and energy, which are co-optimized. In February 2005, a number of enhancements to the RTM systems were implemented, and a two-settlement system was designed for the Reserve and Regulation Markets. NYISO operates markets for Regulation Reserves and four Operating Reserve products: Ten-minute Spinning Reserves, Ten-minute Non-synchronized Reserves, Thirty-minute Spinning Reserves, and Thirty-minute Non-synchronized Reserves [21].

NYSIO consists of three zones for reserve products:

1. West of Central-East (West or Western)

2. East of Central-East, Excluding Long Island (East or Eastern)

3. Long Island

NYISO determines separate DAM and RTM prices for Regulation and each of the three Operating Reserve products in the East and West regions. NYISO also calculates separate reserve prices in the Long Island Region but does not post them or use them for settlement purposes. The regions are illustrated in Figure 1-8.

Figure 1-8 – NYISO East, West, and Long Island regions [22]

1.1.4.1 NYISO Market Process

Ancillary services are procured through a DAM, HAM, and RTM. The DAM ancillary service prices are posted at approximately 1100 hours Eastern time for the East and West regions. In the DAM, resources may submit availability bids for each hour of the upcoming day. NYISO selects operating reserve suppliers for each hour of the upcoming day through a co-optimized day-ahead commitment process that minimizes the total cost of energy, operating reserves, and regulation service, according to the bids submitted by market participants. The HAM ancillary service prices are posted approximately 75 minutes before each Real-time Commitment (RTC) interval for the East and West regions.

The RTM ancillary service prices for the selected date are posted every five minutes for the East and West regions. NYISO will automatically select operating reserve suppliers in the RTM from eligible resources. All suppliers will automatically be assigned a real-time operating reserves availability bid of $0/MW. Suppliers will thus be selected based on their response rates, their applicable upper operating limit, and their energy bid (which will reflect their opportunity costs). This selection takes place through a co-optimized RTC and dispatch process that minimizes the total cost of energy, regulation, and operating reserves.

In order to balance operating reserve settlements, when the real-time schedule is less than the day-ahead schedule, the supplier pays a charge for the imbalance equal to the product of (i) the RTM Clearing Price for the relevant operating reserves product in the relevant location and (ii) the difference between the supplier’s day-ahead and real-time operating reserves schedules. When the supplier’s real-time operating reserves schedule is greater than its day-ahead operating reserves schedule, the NYISO pays the supplier for the imbalance equal to the product of (i) the RTM clearing price for the relevant operating reserve product in the relevant location and (ii) the difference between the supplier’s day-ahead and real-time operating reserves schedules [23, 24].

1.1.5 Pennsylvania New Jersey Maryland (PJM)

PJM implemented several coordinated ancillary service markets in 2001 to co-optimize the provision of energy, regulation and operating reserves. These include a Day-Ahead Energy Market, Real-Time Energy Market, Forward Regulation Market, Forward Synchronized Reserve Market, and Forward Day-Ahead Scheduling Reserve Market. Both generation and demand resources are allowed to participate in each ancillary service market with eligibility validation. Load-serving entities are obliged to acquire a share of the PJM ancillary services requirement in any of three ways: self-scheduling the entity’s own resources; bilateral contracts to purchase services from other participants; and purchasing services from the ancillary service markets. The share of obligation is determined on the basis of the entity’s total load in the PJM RTO.

PJM consists of two zones for reserve products:

1. PJM RTO

2. PJM Mid-Atlantic Dominion (PJM MAD)

The PJM RTO zone spans the entire PJM territory (including PJM MAD), while PJM MAD is a sub-zone covering the eastern portion of the PJM territory. PJM applies a unified regulation requirement for the whole PJM RTO region. Owing to potential deliverability issues, PJM also established the MAD sub-zone for synchronized reserve and primary reserve services, as illustrated in Figure 1-9.

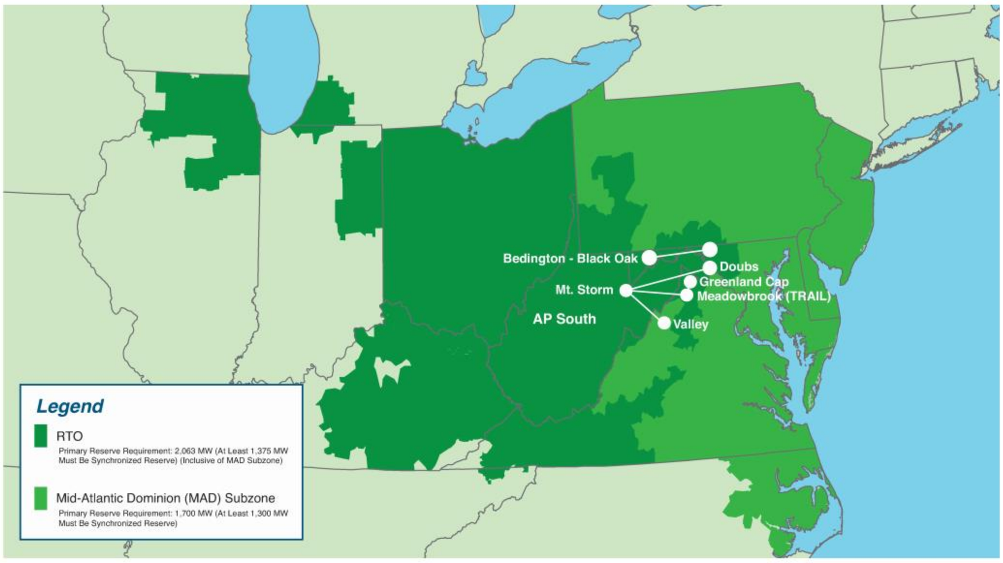


Figure 1-9 - PJM RTO territory and MAD Sub-Zone

1.1.5.1 PJM Market Process

PJM secures energy and reserve through coupled market-based processes [25, 26]. Specifically, PJM's scheduling of energy and reserve for each operating day D is handled by means of a forward Day-Ahead Energy Market (DAEM), a Real-Time Energy Market (RTEM), a forward Regulation Market, a forward Synchronized Reserve Market, a forward Day-Ahead Scheduling Reserve Market (DASRM), and an hourly re-scheduling process.

The DAEM, which produces energy prices and energy commitment and dispatch levels for each hour H of an operating day D, closes at hour 12 on day D-1 [25]. Up to this close, market participants can submit energy demand bids and energy supply offers for each hour of day D. After this close, PJM performs analysis to clear the DAEM. The market-clearing prices for the DAEM are LMPs calculated as the shadow prices for nodal energy balance constraints.

The RTEM is a balancing mechanism in which market-clearing LMPs for imbalance energy are calculated every five minutes based on actual system conditions [27]. Separate daily accounting settlements are performed for the DAEM and RTEM markets. The DAEM settlement is based on scheduled hourly quantities and on day-ahead hourly prices, whereas the RTEM settlement is based on actual hourly quantity deviations from day-ahead scheduled quantities and on hourly real-time LMPs calculated from the five-minute real-time LMPs determined for each hour.

In Day-Ahead Scheduling Reserve Market (DASRM), ancillary service prices and cost-related data must be supplied by 18:00 hours Eastern time one day ahead of operation and are applicable for the entire 24-hour period. All data can be revised until 60 minutes before the operating hour. Sixty minutes prior to the operating hour, PJM executes the Ancillary Services Optimizer to jointly optimize energy, Synchronized Reserves, Primary Reserves, and Regulation on the basis of forecasted system conditions to determine an economical set of inflexible reserve resources to commit for the operating hour.

In the PJM regulation market, resource owners also submit specific offers for regulation capability and regulation performance. PJM optimizes the RTO dispatch profile and forecasts LMPs to calculate an hourly regulation market clearing price (RMCP), regulation market performance clearing price (RMPCP), and regulation market capability clearing price (RMCCP). For each hour, RMCP is the total of RMPCP and RMCCP.

PJM calculates real-time prices for Synchronized Reserves and Primary Reserves simultaneously with the LMP every five minutes in real time. When there is no Synchronized Reserve shortage, the prices will be determined by the cost of the marginal Synchronized Reserve resource, which is defined as the Synchronized Reserve offer plus any opportunity cost for this resource relative to forgone energy or other ancillary service payments. When there is no Primary Reserve shortage, the prices will be determined by the cost of the marginal Primary Reserve resource, which is defined as the opportunity cost for this resource relative to forgone energy or other ancillary service payments. When there is a shortage in Synchronized Reserves, then the price will be the sum of the Primary Reserve and Synchronized Reserve penalty factors. When there is a shortage in Primary Reserves, the Primary Reserves price will be equal to the penalty factor of the location where the shortage occurred [28, 27].

1.1.6 Southwest Power Pool (SPP)

In March 2014, the Southwest Power Pool (SPP) began operating an Integrated Marketplace that conducts a market-based procurement of three types of ancillary services:

Regulation (Regulation-up and Regulation-down), Spinning Contingency Reserves, and Non-spinning Contingency Reserves. These services are supplied by generators and are purchased by SPP on the basis of a pre-determined requirement. The market-based mechanisms for ancillary service procurement are part of the SPP Integrated Marketplace, whereby ancillary services are introduced in conjunction with the SPP's day-ahead energy and the real-time balancing markets. Furthermore, SPP co-optimizes procurement of ancillary services with day-ahead and real-time energy. Regulation is a power supply product that is used to continuously supply the SPP balancing authority area in order to maintain Area Control Error in accordance with NERC control performance criteria. Regulation-up and Regulation-down services are provided by generators that are specially equipped with AGC, which allows near-continuous adjustment to meet the regulation set points. Contingency Reserves are supplied by resources that are able to supply energy to the system within ten-minutes of a contingency event (unexpected generator or transmission equipment outages). Contingency Reserves are comprised of Synchronized (Spinning) Reserves, from online resources that are synchronized with the system, and Non-spinning (Supplemental) Reserves, from offline resources. SPP operates both a DAM and RTM for ancillary services.

The SPP region covers Kansas, Oklahoma, and parts of New Mexico, Texas, Louisiana, Missouri, Mississippi, and Arkansas. As illustrated in Figure 1-10, the SPP regional footprint is composed of 16 balancing authorities.

1.1.6.1 SPP Market Process

The SPP is set to launch its New Integrated Marketplace on March 1, 2014 [29, 30, 31]. The Integrated Marketplace will support the integrated co-optimization of energy, Regulation Up/Down, Spinning Reserve, and Supplemental Reserve in both a Day-Ahead Market (DAM) and a Real-Time Balancing Market (RTBM).

On the morning of each day before (D-1), SPP market participants will be able to submit energy demand bids, energy supply offers, and reserve supply offers into a DAM for each hour of day D. The SPP will set the hourly reserve requirements for each of the twenty-four hours of day D. The DAM will then be cleared to produce a 24-hour schedule of hourly price, commitment, and dispatch levels for energy and reserve for day D.

After the close of the DAM, a Reliability Unit Commitment (RUC) process will be conducted to ensure there is enough capacity committed for day D to cover the forecasted system load and reserve requirements for day D. The RUC process will be executed several times (every four hours at a minimum) during the remainder of day D-1. Both commitment and decommitment decisions will be made during these RUC processes. Resources committed or decommitted during any RUC process will be subject to make whole payments. An RTBM permitting co-optimization of imbalance energy and reserve will be run in parallel with the DAM and RUC processes. The RTBM will be cleared every five minutes to produce dispatch and price levels for both imbalance energy and reserve.

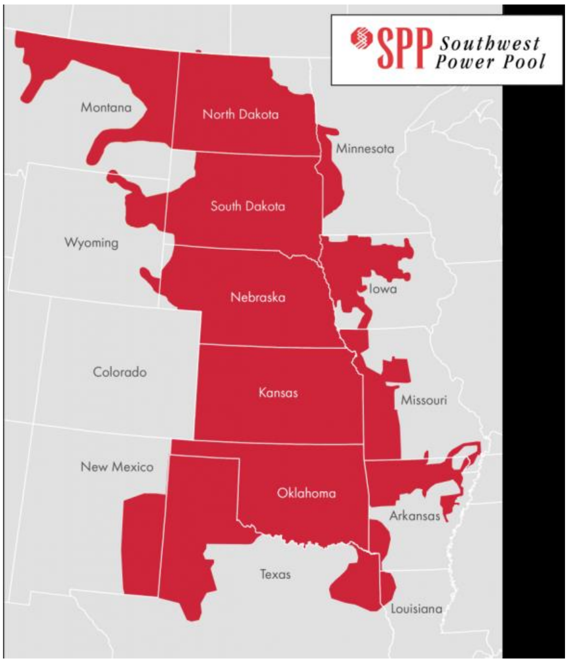


Figure 1-10- The SPP territory [32]

1.1.7 California Independent System Operator (CAISO)

The California Independent System Operator (CAISO) was established in 1996 to operate the region's power grid and wholesale electric markets, which include an energy market, an ancillary service market, and a financial transmission rights market. CAISO procures Regulation-up, Regulation-down, Spinning Reserves, and Non-spinning Reserves in the Day Ahead Market (DAM) and Hour Ahead Market (HAM). Spinning and Non-spinning Reserves are jointly referred to as Contingency Reserves.

CAISO maintains two Ancillary Service Regions and eight Ancillary Service Sub-Regions. The two Ancillary Service Regions are the CAISO System Region and the CAISO Expanded System Region. The CAISO Expanded System Region is defined as the entire CAISO balancing authority area plus all system resources at scheduling points outside of the CAISO balancing authority area. The CAISO System Region is defined as the subset of certified resources defined in the CAISO Expanded System Region that are located internal to the CAISO balancing authority area.

There are eight sub-regions, each of which may have its own minimum ancillary service requirements based on system reliability conditions. Figure 1-11 – CAISO reginal territory illustrates the territory of the CAISO, and its subregions. Zone ZP26 in Figure 1-11 – CAISO reginal territory is divided into SP26 (South of Path 26) and NP26 (North of Path 26). There is an expanded region1 for each of the four regions, with a total of eight sub-regions.

Figure 1-11 – CAISO reginal territory [33]

1.1.7.1 CAISO Market Process

CAISO manages a Day-Ahead Market (DAM) and a Real-Time Market (RTM) for the integrated co-optimization of energy, Regulation Up/Down, Spinning Reserve, and Non-Spinning Reserve [34, 35, 36]. The operation of CAISO's DAM and RTM is similar to the operation of the DAM and RTM in both MISO and NYISO.

Seven days before each operating day D, the DAM is opened and ready to accept virtual and physical bid/offer information from entities called Scheduling Coordinators (SC). Two days before day D, CAISO produces a forecast of CAISO demand. By hour 18 two days ahead of day D, CAISO publishes forecasted reserve requirements and regional constraints by Ancillary Service Region.

Any SC wishing to participate in the DAM for operating day D must submit its bids/offers prior to hour 10 on day D-1. These bids/offers include energy demand bids, energy supply offers, and supply offers for Regulation Up/Down, Spinning Reserve, and Non-Spinning Reserve. CAISO sets hourly reserve requirements for each of the twenty-four hours of day D based on its forecasted reserve requirements and regional constraints.

After the close of the DAM at hour 10 on day D-1, CAISO undertakes an Integrated Forward Market (IFM) process to determine the day-ahead schedule for energy prices (LMPs), energy commitment and dispatch levels, reserve prices, and reserve commitment and dispatch levels. After the completion of the IFM, CAISO carries out multi-interval real-time optimizations to minimize the cost of dispatching imbalance energy and procuring additional needed reserve, subject to resource and network constraints. The Hour-Ahead Scheduling Process (HASP) is included in a special hourly run of real-time unit commitment (RTUC). Reserve procurement in the HASP is done through an optimization process that is based on repeatedly updated system conditions. After the HASP closes for a particular operating hour H, the bids/offers for hour H are validated and a Market Power Mitigation and Reliability Requirement Determination (MPM-RRD) process is performed. Real-time dispatch levels and settlement prices for imbalance energy and reserve are then determined in the RTM for hour H.

The reserve procurement cost allocation for all reserve products is hourly, system-wide, and across IFM, HASP, and RTMs. The cost of procuring reserve is viewed by CAISO as being on behalf of demand and is therefore allocated to demand using a system-wide user rate. The user rate for each form of reserve is the average cost of procuring this form of reserve in both the DAM and RTM for the whole CAISO system.

Ancillary service marginal prices (ASMPs) are produced as a result of the co-optimization of energy and ancillary service for each ancillary region. They represent the marginal cost of providing an additional unit of that service. In supply shortage conditions, when co-optimization fails to clear the market and there is not a well-defined ASMP, CAISO will use scarcity reserve demand curves to set the administrative values for ASMPs. These are based upon a stepwise demand curve corresponding to the shortage of three upward reserve products (i.e. Spinning Reserves, Non-spinning Reserves, and Regulation-up) and a stepwise demand curve corresponding to shortage of Regulation-down service.

1.1.7.2 CAISO Ancillary Services

Based on FERC definition, AS are: “Those services necessary to support the transmission of electric power from seller to purchaser given the obligations of control areas and transmitting utilities within those control areas to maintain reliable operations of the interconnected transmission system” [37]. In general, operating reserve is partitioned into three distinct categories of frequency control: *primary*, *secondary*, and *tertiary*. Each responds faster than the next. Moreover, the mechanism activating reserve in each of these categories is different [38, 39, 40]. “Primary frequency” control is a local automatic control that rapidly (within seconds) adjusts generator output or load to offset large changes in frequency. The adjustment of generator output is termed governor response, as it is provided by controllable synchronous generators fitted with a speed governor. An important aspect of primary frequency control is that, even when fitted with a speed governor, a generator can provide additional power (to oppose frequency drops) only if it is operating at less than full capacity.

“Secondary frequency” control is a central automatic control that acts to adjust active power production to restore the frequency and power interchanges with other systems to their nominal levels following an imbalance [39]. This automatic process, generally termed automatic generation control (AGC) in North America, acts on a time frame of several seconds to counteract frequency deviations. While secondary frequency control can serve to restore frequency following a contingency or the loss of a large block of load, it cannot serve to limit the magnitude of the initial frequency swing following such an event.

Finally, tertiary frequency control consists of manual changes in scheduled unit commitment and dispatch levels in order to bring frequency and/or interchanges back to nominal values when secondary frequency control is unable to perform this task. While primary and tertiary frequency controls are essential for reliable grid operations, secondary frequency control is not. Smaller power systems can be operated using only primary frequency control and manual tertiary control. All large interconnected systems, however, use secondary frequency control because manual control cannot remove transmission line overloads quickly enough [44, 45].

In north America energy market, none of regions defined specific targets or markets for Primary Frequency Control, However in all of them, they defined AS market for secondary and tertiary frequency control as already described in Table 3 [41].

AS is necessary to maintain voltage and frequency in an allowable range by balancing generation and consumption under different contingencies. CAISO divides the AS to four categories including spinning and non-spinning reserve, frequency regulation up, and frequency regulation down while all of the programs can be procured in DA and RT market. AS is one of the most profitable markets meanwhile most challenging since it is erratic and not easy to be predicted. In general, CAISO procures around 90% of its AS from DA market bidding and the rest in RT to have a more accurate forecast on procured capacity and costs. The minimum rated capacity requirement for a resource to participate in AS is 500 kW and participants must be able to reach their maximum offered capacity within 10 minutes [42]. There are three AS markets applicable to BESS described as follows.

1.1.7.2.1 Spinning Reserve

Spinning Reserve is an extra online capacity to reserve capacity that is synchronized to the grid system and ready to meet electric demand within 10 minutes of a dispatch instruction by the ISO. Non-Generative Resources (NGR) is a proper candidate for this market due to their fast ramping and instant adjustment of power. In CAISO the spinning reserve providers should reach to the specified level of operation reserve within 10 minutes and provide service for two hours. The ISO calculates the operating reserve capacity based on imports capacity, available generation of hydroelectric and other existing resources along with possible contingencies in the system [43]. To participate in the spinning reserve, each service provider can bid in DA and RT (FMM) market for capacity and price. After ISO clears the price and defines awarded capacity in DA and RT, each provider is obligated to dedicate the awarded capacity. In case of failure to deliver the committed capacity, the provider should pay penalty based on the amount of failure and the impact level. In case of full failure, the ISO disqualifies the provider for all AS markets and it should pass the requirement tests again.

The net revenue from spinning reserve market depends on the awarded capacity, ancillary services marginal price (ASMP), which is cleared price in DA and RT markets. The revenue from this service can be formulated as (31).

$$In^{Spin} = \; In^{Spin-DA} + In^{Spin-RT} \tag{31}$$

$$In^{Spin-DA} = \sum_{\tau \in T_{DA}} \left(Cap(\tau)^{Spin-DA} . Pr(\tau)^{Spin-DA}\right) \tag{32}$$

$$In^{Spin-RT} = \sum\nolimits_{\tau' \in T_{RT}} \left(Cap(\tau')^{Spin-RT} . Pr(\tau')^{Spin-RT} . h^{Spin-DA}\right) \tag{33}$$

Equation (1) shows the total income of spinning reserve. $Cap(\tau)$ is the awarded (called) power in kW for each interval and $Pr(t)$ is its cleared price in \$/kWh for the same interval. Equation (2) shows the DA income where τ is one-hour time interval within 24 hours of a day (T_{DA}) and for RT market τ' in (3) is 15min time interval for entire day and h is time duration of operation interval, while it is one for DA market. In (2) and (3), $Cap(\tau)$ and $Cap(\tau')$ are the decision variable and Pr(t) is uncertain parameter of scheduling optimization problem. Spinning reserve in DA pays for committed capacity. In addition, if participants are asked to deliver the committed capacity, they will earn extra revenue based on the delivered energy and energy price in the RTD.

In practice, the non-spinning/spinning reserve has an important role in grid management, and when this service is called, it is vital to deliver all committed capacity. Therefore, the penalty rate for this service is high, and in most cases, the participants avoid it. Consequently, for sake of simplicity in many studies, this penalty is not taken into the account.

1.1.7.2.2 Frequency Regulation

The frequency regulation is an ancillary service to mitigate small fluctuations in the grid frequency. Regulation capacity must follow the automated generation control (AGC) signal in a range of couple of seconds. In CAISO, the regulation market is divided into regulation up and down. The regulation up is used to increase the grid frequency and regulation down is the act of absorbing more energy to decrease the frequency. The BESS as a fast and controllable NGRs is one of the best choices for regulation market while this market is a suitable market for NGRs due to its high return. In general, the average clearing price in regulation market is higher than the one in spinning and non-spinning reserve [44]. The frequency regulation can be offered in both DA and RT (FMM) markets. FERC order 755 [45] structured the payment for regulation service by including the performance payment. That is, ISO not only pays for providing this service (capacity payment) but also for the quality of the service (performance payment). The performance is paid based on participants' accuracy and mileage by calculating how accurately service provider can follow the AGC signal. The performance payment is formulated as (34):

$$\begin{Bmatrix} \text{Performance} \\ \text{Payment} \end{Bmatrix} = \begin{Bmatrix} \text{Actual} \\ \text{Mileage} \end{Bmatrix} \times \begin{Bmatrix} \text{Mileage} \\ \text{Price} \end{Bmatrix} \times \begin{Bmatrix} \text{Performance} \\ \text{Accuracy} \end{Bmatrix} \tag{34}$$

The actual mileage is the sum of absolute change of AGC signal, which is updated every four seconds, in a 15-minute interval. This term indicates what mileage the ISO would expect from each provider [46]. The second term in (34) is mileage price, which is mileage cleared price and can be considered as a constant value since the mileage cleared price range is relatively small [47]. The performance accuracy is defined as the level of accuracy in following the AGC signal. Performance accuracy is calculated as the weighted average of absolute deviation from AGC signal, using actual mileage as the weight, during 15 minutes intervals for a calendar month. The minimum performance accuracy must be over 25% and if accuracy drops to less than 25%, the unit should re-certify to provide the corresponding service within ninety days from the date the CAISO provides notice to the provider.

The revenue from regulation market for NGR is calculated based on the regulation awarded capacity, the total cleared capacity price, and mileage price in both DA and RT, see

(35)-(41). In case of failure to deliver committed capacity, the regulation and the mileage payments, awarded in advance, will be cancelled, also the penalties will be applied.

$$In^{Reg} = In^{Reg-DA} + In^{Reg-RT} \tag{35}$$

$$In^{Reg-DA} = \sum\nolimits_{\tau \in T_{DA}} (In(\tau)^{Reg-DA.Up} + In(\tau)^{Reg-DA.Down}) \tag{36}$$

$$In(\tau)^{Reg-DA.Up} = Cap(\tau)^{Reg-DA.Up} \,.\, Pr(\tau)^{Reg-DA.Up} \,.\, h^{Reg-DA.Up} + Perform(\tau)^{DA.Up} \tag{37}$$

$$\begin{aligned} &Perform(\tau)^{DA.Up} \\ &= [(Cap(t)^{Reg-DA.Up} . m(\tau)^{DA.Up}). Pr(\tau)^{mile-DA.Up} \,.\, acc(\tau)^{Up} . h^{Reg-DA.Up}] \end{aligned} \tag{38}$$

$$In^{Reg-RT} = \sum_{t \in T_{RT}} (In(t)^{Reg-RT.Up} + In(t)^{Reg-RT.Down} \tag{39}$$

$$In(t)^{Reg-RT.Up} = Cap_t^{Reg-RT.Up} . Pr_t^{Reg-RT.Up} \,.\, h^{Reg-RT.Up} + Perform(\tau)^{RT.Up} \tag{40}$$

$$\begin{gathered} Perform(\tau)^{RT.Up} = \\ (Cap(t)^{Reg-RT.Up} . m(\tau)^{RT.Up}) \,.\, Pr(\tau)^{mile-RT.Up} \,.\, acc(\tau)^{Up} .\, h^{Reg-RT.Up} \end{gathered} \tag{41}$$

In (35) to (40), $In(.)$ indicates the income and indices "Up" and "$Down$" show the regulation up and down, respectively. According to (35), the total revenue of regulation market is the summation of revenue from RT and DA market. In (36) and (39) the DA and RT market revenue are divided into regulation up and down revenues. (37) and (40) calculate the regulation up revenue in DA and RT, respectively. Equations (38) and (41) describe the performance payment $Perform(\tau)^{(.)}$ in DA and RT, respectively. The same formulas can be applied to regulation down. The optimization variable is the regulation capacity, Cap^{Reg} in kW for each interval. The uncertain parameter of the optimization includes Pr^{Reg}, the cleared capacity price at \$/kWh for each interval, and Pr^{mile} is the cleared mileage price. $acc(t)$ indicates the accuracy of performance response to the AGC signal and is estimated by ISO for the upcoming market interval based on the historical deviation from the AGC signals for the upcoming market interval [48], and $m(t)$ is the regulation mileage multiplier estimated by CAISO and is the amount of total expected resource movement (up or down), or Mileage, for 1 MW of Regulation Up or Down capacity. CAISO, based on historical data and how close the resources follow the AGC signal, calculates the multiplier. The resource mileage multiplier informs how much mileage the CAISO may expect from bid-in or self-provided capacity [47]. Although the AGC signal changes happen every 4 seconds, $h^{Reg-DA.Up}$ in (37) is the settlement interval which is in range of several minutes, and $h^{Reg-RT.Up}$ in (40) is 15 minutes interval which is operational interval.

1.1.7.2.3 Energy Market

The energy market defines as delivering energy to the grid to compensate forecasted demand error. In general, the energy market in CAISO includes DA market, RTD and FMM. The main difference of energy market and other markets such as AS is that participants just bid for the amount of energy based on their available capacity and the local marginal price (LMP) defined by the ISO. The LMPs will be calculated according to System Marginal Energy Cost (SMEC), Marginal Cost of Losses (MCL) and Marginal Cost of Congestion (MCC) from (42). The SMEC is the same for each Aggregated Pricing Node (PNode) and constant in every time interval. On the other hand, MCL and MCC could be negative or positive and might be different for each node. It should be noted that at each time interval new LMPs will be published.

$$\begin{Bmatrix}\text{Local Margial}\\ \text{Price}\end{Bmatrix} = \begin{Bmatrix}\text{System Marginal}\\ \text{Energy Cost}\end{Bmatrix} + \begin{Bmatrix}\text{Marginal Cost}\\ \text{of Losses}\end{Bmatrix} + \begin{Bmatrix}\text{Marginal Cost}\\ \text{of Congestion}\end{Bmatrix} \tag{42}$$

The energy market revenue could be calculated by summation of DA, FMM and RTD incomes.

$$In^{E} = In^{E-DA} + In^{E-FMM} + In^{E-RTD} - Penalty^{E}(\tau) \tag{43}$$

$$In^{E-DA} = \sum_{\tau \in T_{DA}} E(\tau)^{DA}.LMP(\tau)^{DA} \tag{44}$$

$$In^{E-FMM} = \sum_{\tau \in T_{FMM}} E(\tau)^{FMM}.LMP(\tau)^{FMM} \tag{45}$$

$$In^{E-RTD} = \sum_{\tau \in T_{RTD}} E(\tau)^{RTD}.LMP(\tau)^{RTD} \tag{46}$$

Equations (44) - (46) demonstrate the energy market income in DA, FMM and RTD interval where E is the delivered energy and optimization variable and LMP is the cleared energy price. $Penalty^{Reg}$ is the penalty cost for violation from committed capacity and can be formulated as (47). $P^{rate}(\tau)$ is the penalty rate in \$/kWh, $E(\tau)^{Aw}$ is awarded and $E(\tau)^{del}$ is actual delivered energy [34].

$$Penalty^{E}(\tau) = P^{rate}(\tau).\left|E(\tau)^{Aw} - E(\tau)^{del}\right| \quad (47)$$

1.1.7.2.4 Energy Imbalance Market

Since 2014, a new market called the California Western Energy Imbalance Market (EIM) has been introduced in the West region. The main purpose of this market is to export surplus energy production from western states to central and eastern states in U.S. EIM is run as real time dispatch (RTD) in every 5 min by choosing the least-cost resource to meet the needs of the grid and uses the data of DA and FMM and the online load forecasting to make the best decision for maximum profitability based on the latest information. Although EIM has been recognized as CAISO markets, but despite of other markets, external participants out of California region can register and participate in this market. In Figure 1-12 western EIM active and pending participants for following years are illustrated.

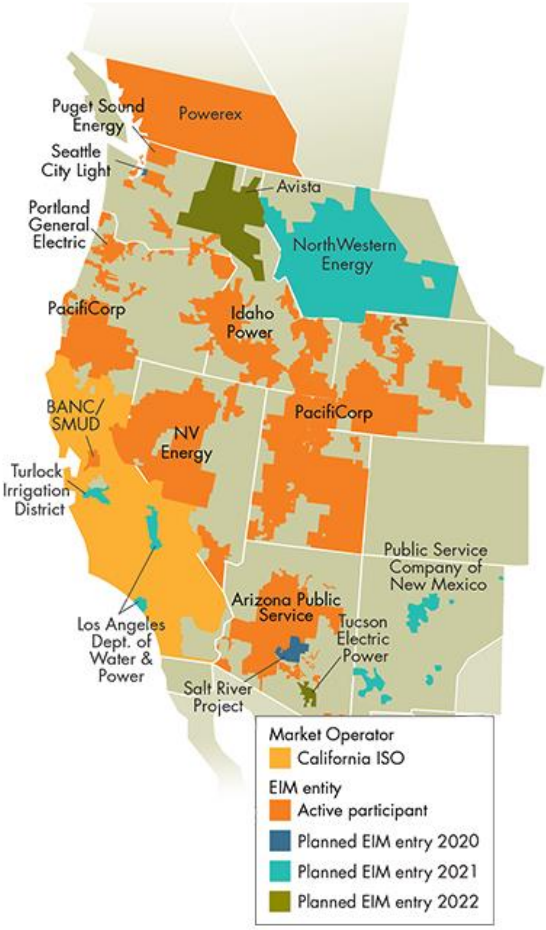


Figure 1-12 - Western EIM active and pending participants [49]

1.2 Energy and Ancillary Services Market Design in Europe

Based on Directives 96/92/EC and 2003/54/EC and the Third Legislative Package (2009), European Union counties start to move from monopoly companies which had control over generation, transmission and distribution to more competitive environment for entering new participants. To achieve the imposed environmental targets and to provide electricity companies competitive electricity markets, the following steps are necessary [50]:

- Privatization to enhance performance and reduce the ability of the state to use these companies as a mean to achieve costly political agendas.
- Unbundling, which means the separation of the electricity business that can be conducted competitively (generation and retail) from the natural monopolies (transmission and distribution), which must be regulated.
- Horizontal restructuring to ensure competition.
- Designation of a System Operator responsible to maintain network stability and to ensure open entry to the wholesale market and full access to the transmission network. This System Operator can be a Transmission System Operator (TSO), which also owns the electrical grid, or an Independent System Operator (ISO), which is not the owner of the grid.
- Establishment of a wholesale market were generators compete to supply electricity on different time interval basis. This market has to suitably integrate market-based mechanisms aimed to acquire operational reserves services.
- Unbundling of retail tariffs and rules to enable access to the distribution networks to promote competition at retail level.

Hence, a liberalized market is a means to obtain the economic efficiency in the energy sector, not only in short term – allocative and productive efficiency – but also in long term because a smart market is capable to provide dynamic efficiency, which means that is able to provide price signals for investments (demand-side and generation-side). In general, most of the electricity industry in Europe is vertically unbundled. Transmission and distribution of electricity are regulated natural monopolies, while generation, suppliers and load operate in a liberalized market. In this situation, generators compete in the wholesale electricity market to sell electricity to large industrial consumers and suppliers, whereas suppliers and load compete in the retail market to acquire electricity at a best price.

The market description presented here is the general structure of electricity markets in EU. In the following chapters, more detailed analysis of the Italian markets is reported.

1.2.1 The Italian Energy Market

In Italy, the production, transmission and distribution of electricity are performed by different companies and controlled by many entities, each one with a specific role:

- The Ministry of Economic Development ("Ministero dello Sviluppo Economico", **MSE**): it is a government ministry responsible for a variety of policies concerning among others the economic development of the power system. It defines strategic and operational guidelines for the production and the economic activities around the energy and the mineral resources, guarantying the security and the cheapness of the system;
- the Italian Regulatory Authority for Energy, Networks and Environment ("Autorità di Regolazione per Energia Reti e Ambiente", **ARERA**) is the independent regulatory entity of the energy markets and the integrated water services. It was established by law n.481in 1995 with the purpose to protect the interests of users and consumers, promote competition and ensure efficient and profitable services, keeping satisfactory quality levels in the electricity and gas sectors. With law n.214 in 2011, new regulatory competences in the integrated water services sector were attributed to ARERA, while Legislative decree n.102 in 2014, new tasks in the district heating and cooling sector. The Authority has to define reliable and transparent tariff system, set quality of service standards, define a framework aimed at the protection and empowerment of consumers in competitive markets, provide specialized advice and report to the Government and Parliament on the regulated sectors, formulating observations and recommendations for further policy actions;
- "Gestore dei Servizi Energetici" (**GSE** S.p.A.) is the public holding company, wholly owned by the Ministry of Economy and Finance, responsible of the development of renewable energy sources by managing support schemes and granting the related incentives;
- "Gestore dei Mercati Energetici" (**GME**): it is the entity, founded by GSE, which organizes and manages the Electricity Market, respecting regulatory forecast defined by the Italian Government and AEEGSI, and it is responsible of the proper functioning of the system. GME maintains obligations and principles

which guarantee the neutrality, transparency, cost-effectiveness of the Italian Electricity Market;

- Terna, the Italian Transmission System Operator (**TSO**) instituted with Bersani Decree n.79/99, manages the national transmission grid under security conditions by balancing supply and demand of electricity. Terna's objective is to guarantee the greatest efficiency of its infrastructures and their maintenance, monitoring their operation and activity through remote control centers.
- Single Buyer ("Acquirente Unico", **AU**) is a public company owned by GSE. Its mission is to procure continuous, secure, efficient and reasonably-price electricity supply for households and small business. AU buys electricity from the market on favorable terms and re-sells it to the distributors of the standard offer market for supplying who did not switch to the open market.
- Antitrust Authority ("Autorità Garante della Concorrenza e del Mercato", **AGCM**) is an administrative independent authority, established by law n.287 in 1990, which introduced antitrust rules in Italy. The missions of AGCM is to guarantee the security of the competition and of the market, counteracting incorrect commercial practices with respect to consumers and small business and avoiding harassment clauses between companies and consumers.

The Italian energy market is characterized by an annual electricity consumption of about 321.9 MWh in 2018 which is highest in past 6 years and an installed capacity of around 120 GW [51] .

The Italian Power Exchange (**IPEX**) [52] was created with the legislative decree 16th March 1999, n.79 (D.lgs. n.79/99) to set up an internal energy market, as part of the process of transposition of the EU directive 96/92/CE. It is active since April 2004 and allows demand participation since January 2005. The purpose of the creation of this market was to promote competition in generation sector and in the wholesale market and to favor transparency and efficiency in the dispatching activity, which is a natural monopoly. The electric system is subdivided into transmission network portions, the so-called market zones, characterized by physical limits of electricity exchange to and from the corresponding neighboring zone.

The electric system is subdivided into transmission network portions, the so-called market zones, characterized by physical limits of electricity exchange to and from the corresponding neighboring zone. The interface of these zones consists of all lines having the highest probability to be congested when injection and withdrawal programs are executed. In addition, inside the area no congestions are assumed when these programs are executed and the location of injections and withdrawals inside one zone does not impact the transport capacity between zones.

The zones identification process takes into account the three-years development plan of the national transmission system and the zones can correspond to physic geographical areas, virtual areas (without a direct physical correspondent) or limited production poles (virtual areas in which the electricity production is subject to constraints to maintain the security of the system). The national transmission grid is interconnected with neighboring countries via 23 lines: 4 with France, 12 with Switzerland, 1 with Austria, 2 with Slovenia and 2 submarine cables with Greece and Malta.

1.2.1.1 Structure of the Italian Electricity Market

The Electricity Market is managed and organized by GME and it consists of the Spot Electricity Market (“Mercato a Pronti”, MPE), Forward Electricity Market (“Mercato a Termine”, MTE) and the Forward Market Accounting Platform, which is a platform for the physical delivery of the financial contracts concluded in the IPEX. From 2007 operators can buy and sell electricity also by stipulating bilateral contracts (Over the Counter, OTC) out with the bidding system. These transactions must be registered on the Forward Market Accounting Platform (PCE).

1.2.1.1.1 The Spot Electricity Market

In the Spot Market, each participant submits its bids for each time interval. Bids could be *Simple* or *Multiple*. “Simple” bids just include value and price for each interval on the other hand, in “multiple” bids, bids are included several volume and prices for different period.

The MPE is composed of Day-Ahead Market (“Mercato del Giorno Prima”, MGP), Infra-Day Market (“Mercato Infragiornaliero”, MI) and Ancillary Services Market (“Mercato del Servizio di Dispacciamento”, MSD). Day-Ahead Market is a wholesale electricity market hourly based and opens at 8 a.m. of the ninth day before the day of delivery and closes at 9:15 a.m. of the day before the day of delivery. Before starting the market resolution process, Terna communicates the programs related to bilateral contracts to GME, which is the central counterpart, as virtual offers with zero price and as virtual bids without price detailed. At the closure, clear prices and volumes would be determined to maximum the transmission limits between zones. So, Market ranks all the valid supply offers in increasing price order and all the valid demand bids in decreasing order. The intersection of these two curves identifies the equilibrium of traded volume and market clearing price. In addition, demand bids in respect of consuming units belonging to geographical zones are always valued at the National Single Price (named "PUN" – "Prezzo Unico Nazionale"), computed as the average of zonal prices, weighted for the total purchases; while supply offers are valued at the zonal equilibrium price in which the respective generating unit is placed.

The Infra-Day Market ("Mercato Infragiornaliero", MI) where operators can adjust their sales and purchase bids/offers and commercial positions with respect to those trading on MGP. Hence, MI allows market participants to submit last updated bids for to modify their own schedules in the DAM. The central counterpart, that is the GME, manages the mechanism of trading and communicates with Terna, aiming the sustainability of the network. Like in the DAM, demand bids and supply offers can be multiple, simple or pre-defined and the price forming mechanism is the same of the previous market (that is adopting the system marginal price method), but the equilibrium price PUN is not anymore computed, and all the sales and the purchases are valued at the zonal price. It consists of four sessions: the first two after DAM closing (MI1 and MI2), in day before, while the other two sessions are infra-day sessions (MI3, MI4) and, hence, occur in day same day. After the market closure, the GME notifies the result to Terna, which needs them to determine preliminary information about residual transmission capacities between zones.

Finally, The Ancillary Services Market ("Mercato del Servizio di Dispacciamento", MSD) in which Terna procures the resources needed to manage and control the system. It is composed by an ex-ante session (MSD ex-ante), aiming to procure those services needed to solve congestions and to create reserve, and an infra-day session (MB), aiming to balance the system in real-time. MSD ex-ante is in turn subdivided into three sub-stages MSD1, MSD2, MSD3, while MB into five sub-stages: MB1, MB2, MB3, MB4, MB5. In the 1.2.1.1.2, this market will be described in a more detailed way.

The scheduling of different sessions of MPE is summed up in Table 4 below:

	MGP	MI1	MI2	MSD1	MB1	MB2	MI3	MSD2	MB3	MI4	MSD3	MB4	MB5
Reference day	D-1				D								
Preliminary information	8:45 a.m.	12:30 p.m.	2:40 p.m.	n.d.	n.d.	n.d.	7:30 a.m.	n.d.	n.d.	11:45 a.m.	n.d.	n.d.	n.d.
Opening session	8:00 a.m.	10:45 a.m.	10:45 a.m.	3:10 p.m.	-	10:30 p.m.	4:00 p.m.	-	10:30 p.m.	4:00 p.m.	-	10:30 p.m.	10:30 p.m.
Closing session	9:15 a.m.	12:30 p.m.	2:40 p.m.	4:40 p.m.	-	5:00 a.m.	7:30 a.m.	-	11:00 a.m.	11:45 a.m.	-	3:00 p.m.	9:00 p.m.
General outcomes	10:30 a.m.	12:55 p.m.	3:05 p.m.	8:30 p.m.	-	-	7:55 a.m.	9:50 a.m.	-	12:10 p.m.	2:05 p.m.	-	-
Individual outcomes	10:45 a.m.	1:00 p.m.	3:10 p.m.	8:40 p.m.	-	-	8:00 a.m.	10:00 a.m.	-	12:15 p.m.	2:15 p.m.	-	-

Table 4- Scheduling of the Spot Electricity Market in Italy

1.2.1.1.2 The Italian Ancillary Service Market (MSD)

The Italian MSD [53, 54] is the market where Terna procures the resources needed to manage, operate, monitor and control the power system, acting as the central counterparty for the overall presented bids. As previously mentioned, it is subdivided into the MSD ex-ante, that takes place in specific interval in the day ahead the reference day in which Terna accepts bids to resolve congestions appearing after MGP and forms an adequate reserve margin that takes place in five different intervals, from 11 p.m. of the day before the reference day to one and half hour before the first hour that can be negotiated in each session, and in which Terna accepts bids to balance injections and withdrawals and to provide secondary regulation. In the MSD, differently from the previous markets, all the offers/bids which expect a remuneration, are recompensed with the pay as bid method [53, 55].

The submitted bids must follow some constraints to allow the convergence of the bidding process in reasonable times such that each enabled PU and for each time period of the reference day, the bids must be composed by:

- One price for the purchasing and selling offer [€/MWh] for the Secondary Reserve, if the PU is qualified to supply this service;
- From one to three pairs of quantities and prices [MWh and €/MWh] for bids the other services for possible increment of energy starting from the quantity defined by the previous MGP or MI section up to the maximum quantity;
- One turn-on bid (valid for each hour of the day);
- One price [€/MWh] for offering minimum power starting from a power lower than the minimum value;
- One price [€/MWh] to turn-off the unit (decrease the power to 0 MW).

As mentioned, the MSD has critical rule for Terna which provides services needed to maintain the security and stability of the system. However, it is not the unique one, the Italian TSO could adopt impositions (also not remunerated) or bilateral contracts. In this situation, System services are distinguished as:

- Ancillary service for "congestion management", it consists in the availability, from operators, to accept modification, up or down, to their updated cumulative programs. The qualified PU must provide to the TSO, the residual margins with respect to the maximum power and the zeroing of the injection (or the minimum power in case of PU not qualified to the turn-off offer). Terna modifies the programs, with a dispatching action, accepting the presented bids according to an economic merit order. This service is provided through the MSD and it is remunerated with the PAB method.

- "Primary reserve", it is used to automatically correct the imbalances between instantaneous total production and the total load of the whole European electricity system in real-time (a few seconds/minutes). The primary reserve must be continuously available and must be distributed in the network as much uniform as possible. In Italy, this service is provided throughout impositions and it is not remunerated.
- "Secondary reserve", in the operating planning stage, the secondary reserve provides remained production in order to make the half-band reserve available; while in real time it is under the control of an automatic devices that able to modulate the electrical power produced as a function of the signal of level sent by the TSO (within 200 seconds). The dispatching user must ensure at least a band for secondary reserve greater than the minimum quantity defined by the TSO which is ±15% of the maximum power for hydroelectric units and greater than ±10 MW and ±6% of the maximum power for thermoelectric PU. In Italy, this service is provided by means of MSD and are remunerated according to market criteria.
- "Tertiary reserve", in the operational planning phase, it is used to establish appropriate margins with respect to the minimum and maximum power; while in real time these margins are activated manually by sending dispatching orders to provide balance service. Two different types of tertiary reserve are "up reserve", which increase the power production in real time; and the "down reserve", which curtails the margin for decreasing the power production. Furthermore, tertiary reserve can be subdivided into *ready* reserve and *replacement* reserve. The first one is made up by the increase/decrease of the production that can be injected/withdrawn into the network within 15 minutes and with a power gradient of 50 MW/min after the request of the TSO and it has been used to replenish the secondary band and keep the system balanced in case of rapid changes in the demand. The replacement reserve, instead, is constituted by the increase/decrease of the production that can be injected/withdrawn into the network within 120 minutes with a gradient of 0.67 MW/min, it can be sustained indefinitely and it is used to reconstitute the tertiary ready reserve in front of deviations of the loads, deviations of the production of non-programmable renewable sources and failures in the generation groups. This service, in Italy, is provided throughout MSD as well.

1.2.1.2 New structure of Italian Ancillary Services

The current electricity grid faces some critical issues due to the increasing amount of energy produced by renewable energy sources. In particular, the installed capacity of non-programmable energy sources, such as wind and solar photovoltaic (PV), have undergone a rapid increase from 1.6 GW in 2005 up to 28.054 GW in 2015 [56] in Italy to reach the European climate/energy target [57]. Unfortunately, these sources are characterized by intermittency and uncertainty which need a provision of a larger amount of tertiary reserve on MSD and require conventional power plants (thermo and hydroelectric) a greater flexibility for balancing purposes. It has also to be considered that the development of these technologies started in 2005 and was followed by the economic crisis 2007-2008, which caused a demand reduction. Consequently, the electricity requirement covered by Renewable Energy Sources (RES) increased (up to 17.5% in 2015), reducing both the available power from traditional generating units, due to dismissing and the reserve margins made available by such plants. Therefore, conventional plants are required to work at partial load to cover the peak load, causing, among other things and reduction of their efficiencies [58] due to continuous turn off/on.

Furthermore, NPR power plants are not homogenously distributed in the whole Italy (Figure 1-13), especially wind plants are present mostly in Southern Italy and in the islands (Figure 1-14), giving rise line congestion problems and wind curtailment, which means limitation of the potentially producible wind generation.

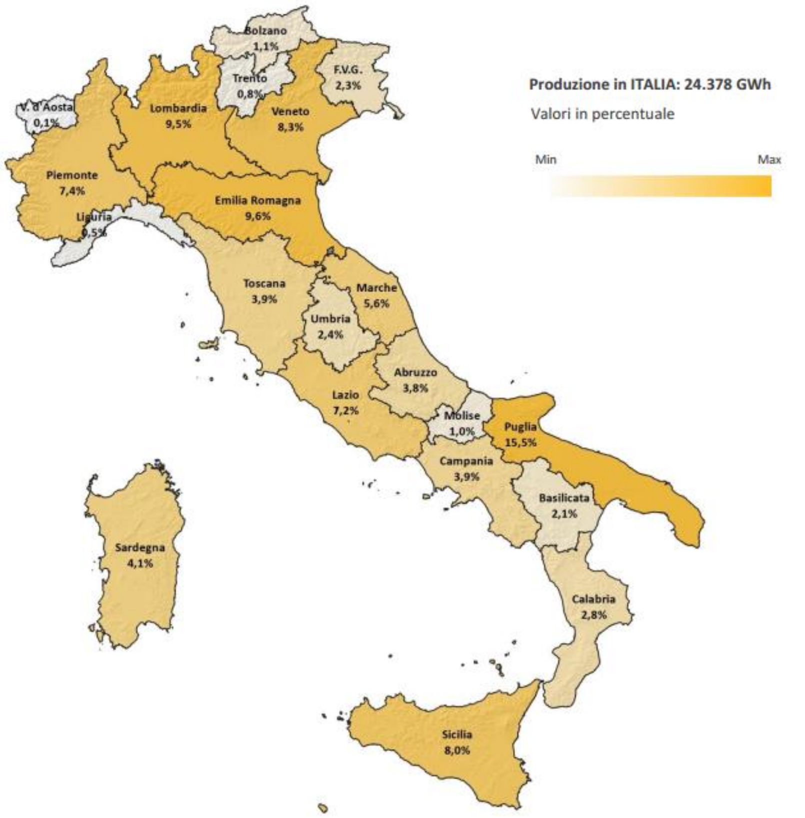


Figure 1-13 - Regional distribution of photovoltaic plant production in 2017 [56]

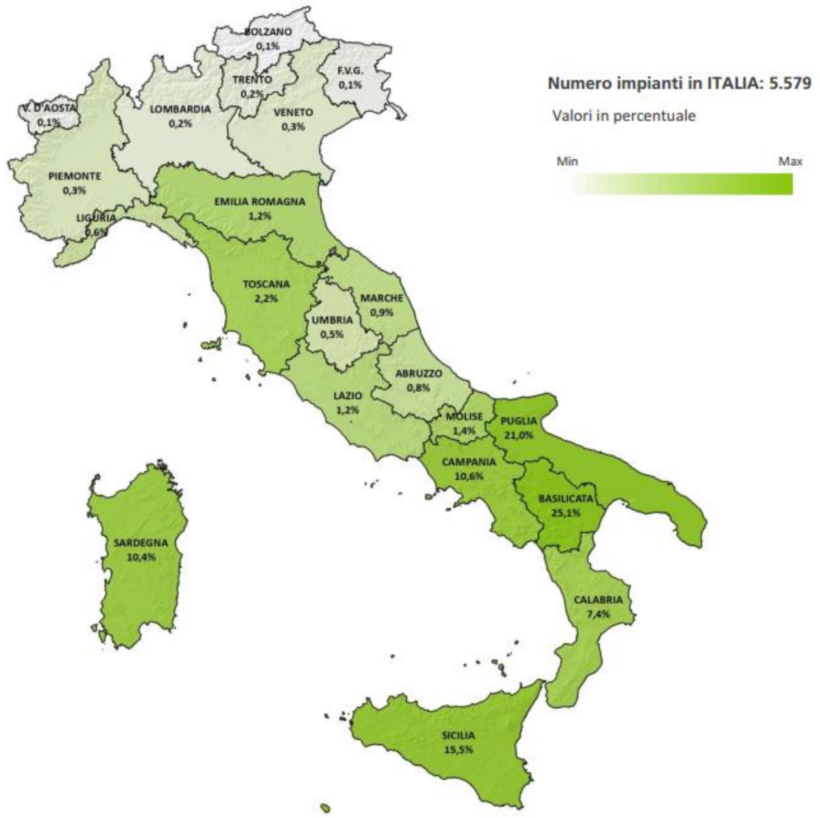


Figure 1-14 - Regional distribution of the number of wind farms at the end of 2017 [56]

As already mentioned, non-programmable renewable energy sources are often placed in zones characterized by low load and, consequently, change electrical fluxes in the grid, causing line congestions and making necessary new infrastructures or transmission network enhancements. Moreover, DG plants which are located in distribution network that were not designed to accept energy injections; for all these reasons new intervention are needed in order to make the grid "smart".

The reduction of energy production by conventional power plants reduces the system inertia, which is the ability of the system to ensure that the frequency excursion remains in acceptable ranges to guarantee the system security [59].This problem is common in all the EU members, but it is more stressed in Italy due to the expansion of NPR plants in areas characterized by poorly developed grid, with stringent transient limits and with a reduced local load compared to the installed capacity.

Hence, the revision of the dispatching discipline is needed in order to make the electric system more flexible and introducing the controllable demand, non-programmable RES, DG and storage system in the electricity market. In this sense, with the Decision 393/2015/R/eel [60], the Authority has started a procedure, named RDE ("Riforma Dispacciamento Elettrico") finalized to the reformation of the dispatching service, coherently with the strategic framework 2015-2018. The Authority is oriented to:

1. Reviewing the criteria that Terna has to define for selection and remuneration of the dispatching services in order to allow a wider participation into the ancillary services from the generating units, the demand and the energy storage according to technology neutrality criteria;
2. Editing the unbalance fees in order to reflect the true value of the electrical energy.

The first phase of this project (RDE-1) was proposed in consultation with the document for consultation 298/2016/R/eel [61], in which the ARERA suggested the first steps toward to allow the DG, demand and non-programmable renewable energy sources to quickly access to MSD. RDE-1 is characterized by technology neutrality, possibility to introduce "variable geometry" aggregation levels, the aggregator figure and by the requirement to define the plant controller to be installed in PU connected to LV or MV. The aggregation geometry has to be large enough to encourage the widespread participation users, but it has not to violate the grid constraints. Moreover, the Authority requires the Italian TSO to allow the participation on MSD to both relevant non-programmable renewable energy sources and non-relevant PU and CU and believes that RDE-1 must be characterized by a double enabling regime: compulsory regime for the relevant PU already enabled on MSD, and a voluntary one for others.

The first MSD opening has been concretized with the Resolution 300/2017/R/eel [62] in which the ARERA has deliberate the pilot projects, identified by Terna, are set up to gain useful information for defining the reform of the MSD and has defined two new aggregate units, in addition to the already existing UVAP (virtual enabled production unit - “Unità Virtuali Abilitate di Produzione”) and UVAC (virtual enabled consumption unit “Unità Virtuali Abilitate di Consumo”), the UVAM (virtual enabled mixed unit “Unità Virtuali Abilitate Miste”) and UVAN (virtual enabled nodal unit “Unità Virtuali Abilitate Nodali”). The TSO must define the aggregation geographical borders that cannot exceed the market zone but may not coincide with them. The UVAP, which includes non-relevant PU regardless the technology and the programmability placed in a unique aggregation border and for which the enabling for bid submission has requested, and the UVAC, which includes CU placed in a unique aggregation perimeter and for which the enabling for bid submission has requested and that have not been contracted for the interpretability, (or super interpretability, described in the Resolution 1/2016/R/eel) service, described in the resolution 301/2017/R/eel, for the whole power of the withdrawn point, can participate only to MSD. The UVAN, which includes PU subject of voluntary enabling and CU under the same node of the transmission network, and the UVAM, which includes non-relevant PU and CU placed in a unique aggregation perimeter, instead, can participate to both the ancillary service and the energy markets. It has to be specified that the Balance Service Provider, which is the responsible for managing the UVA on the MSD, can be different from the one on MGP/MI for the UVAC and UVAP, whilst must be coincident for the UVAM and UVAN. The aggregation units and the production units subject to voluntary enabling can require the participation to the MSD even for just one of the services and have to equip themselves suitable devices to ensure them integration into Terna control systems. The purpose of the Authority is the compilation within 2017 of the new integrated dispatching text (TIDE - “Testo Integrato del Dispacciamento Elettrico”) with the aim of highlighting the actual necessary network services, discussing the concept of aggregation, and the revision of the unbalances regulation.

The first pilot project [63], identified by Terna and accepted by the Authority with the Resolution 372/2017/R/eel [64], regards the participation of the demand to the MSD for the provision of resources for the tertiary replacement reserve and balancing. This project is articulated in two proposals to be implemented in parallel: the qualification of CU plants for participation to MSD and the term supply between June and September 2017. The modulation capacity of CU plants must be associated to an UVAC for the provision of dispatching resources. One UVAC can be associated with one or more power supplies in HV, MV and LV, placed in the same geographical perimeter and each unit must be equipped with a peripheral detachment unit. To be enabled, the maximum control power of the UVAC, which is the maximum withdrawn power that can be modulated in reduction, has to be at least 10 MW and the virtual consumption unit has to be able to modulate the withdrawal of the associated plants within 15 minutes of receiving the dispatching order and keep this reduction for at least 4 consecutive hours. Once enabled, the UVAC acquire the same obligations and faculties expected by the dispatching users' owner of enable PU for these services.

The second pilot project [65], instead, approved with the Resolution 583/2017/R/eel [66], regards the participation on the MSD of the distributed generation, which means of the UVAP, and it is also divided into two proposals: the qualification of the UVAP for the participation on MSD and the bid/offer submission on the aforesaid market. One UVAP can be associated with one or more injection points in HV, MV and LV, placed in the same geographical perimeter, defined by Terna. To be enabled, each injection point must be equipped with a peripheral monitoring of generation unit and the production unit associated with the UVAP must be non-relevant. The new opening of the Italian ASM is a fundamental process that should allow the distributed non-programmable renewable energy sources (in terms of UVAP), the demand (UVAC) and the storage (in terms of UVAP, being classified as PU in the Decision 574/2014/R/eel) to participate in the maintenance of the electrical system in safety and stability condition and, therefore, to develop without burdening on conventional plants.

1.3 Electricity market structure impact on the BESS viability

The conventional electricity market structure had been designed for participation of grid connected and big plants such as nuclear plants or hydro turbine generators rather than fast response, flexible and two-way recourses such battery storage, however, in past decade by significant increases of distributed generators such wind farms, different countries start to revise the market structure for more efficient and profitable participation of these assets in market. In this procedure, regulators face different challenges such as grid limitation, compatibility of new structure with past and future technologies. In this regard, the Italian market start these discussions under the name of RDE ("Riforma Dispacciamento Elettrico") from 2015, which is discussed in sub-section 1.2.1.2. This program is still under review and progress based on two different pilot projects. Following this program and to achieve EU regulations 2015/1222

(CACM) and EU 2017/2195 (Balancing) and on the Clean Energy Package, with references to the new Regulation on the internal electricity market EU 2019/943 (Electric Regulation) and to the new Directive on the internal electricity market EU 2019/944 (Electrical Directive), ARERA introduced consultation document 322/2019/R/eel [67] recently for further consideration of distributed generator for participation in national and international market. The main issue in these discussions are that in new structure the behind meters' assets are still out of scope and they are not allowed to participate in market. Moreover, the focus of these changes is on renewable sources and battery energy storages gained less attention, which by different behaviour of these assets new upgrade to deal with batteries energy storage is necessary.

On the other hand, in North America and specifically California market structure, preparation and revision of the market structure for distributed generators and battery storage systems started since 2007 by FERC order 890 [68] which was aimed at preventing undue discrimination and preference in transmission service. The design of the rule required that non-generator resources like demand response be evaluated comparably for services provided by generation resources in the areas of reliability standards, ancillary services, and transmission expansion planning [69]. In CAISO, the discussion on non-generator resources (NGR) started on 2011 [70] to address the new type of energy producers in market such as EV or batteries. By definition NGRs are "resources that operate as either Generation or Load and that can be dispatched to any operating level within their entire capacity range but are also constrained by a MWh limit to (1) generate Energy, (2) curtail the consumption of Energy in the case of demand response, or (3) consume Energy". At the mean time FERC order 755 [47], to provide more secure and just market for fast response resources such batteries, introduced a payment for performance along with capacity payment for providers of frequency regulation, including energy storage. In next step, CAISO initiated the "Energy storage and distributed energy resources" (ESDER) [71] which focuses on enhancing the ability of ISO connected and distribution-connected resources to participate in the ISO market, including rooftop solar, energy storage, plug-in electric vehicles, and demand response to address issues identified in the California Energy Storage Roadmap in 2014 (CESR) [4]. ESDER defined in four phases which are including:

- **Phase 1** The improvements such as the ability for submitting the state of charge as a daily bid parameter in the day-ahead market, as well as an option to not provide state of charge limits or not have the ISO co-optimize non-generator resources based on state of charge discussed in this phase – Fall 2016 finalized [72].

- **Phase 2** This initiative provided three new types of demand response performance evaluation methods, clarified Station Power treatment for storage resources, and incorporated additional gas indices into the net benefits test calculation to reflect all real-time participation regions. The enhancements are anticipated to lower barriers and enhance the ability of energy storage and distributed energy resources to participate in the ISO market - November 1, 2018, finalized [73].
- **Phase 3** It will continue to identify and evaluate opportunities for increased participation of transmission grid-connected energy storage and distribution-connected resources in the ISO market. Topics suggested by stakeholders in the ESDER Phase 2 initiative will also be addressed in this phase - Started from 2017 and still in progress [74].
- **Phase 4** It will explore refinements to the distributed energy resource (DER) and storage participation models, as well as lower integration barriers for demand response resources. This initiative will also explore expanding the models to optimally capture their value, as well as leverage resource design attributes that support grid reliability and allow for multiple-use applications - Started from 2018 and still in progress [75].

Simultaneously, in Feb 2018 the first draft of FERC order 841 [76] published to remove barriers to the participation of electric storage resources in the capacity, energy, and ancillary service markets operated by Regional Transmission Organizations (RTO) and Independent System Operators (ISO) (RTO/ISO markets). Specifically, this order requires each RTO and ISO to revise its tariff to establish a participation model consisting of market rules that, recognizing the physical and operational characteristics of electric storage resources, facilitates their participation in the RTO/ISO markets. This model must satisfy the following specifications:

(1) Ensure that the eligible resouce which are using this model to provide all capacity, energy, and ancillary services, is technically capable and compatible to participate in the RTO/ISO markets;

(2) Ensure that a resource using the participation model can set the wholesale market clearing price as both a wholesale seller and wholesale buyer with respect to existing market rules that govern when a resource can set the wholesale price.

(3) This model must account for the physical and operational characteristics of electric storage resources through bidding parameters or other means;

(4) Set the minimum requirement size for participation in the RTO/ISO markets that does not exceed 100 kW. Additionally, each RTO/ISO must specify that the sale of electric energy from the RTO/ISO markets to an electric storage resource that the resource then resells back to those markets must be at the wholesale locational marginal price.

Consequently, this order addressed the practical challenges of BTM battery storage for market participation such as minimum size, battery physical and operational characteristic such as SoC range and level, remained and current energy state and even the maximum and minimum running time. Moreover, it also pushed ISO/RTOs to change BESS roles from price taker to price maker who can influence in market. Although, clear and finalize regulation for BESS participation in electricity market is not defined yet but it is under progress by different technical committee.

To sum up, in order to compare European market and specifically Italian one with CAISO, with respect to BTM batteries participation, in Italian new structure the main concern is distributed generator and BESS participation and its unique characteristic is not considered yet. In addition, all discussions and pilot projects have been focused on in front of meter connected assets and larger capacity limits compared with behind the meters. Meanwhile, lack of existing of capacity market and long-term incentive for storage installation brought unjust market situation for these assets. On the other hand, in North America market, by introducing new construction for NGR and BESS as well as revising new requirement for market participation, more attractive and compatible market structure have been shaped for BESS specially behind meters.

2 Energy Storage System

In order to deploy "Smart Grid" architectures, Energy Storage Systems play significate role. By increasing of deployment of renewable sources such as PV and Wind plants and to ensure the reliability of grid ESS are one the best solution. Storage systems can be categorized based on form of energy that they are using which are including mechanical, electrochemical, electrical and thermal. In this research, first different types of energy storage system reviewed 2.1. Then, the battery energy storage system applications and general modelling described in 2.3 and **Error! Reference source not found.** respectively.

2.1 Description of electrical energy storage technology

There are several ways to categorize various EES technologies, such as, in terms of their functions, response times, and suitable storage durations [77, 78, 79]. In this research, the form of energy stored is selected as reference which is shown in summery in Figure 2-1. In this way, storage systems can be categorized into mechanical (pumped hydroelectric storage, compressed air energy storage and flywheels), electrochemical (batteries and fuel cells), electrical (supercapacitors and superconducting magnetic energy storage), and thermal energy storage (sensible heat storage). A detailed description and discussion of each type of EES technology will be given in the next section following the above order of category.

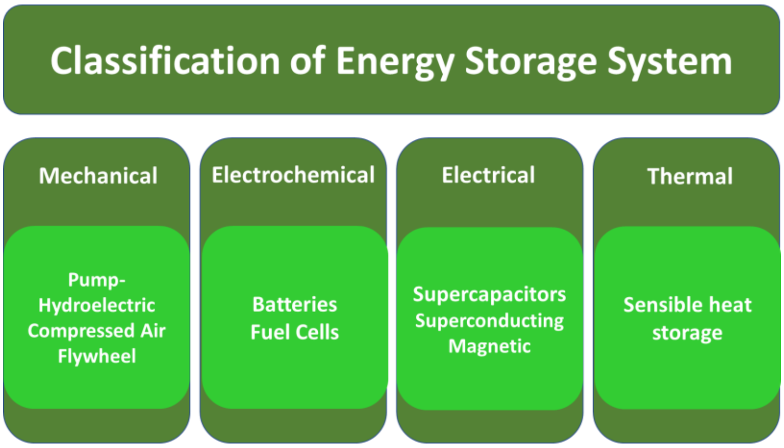


Figure 2-1 – Classification of energy storage system based on energy stored type

➢ **Pumped Hydroelectric Storage (PHS)** PHS is an EES technology with a long history, high technical maturity and large energy capacity. A typical PHS plant uses two water reservoirs, separated vertically. During off-peak electricity demand hours, the water is pumped into the higher level reservoir; during peak hours, the water can be released back into the lower level reservoir. In the process, the water powers turbine units which drive the electrical machines to generate electricity. The amount of energy stored depends on the height difference between the two reservoirs and the total volume of water stored. The rated power of PHS plants depends on the water pressure and flow rate through the turbines and rated power of the pump/turbine and generator/motor units [80]. Pumped hydro is a very consolidated energy storage system: it is the largest capacity form of energy storage available. In fact, about 170GW of energy storage are installed worldwide and more than 95% of this capacity consists of pumped hydro. The main disadvantage is the nature of the site required, that needs both geographical height and water availability. Hence, a further development of this kind of technology is limited. The nature of the operation of PHS systems means that their applications mainly involve energy management in the fields of time shifting, frequency control, non-spinning reserve and supply reserve. However, with the restriction of site selection, PHS plants suffer long construction time and high capital investment.

- **Compressed Air Energy Storage (CAES)** Along with PHS, CAES is another type of commercialized EES technology which can provide power output of over 100 MW with a single unit. The energy is stored in the form of high-pressure air. When the power generation cannot meet the load demand, the stored compressed air is released and heated by a heat source which can be from the combustion of fossil fuel or the heat recovered from the compression process. The compressed air energy is finally captured by the turbines. CAES system can be built to have small to large scale of capacities; CAES technology can provide the moderate speed of responses and good partial-load performance. The practical uses of large-scale CAES plants involve grid applications for load shifting, peak shaving, and frequency and voltage control. CAES can work with intermittent renewable energy applications, especially in wind power, to smooth the power output [81]. The major barrier to implementing large-scale CAES plants is identifying appropriate geographical locations which will decide the main investment cost of the plant. Relative low round trip efficiency is another barrier for CAES compared to PHS and battery technologies.
- **Flywheel** In flywheel energy storage systems (FESS) [82] energy is stored as kinetic energy using a rotor that rotates with high angular speed. The stored kinetic energy is then converted back to electric energy via the motor, slowing the rotor rotational speed. There exist two topologies of this device: (1) low speed FES: it uses steel as the flywheel material and rotates below 6×10^3 rpm; (2) high speed FES: it uses advanced composite materials for the flywheel, such as carbon-fiber, which can

run up to $\sim 10^5$ rpm [83]. Low speed FES systems are typically used for short-term and medium/high power applications. High speed FES systems use non-contact magnetic bearings to mitigate the wear of bearings, thereby improving the efficiency. Flywheels are characterized by very quick response with respect to the other energy storage systems and allow to store energy in the order of magnitude of 10s of kWh, and power can reach 20 kW; therefore, they are interesting for Power Quality application and for grid energy storage for frequency regulation. The cost of high-speed composite systems can be much higher than that of conventional metal flywheel systems. FES has some favourable characteristics, including high cycle efficiency (up to ~95% at rated power), relatively high-power density, no depth-of-discharge effects and easy maintenance.

- **Battery Energy Storage (BES)** The rechargeable battery is one of the most widely used EES technologies in industry and daily life. A BES system consists of a number of electrochemical cells connected in series or parallel, which produce electricity with a desired voltage from an electrochemical reaction. Each cell contains two electrodes (anode, positive, and cathode, negative) with an electrolyte which can be at solid, liquid or ropy/viscous states [84]. A cell can bi-directionally convert energy between electrical and chemical energy. During discharging, the electrochemical reactions occur at the anodes and the cathodes simultaneously. To the external circuit, electrons are provided from the anodes and are collected at the cathodes. During charging, the reverse reactions happen and the battery is recharged by applying an external voltage to the two electrodes. Batteries can be widely used in different applications, such as power quality, energy management, ride-through power and transportation systems. The location for installation can be quite flexible, either housed inside a building or close to the facilities where needed. Currently, relatively low cycling times and high maintenance costs have been considered as the main barriers to implementing large-scale facilities. The disposal or recycling of dumped batteries must be considered if toxic chemical materials are used. Furthermore, many types of battery cannot be completely discharged due to their lifetime depending on the cycle Depth-of-Discharge (DoD). Many chemistries are used for this process, more common ones are the lead-acid, nickel-cadmium (NiCad), lithium-ion (Li-ion), sodium/sulfur (Na/S), zinc/bromine (Zn/Br), vanadium-redox, sodium-nickel-chloride (Zebra).
- **Fuel cells** Fuel cells [85] are electrochemical devices that directly convert chemical energy in hydrogen (or hydrogen-rich fuel) and oxygen (from air) to electricity. They consist of two electrodes (anode and cathode) and an electrolyte medium between them. The anode promotes the oxidation of fuel while the cathode the

reduction of oxidant. Ions generated during oxidation-reduction chemical reactions are transported from one electrode to the other through the ionically conductive but electronically insulating electrolyte. Electrons generated at the anode during oxidation pass through the external circuit and reaches the cathode, where they complete the reduction reaction. Depending on the choice of fuel and electrolyte, there are six major groups of fuel cells, which are: Alkaline Fuel Cell (AFC), Phosphoric Acid Fuel Cell (PAFC), Solid Oxide Fuel Cell (SOFC), Molten Carbonate Fuel Cell (MCFC), Proton Exchange Membrane Fuel Cell (PEMFC) and Direct Methanol Fuel Cell (DMFC) [86]. An advantage of fuel cells, being open systems, is that the storage system's discharge duration can be increased by adding more electrolyte. Moreover, it is relatively easy to replace the electrolyte when it degrades. In general, the electricity generation by using fuel cells is quieter, produces less pollution and is more efficient than the fossil fuel combustion approach. Other features include easy scaling (potential from 1 kW to hundreds of MW) and compact design. Fuel cell systems combined with hydrogen production and storage can provide stationary or distributed power (primary electrical power, heating/cooling or backup power) and transportation power (potentially replacing fossil fuels for vehicles). Such hydrogen EES systems can offer capacity and power independence in energy production, storage and usage, due to the separate processes. It should be noted that the disposal of exhaust fuel cells must consider degradation and recycling while toxic metals are used as electrodes or catalysts.

- **Supercapacitor** Also named electric double-layer capacitors or ultracapacitors, contain two conductor electrodes, an electrolyte and a porous membrane separator [87]. Due to their structures, supercapacitors can have both the characteristics of traditional capacitors and electrochemical batteries. The energy is stored in the form of static charge on the surfaces between the electrolyte and the two conductor electrodes. The supercapacitors with high-performance are based on nano materials to increase electrode surface area for enhancing the capacitance. The power and energy densities of supercapacitors are between those of rechargeable batteries and traditional capacitors. The most important features of supercapacitors are their long cycling times, more than $1 \sim 10^5$ cycles, and high cycle efficiency, ~84–97% [77]. However, the daily self-discharge rate of supercapacitors is high, ~5–40%, and the capital cost is also high, in excess of 6000 $/kW h [87, 77]. Thus, supercapacitors are well suited for short-term storage applications but not for largescale and long-term EES. Typical applications in power quality consist of pulse power, hold-up/bridging power to equipment, solenoid and valve actuation in factories, UPS devices, etc.

➢ **Superconducting Magnetic Energy Storage** A typical SMES system is composed of three main components which include: a superconducting coil unit, a power conditioning subsystem, and a refrigeration and vacuum subsystem [87, 88]. The SMES system stores electrical energy in the magnetic field generated by the Direct Current (DC) in the superconducting coil which has been cryogenically cooled to a temperature below its superconducting critical temperature. In general, when current passes through a coil, the electrical energy will be dissipated as heat due to the resistance of the wire; however, if the coil is made from a superconducting material, such as mercury or vanadium, under its superconducting state (normally at a very low temperature), zero resistance occurs and the electrical energy can be stored with almost no losses. Superconducting coils can be classified into two groups: Low Temperature Superconducting (LTS) coils, working at around 5K, and High Temperature Superconducting (HTS) coils, working at 70 K [87]. The LTS-SMES technology is more mature and commercially available while the HTS-SMES is currently in the development stage. SMES devices in the range of 0.1–10 MW have been used commercially.

The features of SMES include relatively high power density (up to 4000 W/L), fast response time (millisecond level), very quick full discharge time (less than 1 min), high cycle efficiency (95–98%) and long lifetime (up to 30 years). In contrast to rechargeable batteries, SMES devices are capable of discharging near to the totality of the stored energy with little degradation after thousands of full cycles. The drawbacks are that they have high capital cost, high daily self-discharge (10–15%) and a negative environmental impact due to the strong magnetic field [77]. Moreover, the coil is sensitive to small temperature variations which can cause the loss of energy. From the above, SMES is suitable for short-term storage in power and energy system applications.

➢ **Thermal Energy Storage (TES)** TES technology [79, 89] stores thermal energy by heating or cooling a storage medium so that the stored energy can be later used for heating and cooling applications and power production. The system is becoming important for electricity storage in combination with concentrating solar power plants (CSP) where solar heat can be stored for electricity production when sunlight is not available. There exist three kind of TES systems: the first one is the sensible heat storage, based on storing thermal energy by heating or cooling a storage medium (liquid, such as water or thermosoil, or solid such as concrete or the ground) with water. This solution is the least inexpensive but requires large volumes due to its low energy density. The second option is the latent heat storage which uses phase change materials (PCMs), which can be organic or inorganic, and are characterized by a higher storage capacity. The advantage of this system is its capacity to store large amounts of energy in a small volume and with a minimal temperature change, allowing efficient heat transfer. Finally, the thermo-chemical storage adopts chemical reactions to store and release thermal energy: chemical reactions such as adsorption of a substance to the surface of another solid or liquid can be used to accumulate and discharge heat and cold when needed. Nowadays TES systems based on sensible heat are commercially available while PCM and TCS systems are under development.

The TES system can store large quantities of energy without any major hazards and its daily self-discharge loss is small (∼0.05–1%); the reservoir offers good energy density and specific energy (80–500 Wh/L, 80–250 Wh/kg) and the system is economically viable with relatively low capital cost (3–60 $/kWh). However, the cycle efficiency of TES systems is normally low (∼30–60%). TES has been used in a wide spectrum of applications, such as load shifting and electricity generation for heat engine cycles.

2.2 BESS Parameters

The main storage system focus in this thesis is Battery Energy Storage System. Since, these assets are more compatible with current behind the meter’s technologies such as PV panels and they already had been introduced as potential participants in electricity market. In this research the main aim is to develop comprehensive model for BESS to deal with demand side load and whole-sale energy and ancillary services market. Thus, definition of different technical parameters and constraints of battery which can contribute in final model, is important. Thus, in this subsection, all possible parameters are introduced and discussed.

- **Voltage [V]** The voltage at which the BESS is rated is the nominal voltage at that the battery is supposed to operate. Battery voltage can be affected by the state of charge (energy level), current and temperature. In Figure 2-2, it can be noticed that at the beginning of the charge the voltage presents a decreasing exponential trend, followed by a quite linear behavior for almost all the discharge, and, when the nominal voltage is reached, a final non-linear trend, up to the cutoff voltage, in which the extracted capacity corresponds to the maximum dischargeable one, that is when the battery is completely discharged. Note that each battery has its own characteristic nominal voltage and discharge curve. It can be deducted that higher the discharge current, the lower the battery voltage to terminals. In fact, it can be assumed the battery as an ideal voltage generator with an impedance connected in series: if the discharge current increases, the impedance voltage drop increases and, consequently, the voltage to terminals decreases [90].

In Figure 2-3, the temperature effect is an issue because Li-ion batteries, for example, suffer both at low temperatures and at high ones. In fact, at low temperatures the chemical reactions are limited by velocity, decreasing the extractable capacity. Increasing the operating temperature, the capacity increases, making the voltage raise and, keeping the current constant, the temperature too, creating a cascade effect that has to be controlled to avoid battery explosion.

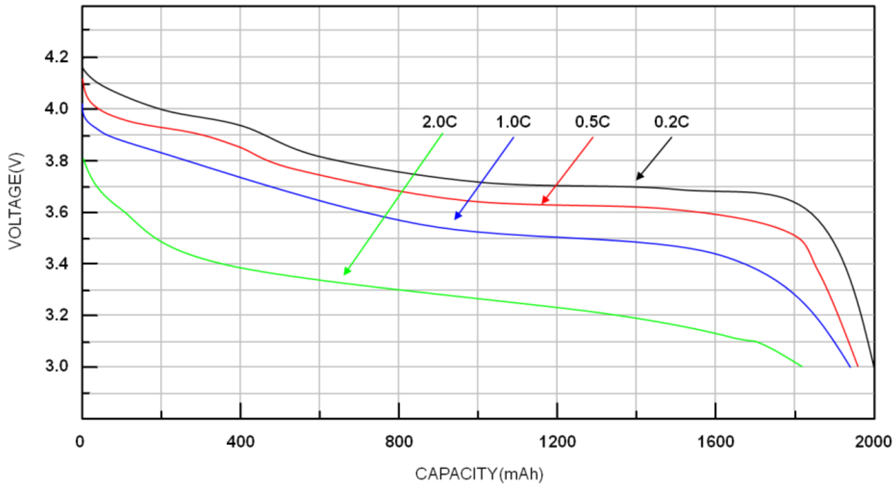


Figure 2-2- Discharge Voltage curve in different discharge current

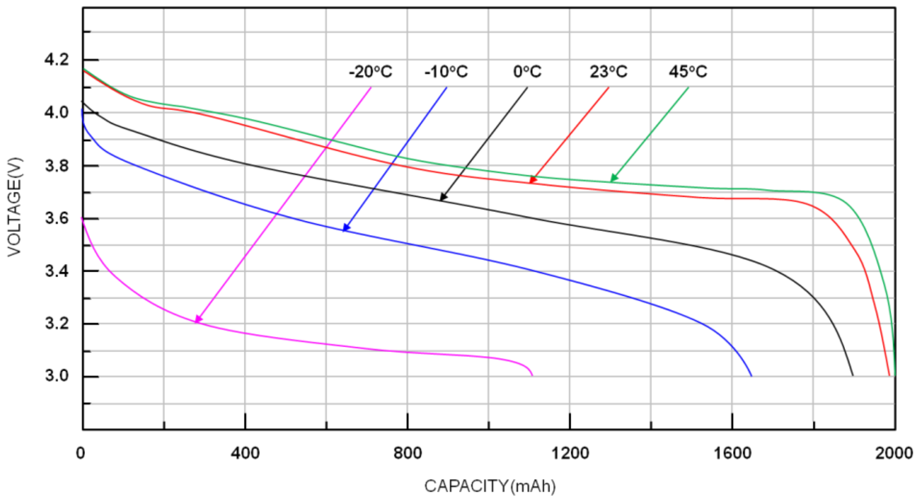


Figure 2-3- Discharge voltage curve in different temperature

- **Capacity [Ah]** is defined as the available current a battery can supply over a given time period. It is a measure of electrical charge and represents the amount of charge that the battery can deliver at the rated voltage. The capacity is directly proportional to the amount of the electrode material in the battery. In the majority of batteries, the capacity is not a constant value, but it depends on both the discharging current and the ambient temperature, following the Peukert's law:

$$C_{dis} = t_{dis} \times I_{dis}^{k} \quad (48)$$

Where C_{dis} represents the discharge capacity [Ah], t_{dis} is the discharge time [s], is the I_{dis}^{k} discharge current [A], and k is the Peukert constant, which strongly depends on the battery technology (for lead-acid, for example, k varies between 1.1 and 1.3, while for lithium-ion between 1 and 1.28). When k is equal to 1, the discharge capacity is independent of the applied current, whilst when k is higher than 1, the discharge capacity will decrease [91].

- **Nominal energy [Wh]** is the energy which can be delievered by the BESS during the discharge, starting from fully charged up to fully discharged state. It is defined as the product between the voltage and the capacity of the system at each moment.
- **The specific energy [Wh/kg]** depends on the operational conditions and the ambient temperature, while the nominal energy is defined for the discharge at nominal power at reference ambient temperature (20 or 25°C).
- **Power [W]** the actual output power of a battery cannot be uniquely defined because it depends on the applied load. Hence the nominal power must be difine since it limits the charge/discharge operation.
- **Specific power [W/kg]** defined as the power per unit mass, and the power density [W/l], that is the power per unit volume of the storage system.
- **C-rate** is defined as the current over the discharge (or charge) current that the battery can sustain over one hour. C-rate can be calculted as ratio of discharge current and rated capacity. The higher C-rate, charging/discharging time is faster and more pressure on battery. Thus, the battery temperature will increase respectively. In concolusion the battery life time decrease by selecting higher level of C-rate.
- **State of Charge (SoC) [%]** is defined as the percentage of the available battery capacity at a certain instant of time for discharge over full range of battery capcity as it is shown in (49).

$$SoC(t) = \frac{E_{batt}(t) - E_{batt,min}}{E_{batt,max} - E_{batt,min}} \quad (49)$$

When the battery is fully charged the SoC is 100% and when the battery is fully discharged the SoC is 0%. SoC varies with the change of capacity caused by charging and discharging of the battery, thereby affecting the maximum charging and discharging power of the battery. It must take into account that, battery cells are sensitive to deep discharge and overcharge and to operation at too high or too low SoCs and these behaivours must be prevented.

- **Depth of Discharge (DoD) [%]** defined as the percentage of the battery capacity that has been discharged. It is the one complement of the state of charge. The cycle life of a battery is often reported at 100% DoD of the capacity and it usually corresponds to a worst-case scenario. In fact, in different average cycling life, the battery has different DoD respectively as shown in Figure 2-4.

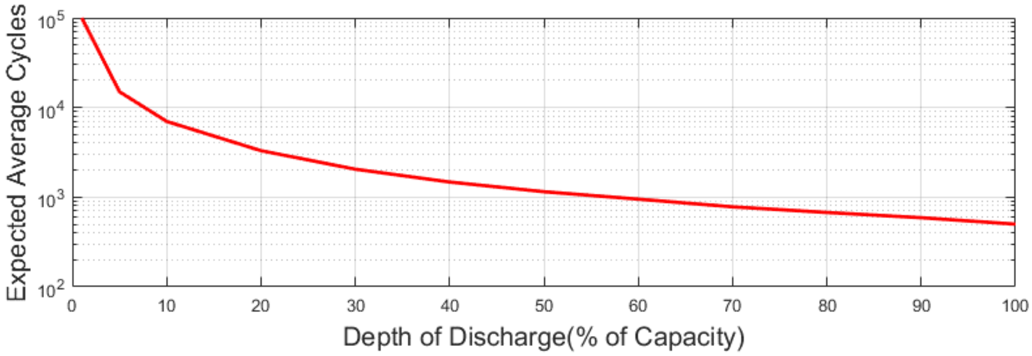


Figure 2-4 - Cycling life vs DoD

- **State of Health (SoH)** is defined as the ratio between the actual capacity and the nominal capacity of the battery. It is a usury measure because it specifies the amount of capacity that the battery is able to provide with respect to the designed value.
- **Cycle lifetime [cycles]** is defined as the number of charging and discharging cycles that the battery is able to complete after that the battery capacity drops below 80%. Generally, it is specified by the manufacturer as an absolute value. However, in reality the battery lifetime depends on temperature and operating condition. Moreover, it strongly depends on DoD: the smaller the DoD, the higher the cycle lifetime, as it is shown in Figure 2-4.

In this research, since the focus is BTM batteries and these assets are usually deployed indoor and in safe area, we assume that we almost have constant temperature. In addition, we assume that in all charge/discharge cycle, it works with constant current and linear area. To prevent the aging of the battery the C-rate is assumed as constant value and the SoC is limited between upper and lower band. Finally, the main approach of this research is to develop a solution for installed assets, thus the design parameters such as specified power and energy are neglected.

2.3 BESS applications

In general, BESS depends on the wherein grid they are deployed, they can provide variety of services. BESS can be sited at three different levels: behind the meter, at the distribution level, or at the transmission level. In general, in North America, energy storage deployed at all levels on the electricity system can add value to the grid. Customer-sited or behind the meter energy storage can provide 13 services to three stakeholders which are including costumers, utility services and RTO/ISO services [92]. On the other hand, technology development and huge costs drop of battery system especially Lithium Ion batteries, move them from niche to the one of the most important parts in near future grid. In this situation, optimal scheduling of these system in order to provide more services are essential. In following subsection, first the possible usage and services that BESS can provide are discussed.

2.3.1 BESS services for demand side

In case of deployment of battery behind meter, these systems can provide 4 general services:

1- **Backup Power** After losing the main power supply for any reason such as line fault, malfunctions at sub-station or any kind of blackouts, in an emergency situation, an independent power system source will provide an electrical power that supports important electrical systems on loss of normal power supply. Traditionally, diesel generator or other sources had been used for this problem, however, Battery storage as fast and clean sources are one of the potential substitutions for this problem. In these events, energy storage paired with a local generator can provide backup power at multiple scales, ranging from second-to-second power quality maintenance for industrial operations to daily backup for residential customers.

2- **Increase PV self-consumption** One of the main challenges of using PV panels in household sector is the limited available production duration and uncertain and unreliable during day. To minimize the export of electricity generated by behind-the-meter photovoltaic (PV) systems and to maximize the financial benefit of solar PV in areas with utility rate structures that are unfavourable to distributed PV and increase the reliability of PV generation, joint battery-PV has been used.

3- **Demand Charge reduction** In the event of grid failure, energy storage paired with a local generator can provide backup power at multiple scales, ranging from second-to-second power quality maintenance for industrial operations to daily backup for residential customers.

4- **Time-of-Use bill management** By minimizing electricity purchases during peak electricity-consumption hours when time-of-use (TOU) rates are highest and shifting these purchases to periods of lower rates, behind-the-meter customers can use energy storage systems to reduce their bill.

2.3.2 BESS services for Utility services

1- **Resource Adequacy** Instead of investing in new natural gas combustion turbines to meet generation requirements during peak electricity-consumption hours, grid operators and utilities can pay for other assets, including energy storage, to incrementally defer or reduce the need for new generation capacity and minimize the risk of overinvestment in that area.

2- **Distribution Deferral** Delaying, reducing the size of, or entirely avoiding utility investments in distribution system upgrades necessary to meet projected load growth on specific regions of the grid.

3- **Transmission Congestion Relief** ISOs charge utilities to use congested transmission corridors during certain times of the day. Assets including energy storage can be deployed downstream of congested transmission corridors to discharge during congested periods and minimize congestion in the transmission system.

4- **Transmission Deferral** Delaying, reducing the size of, or entirely avoiding utility investments in transmission system upgrades necessary to meet projected load growth on specific regions of the grid.

2.3.3 BESS services for ISO/RTO

1- **Energy Arbitrage** The purchase of wholesale electricity while the locational marginal price (LMP) of energy is low (typically during night-time hours) and sale of electricity back to the wholesale market when LMPs are highest. Load following, which manages the difference between day-ahead scheduled generator output, actual generator output, and actual demand, is treated as a subset of energy arbitrage in this report.

2- **Frequency Regulation** Frequency regulation is the immediate and automatic response of power to a change in locally sensed system frequency, either from a system or from elements of the system.1 Regulation is required to ensure that system-wide generation is perfectly matched with system-level load on a moment-by moment basis to avoid system-level frequency spikes or dips, which create grid instability.

3- **Spin/Non-Spin Reserves** Spinning reserve is the generation capacity that is online and able to serve load immediately in response to an unexpected contingency event, such as an unplanned generation outage. Non-spinning reserve is generation capacity that can respond to contingency events within a short period, typically less than ten minutes, but is not instantaneously available.

4- **Voltage Support** Voltage regulation ensures reliable and continuous electricity flow across the power grid. Voltage on the transmission and distribution system must be maintained within an acceptable range to ensure that both real and reactive power production are matched with demand.

5- **Black Start** In the event of a grid outage, black start generation assets are needed to restore operation to larger power stations in order to bring the regional grid back online. In some cases, large power stations are themselves black start capable.

3 Optimization Methods Review

The main aim in this research is to find an optimal scheduling of BESS for participating in electricity market and managing demand side. In this regard, different approach could be used, however, due to intermittency of PV production, unpredictable load and uncertain market price, the optimization method must take into account these factors. Thus, to choose and implement the best fit optimization method a literature review on different optimization method has been done and in this section these methods have been discussed.

Note: It must be considered that in this research, we didn't perform any forecasting method and instead the real data to train and test the optimization method has been used.

Most real-life optimization problems contain parameters that are not known precisely. Potential sources of this uncertainty are measurement, estimation and implementation errors in the underlying processes [93]. Traditionally, to deal with such uncertainty two classes of techniques exist: “Stochastic Programming” and “Robust Optimization”. Recently, new method which is called “Distributionally Robust Optimization” [94] (DRO) has been introduced, which is the main contribution of this research. In following sections, first Stochastic (section 3.1) and Robust (section 3.2) optimization have been explained. In subsection 3.3, the main issues and draw backs of stochastic and robust optimization discussed and finally DRO has been introduced as main contribution of this research.

3.1 Stochastic Optimization

Stochastic optimization plays a significant role in the analysis, design, and operation of modern systems. Stochastic optimization refers to a collection of methods for minimizing or maximizing an objective function with inherent system noise and coping with models or systems that are highly nonlinear, high dimensional, or otherwise inappropriate for classical deterministic methods of optimization [95]. Stochastic optimization algorithms have broad application to problems in statistics, science, engineering, and business. Algorithms that employ some form of stochastic optimization have become widely available.

Stochastic programming is a class of techniques in which all uncertain parameters are assumed to follow a known probability distribution. Instead of regular (in)equalities, stochastic programming problems contain chance or expectation constraints. Usually, the uncertainties enter the problem through the cost function or the constraint set. Moreover, same as classical deterministic optimization, there is no single solution method that works well for all problems.

Some structural assumptions, such as limits on the size of the decision and outcome spaces, or convexity, are needed to make problems tractable [96].

The most prominent division in stochastic optimization is the solution with a single time period (single stage problems) and those with multiple time periods (multistage problems). Single stage problems try to find a single, optimal decision, such as the best set of parameters for a statistical model given data by solving the problem in single level. On the other hand, multistage problems try to find an optimal sequence of decisions, such as scheduling of BESS for day-ahead and real-time market. Single stage problems are usually solved with modified deterministic optimization methods. However, the dependence of future decisions on random outcomes makes direct modification of deterministic methods difficult in multistage problems. Multistage methods are more reliant on statistical approximation and strong assumptions about problem structure, such as finite decision and outcome spaces, or a compact Markovian representation of the decision process. In following subsection, Single and Multiple stages stochastic optimization have been described.

3.1.1 Single Stage Stochastic Optimization

Single stage stochastic optimization is the study of optimization problems with a random objective function or constraints where a decision is implemented with no subsequent recourse. It means that there is no specific statistical information about future of system available.

For more deep understanding of single stage stochastic optimization, general problem including some formal concepts and notation have been explained here on. Let $\mathcal{X}$ be the domain of all feasible decisions and x a specific decision. We would like to search over $\mathcal{X}$ to find a decision that minimizes a cost function, f . Let ξ denote random (uncertain) information that is available only after the decision is made. Unless otherwise noted, we will limit our discussion to random cost functions, denoted $f(x;\xi)$. Since finding the optimal solution of $F(x;\ \xi)$ is not possible, instead minimum of the expected value has been calculated, $\mathbb{E}[F(x;\xi)]$. The general single stage stochastic optimization problem becomes as formula (50).

$$\zeta^* = \min_{x\in\mathcal{X}} \{f(x) = \mathbb{E}[f(x;\xi)]\} \tag{50}$$

For all single stage problems, it has been assumed that the decision space $\mathcal{X}$ is convex and the objective function $F(x;\xi)$ is convex in x for any realization ξ. Problems that do not meet these assumptions are usually solved through more specialized stochastic optimization methods such the stochastic ruler [97], nested partitions [98] or other method which are out of scope of this research. In following subsection sample average approximation Sample Average Approximation as one of the common applications of single stage SO explained.

3.1.1.1 Sample average approximation (SAA)

Sample average approximation (SAA) [99, 100] is a two-part method that uses sampling and deterministic optimization to solve equation 50. The first step in SAA is sampling. While directly computing the expected cost function, $\mathbb{E}[F(x;\xi)]$, is not possible for most problems, it can be approximated through Monte Carlo sampling in some situations. Let $(\xi_i)_{n=1}^{i}$ be a set of independent, identically distributed realizations of ξ, and let $F(x;\xi_i)$ be the cost function realization for ξ_i. The expected cost function is approximated by the average of the realizations as formula (51):

$$\mathbb{E}[f(x;\xi)] \approx \frac{1}{n}\sum_{i=1}^{n} f(x;\xi_i) \tag{51}$$

The second step in SAA is search. The right-hand side of equation 51 is deterministic, so deterministic optimization methods can be used to solve the approximate problem:

$$\zeta_n^* = \min_{x\in\mathcal{X}} \left\{ f_n(x) = \frac{1}{n}\sum_{i=1}^{n} f(x;\xi_i) \right\} \tag{52}$$

The set of approximate optima is $\{S_n^* = x \in \mathcal{X} : f_n(x) = \zeta_n\}$.

Deterministic search is the main benefit of SAA. Many commercial software packages, including Matlab and R, offer implementation of basic deterministic optimization methods, while more specialized packages like CPLEX and Gurobi provide a wider array of deterministic methods. To guarantee convergence of the search method to a global optimum, it is assumed that is $\mathcal{X}$ convex and that $F(x;\xi_i)$ is convex in x for every realization of ξ.

Note: It worth to mention that in this research the CVX toolbox in Matlab linked with CPLEX has been used.

One of the main limitations is that SAA is only available for problems with independent noise with respect to decision variable x. Moreover, all determined data must be used at once to generate a decision. Because of its inherent simplicity, SAA has been independently proposed in a variety of fields under a variety of names. SAA-type methods were generalized in the operations research community under a variety of names such as “sample path optimization” [101, 102], “scenario optimization” [103], and “sample average approximation” [100, 104].

SAA joint with Monte Carlo to generate various scenarios widely have been used in literature. In [105] the stochastic modeling with Monte Carlo Simulation (MCS) is used to evaluate the adequacy and reliability of smart grids in the widespread presence of PHEVs, renewable resources, availability of devices, etc.

3.1.2 Multi-stage Stochastic Optimization

The multi-stage Stochastic problem or recourse method is composed of more than one stage. In each stage some uncertainties will be considered, and decisions made, and then other decisions will be clear based on decisions in preceding stages. This procedure will continue till last stage. The objective is to minimize the expected costs of all decisions made. The most difficult part of this recourse problem is the evaluation of the expected value at each stage except the first stage [106, 107].

Multistage stochastic optimization problems aim to find a sequence of decisions, $(x_t)_{t=0}^{T}$, that minimize an expected cost function. The subscript t denotes to the time at which decision x_t has been made. Usually decisions and random outcomes at time t affect the value of future decisions. An example in our case would be the value of commitment in day-ahead market will limits the remained capacity of battery for participation in intra-hour markets. Mathematically, multistage stochastic optimization problems can be described as an iterated expectation such formula (53) bellow in a general form.

$$\zeta^* = \min_{x_0 \in \mathcal{X}_0} \mathbb{E}\left[\inf_{x_1 \in \mathcal{X}_{1(x_0,\xi_1)}} f_1(x_1;\xi_1) + \mathbb{E}\left[\,.\,.\,.+\mathbb{E}\left[\inf_{x_T \in \mathcal{X}_{T((x_{0:T-1},\xi_{1:T})}} f_T(x_T;\xi_T)\right]\right]\right] \tag{53}$$

Here T is the number of stages; $x_{0:t}$ is the collection of all decisions between 0 and t; ξ_t is a uncertain outcome at time t; $\mathcal{X}_{t((x_{0:t-1},\xi_{1:t})}$ is a decision set that depends on all decisions and uncertain outcomes between times 0 and t; $f_t(x_t;\xi_t)$ is a cost function for time period t that depends on the decision and random outcome for period t. The time horizon T may be either finite or infinite. The decision sequence space is affected by the curse of dimensionality; the size of the space grows exponentially with T, the number of possible outcomes for ξ_t, and the size of the decision space each time period, X_t.

One specific case of multi-stage stochastic problem is a two-stage. In two-stage decisions are divided into two categories: day-ahead versus real-time decisions. This is shown in the equation (54).

$$\zeta = \min_{x \in \mathcal{X}} c^T x + \mathbb{E}_{\xi}[f(x; \xi)] \tag{54}$$

In the day-ahead category (first stage), commitment decisions of units (e.g., coal and nuclear generators or in our case battery), x are made ahead of time. $\mathcal{X}$ represents the set of feasible commitment decisions (constraints only on commitments, such as minimum up/down requirements). The second term in the objective function of (54) is the expected cost of real-time operations, where is the uncertain vector with a known joint probability distribution. For each realization scenario, s, of the random vector ξ, the second-stage problem can be formulated as follows:

$$\begin{aligned} f(x, s) = \min_{p_s, l_s} \quad & f(p_s) \\ s.t. \quad & A_s x + B_s p_s + H_s l_s \geq d_s \end{aligned} \tag{55}$$

Where p_s includes decisions of multiple periods, and l_s is the vector of other second-stage decisions (such as power flows in [108, 109]). The function $f(.)$ represents the cost function of participation in markets, which is typically convex. According to different modeling perspectives, different sets of parameters in (55) are treated as uncertain. For example, the uncertain left-hand side matrices (A_s, B_s, H_s) are usually used to model contingencies (e.g., power system equipment limitations) as in [110]; uncertain right-hand-side vectors d_s usually model the uncertain demand and renewable energy outputs as in [111, 109, 108].

In objective function (54), large number of scenarios simulated, and the resulting deterministic problem could be quite large. However, in the second stage, different scenarios are not directly linked to each other. Thus, decomposition has been used as an efficient tool for stochastic problems. In the two-stage model (54), once the first-stage decision is made, the second stage 55 of different scenarios can be treated independently, resulting in a group of much smaller individual optimization problems. Benders Decomposition or the L-shaped algorithm [103] is usually applied when 55 is a linear program (e.g., [110]).

3.2 Robust Optimization

Robust Optimization (RO) is a class of techniques that does not need any information on the distribution of the uncertain parameters and was initiated by Soyster [112] and then in several papers by Ben-Tal and Nemirovski [113, 114, 115]; El Ghaoui and Lebret [116] has been developed. Instead, it requires the definition of an uncertainty set that contains all scenarios one wants to safeguard against. Subsequently, RO forces every constraint to be feasible for all possible parameter values in the uncertainty set. An advantage of this approach is that the resulting problems are generally not much more difficult to solve than the original problem.

The main idea behind robust optimization is to find the optimal solution based on worth case scenario instead of using expected value such as stochastic programming. In this way, simple linear robust programming can be defined as formula (56) which is the strict robust problem [114, 115].

$$\begin{aligned} &\min_{x \in \mathcal{X}} \quad \max_{c \in U_c} c^T . x \\ s.t. \quad & a_i^T x \ \leq b_i \ ; \quad \forall a_i \in U_{a_i}, \forall b_i \in U_{b_i}, i = 1, \ldots, m \end{aligned} \tag{56}$$

Where $x \in \mathcal{X}$ is the decision variable and $U_{a_i} = \{a_i \,|D_i \, a_i \ \leq d_i\}$ is a set of uncertainties upper-band. As its obvious from (56), the optimization is much simpler compare with stochastic programming and meanwhile it is independent from any statistical distribution of uncertainty sets. However, considering the worth-case scenario could cause overconservative which is one of the main challenges in robust optimization [117].

The most straightforward and basic uncertainty sets used in robust-optimization-based planning and scheduling models are the box intervals (formula (57)),where $\bar{d}$ is the expected value and σ is the variance of a random variable, respectively; b_α and b_β are the α- and β-quantile of the probability distribution. The random variable can be renewable power outputs and nodal load such as [118].

$$U_b = [\max\{0, \bar{d} + b_\alpha \sigma\}, \bar{d} + b_\beta \sigma] \tag{57}$$

In literature different types of uncertainties including polyhedral and ellipsoidal uncertainty sets has been used in robust optimization. In [119], authors developed two-stage optimization with polyhedral uncertainties in second stage for considering the production unit uncertainties. Authors in [120], also two stage optimizations with robust optimization for second stage used for considering wind production uncertainties.

Finally, in some cases instead of directly using the box intervals, uncertainty sets can also be derived based on risk measures (Value-at-Risk) as in [121] and [122]. Particularly notable is that constraints on coherent risk measures (such as Conditional-Value-at-Risk) can be translated to polyhedral uncertainty sets for some types of distributions [123]. In this way, instead of using exact or range of value for worth case by generating different scenarios the expected value of worth scenarios will be used.

3.3 Distributionally Robust Optimization

Stochastic programming is a powerful modeling paradigm for optimization under uncertainty. The goal of a single-stage stochastic program is to find a decision $x \in \mathcal{X}$ that minimizes an expected cost $\mathbb{E}^{\mathbb{P}}[f(x,\xi)]$, where the expectation is taken with respect to the distribution $\mathbb{P}$ of the continuous random vector $\xi \in R_m$. However, classical stochastic programming is challenged by the large-scale decision problems encountered in today's increasingly interconnected world and high number of scenarios cause burdensome calculation time [124]. Moreover, the distribution $\mathbb{P}$ is never observable but must be inferred from data. However, if we calibrate a stochastic program to a given dataset and evaluate its optimal decision on a different dataset, then the resulting out-of-sample performance is often disappointing, even if the two datasets are generated from the same distribution. This phenomenon is termed the "optimizer's curse" and is reminiscent of overfitting effects in statistics [125].

The second possible approach, which has been explained, is robust optimization (RO). RO does not require the exact knowledge about probability distribution (PD), and minimize the cost function under worth-case realization. However, the worst-case scenario is always the extreme case with relatively low probability, therefore, the solution could be over-conservative and thus not the most economical solution. To deal with this problem few methods such as [126] has been introduced.

The alternative solution to deal with uncertainties is data-driven distributionally robust optimization (DRO) which was proposed by Scarf at 1958 [127] for the first time. In conventional stochastic optimization, the probability distribution is tuned based on the specific data set, however, it is quite often that PD performs poorly when confronted with a different data set, even if it is drawn from the same distribution [128]. Thus, the main feature in DRO is to immunize the optimal solution by finding the worst-case expected value over a family of uncertainty sets (ambiguity sets) instead of worst-case observations (robust optimization). The ambiguity set must be rich enough to cover all possible distributions with high confidence, meantime, it must be small enough to prevent the over-conservative results [128]. In other to formulate the objective function based on DRO and ambiguity sets, formula (58) can be obtained.

$$\hat{J}_N := \inf_{x \in \mathcal{X}} \sup_{\mathbb{Q} \in \hat{\mathcal{P}}_N} \mathbb{E}^{\mathbb{Q}}[f(x,\xi)] \tag{58}$$

Where $x \in \mathcal{X}$ is decision variable, $\mathbb{Q}$ is distribution of uncertainty ξ and ambiguity set $\hat{\mathcal{P}}_N$ which contains all possible distributions from training data. From now on, the main challenge is to find ambiguity set. Two main approaches to construct the ambiguity sets for DRO are a "*moment-based*" and "*statistical-distance*".

3.3.1 Moment-Based Ambiguity Set

In the moment-based approach, all distributions, which are applicable with certain known moments (mean and covariance matrix), are considered as ambiguity sets [129, 130]. In this approach, for all given data samples such as $(\xi^i)_{i=1}^N$, the empirical mean vector and covariance matrix define as (59) and (60) respectively.

$$\mu_0 = \frac{1}{N}\sum_{i=1}^{N}\xi^i \tag{59}$$

$$Cov_0 = \frac{1}{N}\sum_{i=1}^{N}(\xi^i - \mu_0)\,(\xi^i - \mu_0)^T \tag{60}$$

Thus, based on defined mean and covariance an ambiguity set $\hat{\mathcal{P}}_N$ can be define such as (61).

$$\hat{\mathcal{P}}_N = \left\{ f(\xi): \quad \begin{array}{c} \int_{\xi\in\mathbb{D}} f(\xi)\, d\xi = 1 \\ (\mathbb{E}[\xi] - \mu_0)^T . Cov_0^{-1}(\mathbb{E}[\xi] - \mu_0) \le \gamma_1 \\ \mathbb{E}[(\xi - \mu_0)(\xi - \mu_0)^T] \preccurlyeq \gamma_2 Cov_0 \end{array} \right. \tag{61}$$

The ambiguity set $\hat{\mathcal{P}}_N$ is determined by μ_0 and Cov_0, and by parameters γ_1 and γ_2. The three constraints in $\hat{\mathcal{P}}_N$ ensure that (i) the integral of pdf $f(\xi)$ is one; (ii) the true mean of ξ lies in a μ_0- centred ellipsoid bounded by γ_1; and (iii) the true covariance matrix lies in a positive semi-definite cone bounded by $\gamma_2 Cov_0$. In reference [129], authors described how the values of γ_1 and γ_2 can be chosen based on the data sample size, risk parameter, and desired confidence. In practice, the values of γ_1 and γ_2 represent a decision maker's risk preference and can be used to change solution conservatism. In general, larger values of γ_1 and γ_2 will lead to more conservative (robust) solutions.

In literature, this approach has been deployed widely since only the moment condition is required [131, 132, 133]. Although the mean-variance DRO approach is intuitive and is tractable under certain conditions, it is unsatisfactory from at least two aspects. First, when constructing the distribution set in such an approach, one only uses the moment information in the sample data, while all the other information is ignored. This procedure may discard important information in the data set. Second, in the DRO approach, the worst-case distribution for a decision is often unrealistic [134].

3.3.2 Statistical-Distance Ambiguity Set

The statistical-distance approach constructs all distributions that are close enough to the target distribution with predefined probability specification. In this way, the degree of conservatism can be controlled by adjusting the radius (distance) of ambiguity set. To implement statistical-distance several methods such as the Prohorov metric [135], the Kullback–Leibler divergence [136], or the Wasserstein metric [128, 137] has been introduced. In general ambiguity set based on statistical-distance define as (62).

$$\hat{\mathcal{P}}_N = \{P \in \mathbb{D} : \ D(P, P_0) \leq \varepsilon\} \tag{62}$$

Where $\mathbb{D}$ is probability distribution of uncertainty data and $D(P, P_0)$ denotes the statistical distance pf distribution P to the nominal distribution P_0. As mentioned earlier in literature different kind of statistical-distance has been used however, this research focuses on data-driven distributionally robust optimization over Wasserstein ball in line with [128, 138, 139], since it has a tractable reformulation and out-of-sample performance has been guaranteed [128, 140]. In this regard, Wasserstein metric defines as bellow:

Definition [Wasserstein metric]. The Wasserstein metric is defined as a distance function between two probability distributions on a given supporting space $\mathcal{M}(\Xi)$. More specifically, given two probability distributions $\mathbb{Q}_1$ and $\mathbb{Q}_2$ on the supporting space $\mathcal{M}(\Xi)$, the Wasserstein metric is defined as (63):

$$dw(\mathbb{Q}_1, \mathbb{Q}_2) := \inf_{\Xi} \{\mathbb{E}_\Xi[\rho(X, Y)] : X\sim\mathbb{Q}_1, Y\sim\mathbb{Q}_2\} \tag{63}$$

Where $\rho(X, Y)$ is distance between to random variable X and Y from $\mathbb{Q}_1$ and $\mathbb{Q}_2$. The Wasserstein metric quantifies the minimum “transportation” cost to move mass from one distribution to another.

The ambiguity set $\mathbb{B}_\varepsilon(\widehat{\mathbb{P}}_N)$ can be formulated as Wasserstein ball centered at a uniform empirical distribution $\widehat{\mathbb{P}}_N$ on training dataset Ξ_{N_s} and within ε as confidence level (64). The ε is a control variable for conservativeness and robustness of optimization compare to specific features of dataset.

$$\mathcal{P}_N = \mathbb{B}_\varepsilon(\widehat{\mathbb{P}}_N) := \left\{\mathbb{Q} \in \mathcal{M}(\Xi) : dw(\widehat{\mathbb{P}}_N, \mathbb{Q}) \leq \varepsilon \right\} \tag{64}$$

4 Approach Proposed

In this section, the detailed formulation and modelling of PV cell join with BESS based on two general scenarios and with different optimization approach described. The main aim of this research is to find optimal scheduling plan for BESS in order to participate in possible electricity markets and manage the demand side loads. The first step which is the simplest one which is to find the optimal solution for BESS only for demand side management and improving the PV self-consumption that is discussed in subsection 4.1. Then, full participation of BESS in both demand side and electricity market has been discussed in subsection 4.2.

4.1 Optimal BESS scheduling for DSM

The term demand side management is announced to optimal scheduling and management of energy consumption in demand side. In recent year, based on increasing deployment of renewable sources such as PV cells joint with battery storage systems, the idea of economical energy management becomes much more practical and feasible. In general, two category of demand side management is discussed in literature, the first one is focused on demand's usage behind the meter and minimizing the cost of energy by ideas such as optimal charging of BESS, shifting the time of use (ToU) and improving the performance and self-consumption of renewable source. The second one is called "Demand Response" which is work directly under supervision of independent system operators (ISO) and make profit based on contracts to decrease the usage in specific day time. The former is recently introduced in official market and is out our research scope.

Several researches are focused on optimal scheduling and DSM by considering different setups, criteria and optimization techniques. Wu et al. [141] modelled the hybrid PV cells with BESS under time of use (ToU) to sell the surplus energy to the grid to minimize the costs. Then the close loop controller with model predictive controller (MPC) approach was developed to have more economic, robust and safe operation of the hybrid system with respect to load and solar uncertainties. The main problem of research is that only deterministic optimization proposed to deal with uncertainties and has assumed that uncertainties are fixed. In [142] the objective is to maximize the economic benefits for the system owner while optimally contributing to over-voltage mitigation in the grid in case of hybrid PV-BESS. It investigates whether residential PV systems coupled with BESS can participate in grid load-levelling and identify the requirements for utilizing them for such applications. A limit storage capacity compare to PV penetration is considered and the dynamic programming is developed to deal with nonlinear objective function. Authors in [143] investigate the optimal dispatch schedule of BESS with PV to peak shaving the demand usage in day ahead interval. They focused on financial value of these assets by analysing the net present value (NPV). Moshövel et al. in [144] developed the forecasting method for hybrid solar battery system which is applicable for forecasting and implementing in behind the meter systems without need of external data. They develop this forecasting on Matlab model and provided the optimal solution based on their forecasting for minimum cost. Atzeni et al. in [145] proposed the game theoretical approach to solve the problem of optimal solution for distributed energy generation (DG) and distributed energy storage (DS) hybrid PV-BES. They focus on those demand-side users whose energy consumption is greater than their energy production capabilities. The objective function is to reduce monetary expense during the time period of analysis by producing and/or storing energy rather than just purchasing their energy needs from the grid in DA interval.

The first scenario in this research is to schedule BESS join with PV cell to increase the self-consumption and decrease the demand cost. In this regard, the following configuration has been considered for interconnection between different sectors (Figure 4-1).

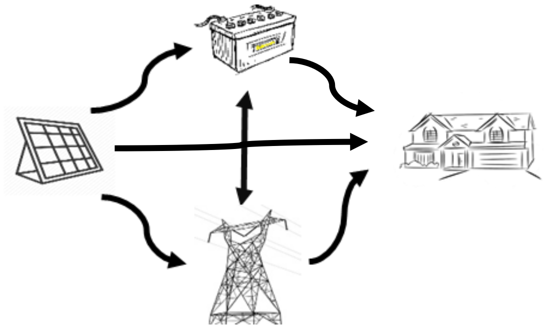


Figure 4-1 – Schematic of Hybrid System Connection

In this way, the cost function can be written as formula (65); which shows the total energy consumption cost for load and charging the battery, total energy revenue from delivering of surplus PV production and available storage energy to the grid and Operational cost which is illustrated in detail in formula (66).

$$J = \min_{v \in \mathcal{V}} \sum_{t=0}^{23} \{(P_t^{G2L} + P_t^{G2Bat}) - (P_t^{Bat2G} + P_t^{PV2G}) r_{cont}] h. Price_t^E - Cost_t^{Op}\} \tag{65}$$

$$Cost_t^{Op} = \gamma \left(P_t^{Bat2G} + P_t^{Bat2L} + P_t^{PV2Bat} + P_t^{G2Bat}\right) \tag{66}$$

Subject to:

$$0 \leq P_t^{Bat2G} + P_t^{PV2G} \leq P_{max} \tag{67}$$

$$0 \le P_t^{G2L} + P_t^{G2Bat} \le P_{max} \tag{68}$$

$$P_t^{G2L} + P_t^{PV2L} + P_t^{Bat2L} = P_t^{Load} \tag{69}$$

$$0 \le P_t^{PV2L} + P_t^{PV2G} + P_t^{PV2Bat} \le P_t^{PV} \tag{70}$$

Where $P_t^{(.)}$ shows the power at time instance t, h is time duration and $Price_t^E$ is the energy price. The selling energy price assumed to be contracted as ratio r_{cont} of buying price. Constraints (67) – (68) show the behind meter and inverter power limitation during both grid to demand side and vice versa. Constraint (69) is the load curtailment from grid, PV and battery and constraint (70) shows the limitation of PV production at each time instance. In objective function (65), the time horizon is 24 hour and day-ahead scheduling based on each hour considered. However, the battery constraints will be described in next sub-section 04.1.1.

4.1.1 Battery Constraints for DSM

In general, for electrical battery energy storage, some mutual parameters are important to take into account. The first one shows the capacity limitation of battery and called as State of Charge (SoC). Usually, must be kept in specific range to prevent any damage to the battery during charging and discharging. The second type of constraints belong to inverter power limitation and shows how fast battery can charge/discharge. Moreover, in some specific cases battery life-time constraints also takes into account such [146] where the total income of storage system depends on cycle life of battery.

Energy of battery at each moment follows the remained energy from preceding moment and change of energy at current moment and can be shown as formula 71.

$$E_{t+1} = (1 - \beta)E_t + \Delta E_t \tag{71}$$

In this formula, β is self-discharge rate of battery storage. Thus ΔE_t can be defined as formula 72 based on charging and discharging capacity.

$$\Delta E_t = -\frac{1}{\eta_{discharge}} P_t^{discharge} h + \eta_{charge} P_t^{charge} h \tag{72}$$

Where $\eta_{discharge}$ and η_{charge} are discharge/charge efficiency of battery, $P_t^{discharge}$ and P_t^{charge} are total discharge/charge energy of battery. In this section, total charging capacity comes form grid and PV to the battery and total discharge is the delivered energy from battery to grid and load which are shown in equations (73).

$$P_t^{discharge} = P_t^{Bat2G} + P_t^{Bat2L} \tag{73}$$

$$P_t^{charge} = P_t^{PV2Bat} + P_t^{G2Bat}$$

Consequently, the SoC constraints can be written as following constraints:

$$E_{min} \leq E_t \leq E_{max} \tag{74}$$

$$E_T \geq E_0 \tag{75}$$

Where constraint (74) is the energy limits and (75) force the final energy state E_T to equal or more than initial energy state. This constraint is important because in this way battery will be prepared for following day. Next important constraint, as mentioned earlier, is charging/discharge rate limitation based on maximum inverter and battery capacity. Meanwhile, it is important to set a constraint to prevent simultaneous charge and discharge which is called complementary charge/discharge constraint. Inequality (76) and (77) cover both problem constraints at the same time.

$$0 \leq P_t^{charge} \leq M \,.\, P_{max} \tag{76}$$

$$0 \leq P_t^{discharge} \leq (1 - M) \,.\, P_{max} \tag{77}$$

In these constraints, M is binary variable and shows charging (equal to 1) and discharge (equal to 0). These constraints include more complexity to optimization problem since the mixed integer programming must be solve. In next Chapter the solution to solve this issue has been explained.

4.1.2 Uncertainties of DSM problem

Up to now, the general formulation for DSM including cost function (65) and all related constraints have been explained in previous sections. In problem of DSM, there are two main sources of uncertainty exist. The first one is PV production fluctuation and second one is Load consumption. Although, Load forecast uncertainty is one of the most influential factors affecting the final results. In order to address these uncertainties, different forecasting method has been proposed in literature. In this research, the distribution fitting method has been used for adding possible fluctuation to Load and PV production. The distribution fitting method includes a hypothesis regarding a standard probability distribution of the forecast error and a fitting procedure used to find its parameters. Load and solar forecast errors are assumed to follow truncated normal distribution (TND) [147]. Probability density function (PDF) of the TND is:

$$PDF_{TND}(x; \mu, \sigma, a, b) = \frac{\frac{1}{\sigma} PDF_N(\frac{x-\mu}{\sigma})}{CDF_N\left(\frac{b-\mu}{\sigma}\right) - CDF_N\left(\frac{a-\mu}{\sigma}\right)} \tag{78}$$

where μ is the mean value of nontruncated normal distribution; σ is standard deviation of nontruncated normal distribution; a and b are upper and lower limits of TND; $PDF_N(.)$ is PDF of standard normal distribution; and $CDF_N(.)$ is cumulative distribution function (CDF) of standard normal distribution. $PDF_N(.)$ and $CDF_N(.)$ are defined as

$$PDF_N(x;\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2} \tag{79}$$

$$CDF_{TND}(x;\mu,\sigma,a,b) = \frac{CDF_N\left(\frac{x-\mu}{\sigma}\right) - CDF_N\left(\frac{a-\mu}{\sigma}\right)}{CDF_N\left(\frac{b-\mu}{\sigma}\right) - CDF_N\left(\frac{a-\mu}{\sigma}\right)} \quad ; \quad a \le x \le b \tag{80}$$

In order to add forecasted error to the preceding DA scheduling, Model predictive control with has been designed. In this way, first pre-scheduling based on deterministic optimization perform. After that based on forecasting horizon (here is one hour), D_{PV} and D_L which are PV generation and Load uncertainty respectively, the necessary changes for each pre-scheduled power flow due to following rules considered and the optimization will repeat for remained time till end of day.

4.2 The model proposed for CAISO market

In the recent year, new FERC orders promote the installation and participation of battery energy storage in electricity market. The initial point was FERC Order. 755 [47] that proposed the performance payment mechanism for frequency regulation market where fast acting resources such as battery storage are rewarded for the quality of service to follow the automated generation control (AGC) signal. The second clear step was FERC order. 841 [76] in 2018 which clearly focused on removing participation barriers for electric energy storage, it is expected to have BESS with higher capacity in the market. BESS participation in market is promoted by different Independent System Operators (ISO) regulations such as NYISO [148], PJM [25] and CAISO [34]. In this research, CAISO Day-Ahead (DA) and Real-Time (RT) market structure is considered. CAISO wholesale energy markets provides the opportunity to buy and sell both power and energy which is comprised of energy market and Spinning reserve, regulation up and down market through DA and RT interval.

The main scope of this research is to maximize the total revenue of battery energy storage systems installed behind the meter by participating in energy, spinning reserve and regulation market as well as simultaneous management of the demand side usage. However, due to uncertain nature of the market price, demand and PV production, the main challenge would be developing the proper optimization method for BESS scheduling. The problem formulation consists of two stages. In first stage, day-ahead optimization is developed to determine preliminary charging and discharging strategy of the battery and commitments for day-ahead market. The second stage would be in real-time interval (intra-hour) to update the initial scheduling based on updated values of the demand and real-time markets. In this section, first the market modelling formulation for both DA and RT has been presented and then in second part the reformulation based on DRO is provided.

Based on this market structure, the total cost and revenue of PV-BESS participating in DA multiple markets and demand side can be formulated as (81):

$$\mathrm{J}_{\mathrm{T}}(v_t) := \min_{v_t} \sum_{t=1}^{T} \left\{ \begin{matrix} \left(C_t^D + C_t^{Op}\right) \\ -\left(R_t^{Spin} + R_t^{Reg} + R_t^E\right) \end{matrix} \right\} \tag{81}$$

Where C_t^D and C_t^{Op} are the demand and operational cost and $R_t^{(.)}$ is the revenue of different markets at each time interval. C_t^D in equation (82) depends on time of use ρ_t^{DA} price in DA and the total energy that delivered from grid to procure demand P_t^{G2L}, charge the battery P_t^{G2Bat} and regulation down market P_t^{RegD} usage. The operational cost C_t^{Op} is proportional to the total exchange energy in storage for charging and discharging of battery, as derived in (83).

$$C_t^D = \rho_t^{DA}.\left(P_t^{G2L} + P_t^{G2Bat} + P_t^{RegD}\right) \qquad ; \quad \forall t \in T \tag{82}$$

$$C_t^{Op} = c_{op}.\left\{ \begin{matrix} \left(P_t^{RegD} + P_t^{G2Bat} + P_t^{PV2Bat}\right) + \\ \left(P_t^{Bat2L} + P_t^{Spin} + P_t^{RegU} + P_t^E\right) \end{matrix} \right\}.h \qquad ; \quad \forall t \in T \tag{83}$$

The revenue of spinning reserve R_t^{Spin} is determined by spinning reserve capacity P_t^{Spin} and spinning price at each moment π_t^{Spin} in (84). The regulation market revenue R_t^{Reg} is structured as capacity payment and performance payment based on FERC order 755 [45]. The capacity payment is related to committed capacity for regulation market P_t^{Reg} and its price π_t^{Reg}, first part in (85), and performance payment is paid based on participants' accuracy acc_t and mileage price π_t^{Mile} by calculating how accurately service provider can follow the automated generation control (AGC) signal as shown in in second part of (85), where m_t is regulation multiplier estimated by CAISO and is the amount of total expected resource movement (up or down), or Mileage, for 1 MW of Regulation Up or Down capacity.

$$R_t^{Spin} = P_t^{Spin}.\pi_t^{Spin}.h \qquad ; \quad \forall t \in T \tag{84}$$

$$R_t^{Reg} = P_t^{Reg}.\pi_t^{Reg}.h + P_t^{Reg}.m_t.\pi_t^{Mile}.acc_t \qquad ; \quad \forall t \in T \tag{85}$$

And finally, the energy revenue R_t^E comes from all energy sectors delivered to grid including regulation up P_t^{RegU}, spinning reserve P_t^{Spin} capacity and extra energy from battery to the grid P_t^E and energy price at time t π_t^E as illustrated in (86).

$$R_t^E = \pi_t^{E.DA}.\left(P_t^{RegU} + P_t^{Spin} + P_t^E\right).h \qquad ; \quad \forall t \in T \qquad (86)$$

It must mention that, in DA market, time horizon T in objective function (81) is 24 hour and t is change based on hourly steps (24 steps/day). However, in RT market, which is also called Fifteen Minutes Market (FMM) in CASIO, time step t is change every 15 min (96 steps/day). It is also important to take into account that spinning reserve and regulation market both up and down (ancillary services) are capacity commitment market in DA which might accrue and call-in real-time dispatch or not. Although, in RT both of them are real time dispatch and that is the main reason of existence of coefficient h in formula (84) and (85) to show this point. Finally, as RT ancillary services are real energy dispatch, they also will be paid as energy delivery to the grid which is shown in (86).

In objective function (81), the optimization variables are participation capacities $P_t^{(.)}$, and market prices are uncertain parameters. Total charging and discharging powers are defined as (87) and (88) respectively. Equations (89) - (95) are the problem constraints. The constraints (89) and (90) are power limits of battery storage in charging and discharging mode respectively as well as complementary charging and discharging constraints for the battery which prevent battery to simultaneous charge and discharge.

$$\mathrm{P_t^{ch}} = \mathrm{P_t^{RegD}} + \mathrm{P_t^{G2Bat}} + \mathrm{P_t^{PV2Bat}} \qquad ; \quad \forall t \in T \qquad (87)$$

$$P_t^{dch} = P_t^{RegU} + P_t^{Spin} + P_t^E + P_t^{Bat2L} \qquad ; \quad \forall t \in T \qquad (88)$$

$$0 \le P_t^{ch} \le P_{Max}.M_t \qquad ; \quad \forall t \in T \qquad (89)$$

$$0 \le P_t^{dch} \le P_{Max}.(1 - M_t) \qquad ; \quad \forall t \in T \qquad (90)$$

State of charge of battery is defined as equation (91), which depends on previous SoC_{t-1} and the charging and discharging capacity at that moment. SoC must be kept in certain limit as shown in (92). Equation (93) forces the final values of SoC to be more than or equal to initial value of the SoC at the beginning to prepare the battery for the next day.

$$SoC_t = SoC_{t-1} + \eta^{ch} P_t^{ch}.h - \frac{1}{\eta^{dch}} P_t^{dch}.h \qquad ; \quad \forall t \in T \qquad (91)$$

$$SoC_{Min} \leq SoC_t \leq SoC_{Max} \qquad ; \quad \forall t \in T \qquad (92)$$

$$SoC_{t=0} \leq SoC_{t_{end}} \qquad ; \quad \forall t \in T \qquad (93)$$

Constraint (94) provides the demand side management where the total demand power request Cap_t^D is procured by PV P_t^{PV2L} , battery P_t^{Bat2L} and grid P_t^{G2L}. Finally, constraint (95) shows the PV production Cap_t^{PV} at each moment.

$$P_t^{PV2L} + P_t^{Bat2L} + P_t^{G2L} = Cap_t^D \qquad ; \quad \forall t \in T \qquad (94)$$

$$P_t^{PV2L} + P_t^{PV2Bat} + P_t^{PV2G} \leq Cap_t^{PV} \qquad ; \quad \forall t \in T \qquad (95)$$

In context of RT scheduling, not only RT markets and demands but also the committed values in DA must consider. Specifically cost function (81) will modify as (96).

$$\mathrm{J}_{\mathrm{T}}^{\mathrm{RT}}(v_t) := \min_{v_t} \sum_{t=1}^{T} \left\{ \begin{array}{c} \left(C_t^{RT,D} + C_t^{Op}\right) \\ -\left(R_t^{Spin} + R_t^{Reg} + R_t^{RT,E}\right) \\ +U_t^D + U_t^E \end{array} \right\} \qquad (96)$$

$$C_t^{RT,D} = \rho_t^{DA} . E_t^{DA,Im} + \rho_t^{RT} . \Delta E_t^{RT,Im} \qquad ; \quad \forall t \in T \qquad (97)$$

$$R_t^{RT,\mathrm{E}} = \pi_t^{E,DA} . E_t^{DA,Ex} + \pi_t^{E,RT} . \Delta E_t^{RT,Ex} \qquad ; \quad \forall t \in T \qquad (98)$$

Subject to

$$U_t^D \geq l^{Im} . \left(\Delta E_t^{RT,Im} - \vartheta^{Im} . E_t^{DA,Im}\right) \qquad ; \quad \forall t \in T \qquad (99)$$

$$U_t^E \geq l^{Ex} . \left(\Delta E_t^{RT,Ex} - \vartheta^{Ex} . E_t^{DA,Im}\right) \qquad ; \quad \forall t \in T \qquad (100)$$

Where $C_t^{Op}, R_t^{Spin}$and R_t^{Reg} are following equations (83), (84) and (85) respectively. However, demand cost and energy income have been updated as (97) and (98) where $E_t^{DA,Im}$ is total energy import from grid in DA including grid to battery, grid to load and regulation down and $\Delta E_t^{RT,Im}$ is its deviation from day-ahead amount which must calculate based on real-time price ρ_t^{RT} instead of day-ahead. In the same way, energy income must update based on value committed to export to grid in DA $E_t^{DA,Ex}$, including spinning reserve, regulation up and committed energy which must calculated in DA energy price $\pi_t^{E,DA}$ and second part that is deviation from DA values $\Delta E_t^{RT,Ex}$. Two last terms in RT cost function (96) is penalty for deviation from DA commitments. Accordingly, U_t^D and U_t^E are introduced to, respectively, present the penalties for deviation form committed values in RT at hour t in \$. l^{Im} and l^{Ex} are, respectively, the price penalties for energy import and export, in \$/kWh. ϑ^{Im} and ϑ^{Ex} are, respectively, ϑ^{Im} threshold which can be used for RT markets and uncertainties fluctuations, expressed as the percentage of the DA quantity, above which energy deviations are penalized.

In second stage, in order to update general problem (96) with last estimation of demand power request and PV power production, model predictive control (MPC) algorithm over planning horizon $\mathcal{H}_t$ is developed. In this term, $Cap_t^{PV} = \bar{P}_t^{PV} + \tilde{P}_t^{PV}$ has been redefined as a summation of nominal value $\bar{P}_t^{PV}$ and forecasted error $\tilde{P}_t^{PV}$ in RT. Likewise, for $Cap_t^{D} = \bar{P}_t^{D} + \tilde{P}_t^{D}$.

$$\mathrm{J}_{\mathrm{T}}^{*}(v_t) = \min_{v_t} \sum_{t=1}^{T} \sum_{\tau=t}^{t+\mathcal{H}_t} \mathrm{J}_{\mathrm{T}}(v_t, \xi_\tau) \tag{101}$$

Only the immediate control decisions for time t till $\mathcal{H}_t$ are considered as BESS plan. Then time shifts forward one step, new forecast errors are realized, the optimization problem (101) is re-solved at time $t + 1$ hour, and the process repeats. This approach allows any forecasting methodology to be utilized to predict uncertainties over the planning horizon and recalculate intra hour decisions based on short term and more accurate forecasting.

4.2.1 Uncertainties of market and DSM

In our research formulation, by considering demand side management and electricity market, three sources of uncertainty exist. The first source is related to demand load and PV production. To deal with this kind uncertainties open loop MPC has been developed in RT which is described in (101) and section 4.1.2 in details. The second source of uncertainty is associated with the actual resource being deployed in the market or in other word, the actual amount of energy that awarded in DA market. This category is complicated and not easy to foreseen, however, due to small size of BTM battery capacity compare to other market participants and the fact that these assets are price-taker at this moment (they are following the market price and cannot influence market price), we can assume that a high percentage of DA schedules volume has been accepted for RT dispatch. The last source of uncertainty is back to market prices. There are various price forecasting methods based on historical price fluctuations could be used [149]. This category is easy to fit to any distribution probability since it has been affected by various factors such as demand, grid contingencies, weather condition and etc. In this research two approaches have been implemented to deal with these uncertainties. The first one is robust optimization which is described earlier in subsection 3.2 and updated formula has been discussed in subsection 4.2.1.1.. The second approach which is the main contribution of this research is data-driven distributionally robust optimization approach which has been described and discussed in subsection 3.3 and 4.2.1.2.

4.2.1.1 Robust Optimization

Robust optimization is non-probabilistic method which considers the worth case scenario of uncertain variables. As mentioned before, the main challenge in our research is market price fluctuation. To revise the cost function (81) based on RO method, it can be rewritten as formula (102) where demand cost and operational costs follows the equations (82) and (83) same as deterministic method respectively. However, the markets revenue formulations have been updated as (103)-(105).

$$\widetilde{\mathrm{J}}_{\mathrm{T}}(v_t) := \min_{v_t} \min_{\Delta} \sum_{t=1}^{T} \left\{ \begin{array}{c} \left(C_t^D + C_t^{Op}\right) \\ -\left(\tilde{R}_t^{Spin} + \tilde{R}_t^{Reg} + \tilde{R}_t^E\right) \end{array} \right\} \tag{102}$$

$$\tilde{R}_t^{Spin} = P_t^{Spin}.(\pi_t^{Spin} + \Delta\pi_t^{Spin}).h \qquad ; \quad \forall t \in T \tag{103}$$

$$\tilde{R}_t^{Reg} = P_t^{Reg}.(\pi_t^{Reg} + \Delta\pi_t^{Reg}).h + P_t^{Reg}.m_t.\pi_t^{Mile}.acc_t \qquad ; \quad \forall t \in T \tag{104}$$

$$\tilde{R}_t^E = (\pi_t^E + \Delta\pi_t^E).\left(P_t^{RegU} + P_t^{Spin} + P_t^E\right).h \qquad ; \quad \forall t \in T \tag{105}$$

The new constraints related to confidence gap of market prices can be written as formula (106)-(108) where $\alpha^{(.)}$ is the robustness gap of each market. The rest of constraints are the same as deterministic method.

$$-\pi_t^{Spin}\alpha^{Spin} \le \Delta\pi_t^{Spin} \le \pi_t^{Spin}\alpha^{Spin} \qquad ; \quad \forall t \in T \tag{106}$$

$$-\pi_t^{Reg}\alpha^{Reg} \le \Delta\pi_t^{Reg} \le \pi_t^{Reg}\alpha^{Reg} \qquad ; \quad \forall t \in T \tag{107}$$

$$-\pi_t^E\alpha^E \le \Delta\pi_t^E \le \pi_t^E\alpha^E \qquad ; \quad \forall t \in T \tag{108}$$

In this kind of robust formulation as the uncertain variable just have been appeared in cost function and robustness gap in separate constraints, therefore in order to solve the inner side minimization, the variables of the outer side minimization of (81) should be considered fixed and as parameters. In this way, the minimization part would be a linear simple optimization problem constrained to (106)-(108). The minimum value of such linear optimization problem is obtained in one of the boundaries of uncertainty horizons, depending on their coefficients. The coefficients of minimization part variables, i.e., $\Delta\pi_t^{Spin}$, $\Delta\pi_t^{Reg}$ and $\Delta\pi_t^E$ are P_t^{Spin}, P_t^{Reg} and P_t^E, respectively, which are all positive. Therefore, their worst-case realization can be easily obtained by setting them to their lower level bounds. In other words, the worst case of this group of uncertain variables is as follows (109) and (111).

$$\Delta\pi_t^{Spin} = -\pi_t^{Spin}\alpha^{Spin} \qquad ; \quad \forall t \in T \tag{109}$$

$$\Delta\pi_t^{Reg} = -\pi_t^{Reg}\alpha^{Reg} \qquad ; \quad \forall t \in T \tag{110}$$

$$\Delta\pi_t^{E} = -\pi_t^{E}\,\alpha^{E} \qquad ; \quad \forall t \in T \tag{111}$$

4.2.1.2 Data-Driven Distributionally Robust Optimization

In Equation (81), described in preceding section **Error! Reference source not found.**, the m ean value of historical data is assumed instead of uncertain parameters such as market prices to solve deterministic optimization. In order to consider the risk of different uncertainties, data-driven distributionally robust optimization method is introduced in this section. The conventional approach to optimize the objective function is the stochastic approach where the different scenarios based on assumed partial distribution (PD) will be defined and the main aim is to minimize the expected cost such as expressed in (112).

$$J^* = \inf_{v\in\mathbb{V}}\left\{\mathbb{E}^{\mathbb{P}}[h(v,\xi)] := \int_{\Xi} h(v,\xi)\mathbb{P}(d\xi)\right\} \tag{112}$$

with decision variable $v \in \mathbb{V} \subseteq \mathbb{R}_n$, random vector ξ with probability distribution $\mathbb{P}$ supported on uncertainty set $\Xi \subseteq \mathbb{R}_m$ and cost function $h: \mathbb{R}_n \times \mathbb{R}_m \to \overline{\mathbb{R}}$. A common approach to find $\mathbb{P}$ is to estimate the distribution from limited available data which usually leads to a poor out-of-sample performance since it is not precise and based on limited data. Moreover, more accurate results require more scenarios to be generated which increases the computational burden and time. The possible approach to guaranty out-of-sample performance is to define an ambiguity set $\hat{\mathcal{P}}_N$ which contains all possible distributions from training data [128]. In this way, the distributionally robust optimization (113) defines as the minimum worst-case expected cost over $\hat{\mathcal{P}}_N$.

$$\hat{J}_N := \inf_{v\in V}\ \sup_{\mathbb{Q}\in\hat{\mathcal{P}}_N} \mathbb{E}^{\mathbb{Q}}[h(v,\xi)] \tag{113}$$

To instruct the ambiguity set, in this research, we focus on the Wasserstain metric since it has a tractable reformulation and out-of-sample performance guarantees [128], [140]. We construct $\hat{\mathcal{P}}_N$ as a ball around empirical distribution with radius based on Wasserstain metric to measure the distance between true PD and estimated one.

The ambiguity set $\mathbb{B}_\varepsilon(\widehat{\mathbb{P}}_N)$ can be formulated as Wasserstein ball centered at a uniform empirical distribution $\widehat{\mathbb{P}}_N$ on training dataset Ξ_{N_s} and within ε as confidence level (114). The ε

is a control variable for conservativeness and robustness of optimization compare to specific features of dataset.

$$\hat{\mathcal{P}}_N = \mathbb{B}_\varepsilon(\widehat{\mathbb{P}}_N) := \{\mathbb{Q} \in \mathcal{M}(\Xi) : dw(\widehat{\mathbb{P}}_N, \mathbb{Q}) \leq \varepsilon\} \tag{114}$$

In this research, the mean-risk portfolio for our problem structure in Equation (81) has been developed to solve single stage stochastic optimization which minimizes a weighted sum of the mean and the conditional value-at-risk (CVaR) of the portfolio revenue amount $\langle v, \pi \rangle$. Consider a total capacity of battery is divided between multiple services at each time interval and is encoded by a vector of percentage weights $v = [v_1, \dots, v_m]^T$ ranging over probability simplex $\mathbb{V} = \{v \in \mathbb{R}_+^m : \sum_{i=1}^m v_i = 1\}$. Uncertain price for each service is shown by the vector $\pi = [\pi_1, \dots, \pi_m]^T$ (115).

$$\mathrm{J}_{\mathrm{T}}^*(v_t) = \inf_{v_t \in \mathbb{V}} \{\mathbb{E}^{\mathbb{Q}}[-\langle v_t, \pi \rangle] + \zeta . \mathbb{Q}\_CVaR_\alpha(-\langle v_t, \pi \rangle)\} \tag{115}$$

Definition: Conditional Value-at-Risk (CVaR), which is known also as "Mean Excess Loss", "Mean Shortfall", or "Tail VaR". By definition with respect to a specified probability level ζ, the $\zeta -$ VaR of a portfolio is the lowest α amount such that, with probability ζ, the loss will not exceed α, whereas the $\zeta -$ CVaR is the conditional expectation of losses above that amount α [150].

Here $CVaR_\alpha$ is conditional value at risk with confidence level of $\alpha \in (0,1]$ and $\zeta \in \mathbb{R}_+$ quantifies the investor's risk-aversion. The formula (115) can be reduced to piecewise affine form such as (116) by replacing CVaR in with its formal definition [151].

$$J^* = \inf_{v \in \mathbb{V}} \left\{ \begin{matrix} \mathbb{E}^{\mathbb{Q}}[-\langle v, \pi \rangle] + \\ \zeta \inf_{\tau \in \mathbb{R}} \mathbb{E}^{\mathbb{Q}}[\tau + \frac{1}{\alpha} \max_{v \in \mathbb{V}} \{-\langle v, \pi \rangle - \tau, 0\}] \end{matrix} \right\} = \inf_{v \in \mathbb{V}, \tau \in \mathbb{R}} \mathbb{E}^{\mathbb{Q}}[\max_{k=1,2} a_k \langle v, \pi \rangle + b_k \tau] \tag{116}$$

where $k = 2$, $a_1 = -1$, $a_2 = -1 - \frac{\zeta}{\alpha}$, $b_1 = \zeta$, and $b_2 = \zeta(1 - \frac{1}{\alpha})$. Supposed that uncertainty $\Xi := \{\pi \in \mathbb{R}^m : C\pi \leq d\}$ and a polytope, then the stochastic formula of (116) can be solve in distributionally robust form counterpart of (58) with respect to the Wasserstein ambiguity set $\mathbb{B}_\varepsilon(\widehat{\mathbb{P}}_N)$ such as:

$$\hat{J}_{N,t}(\varepsilon) = \left\{ \begin{matrix} \inf_{v_t, \tau_t, \lambda_t, s_{t,i}, \gamma_{t,i,k}} \lambda_t \varepsilon + \frac{1}{N} \sum_{i=1}^{N} s_{t,i} \\ s.t. \quad v_t \in V \\ b_k \tau_t + a_k \langle v_t, \hat{\pi}_{i,t} \rangle + \langle \gamma_{t,i,k}, d - C\hat{\pi}_{i,t} \rangle \leq s_{t,i} \\ \left\| C^T \gamma_{t,i,k} - a_k v_t \right\|_\infty \leq \lambda_t \\ \gamma_{t,i,k} \geq 0 \qquad ; \forall i \in N_s, k \leq 1,2 \end{matrix} \right. \tag{117}$$

Where τ_t is a CVaR auxiliary valuable and $s_{t,i}$, $\gamma_{t,i,k}$ and λ_t are auxiliary variables associated with the distributionally robust Wasserstein ball reformulation. In formula (117), the optimum cost $\hat{J}_{N,t}$ for each time interval t and N training samples is calculated. Subsequently, the final objective function for our problem will be formulated as (118) in DRO form with the constraints (89) - (95) and (117).

$$\hat{\mathrm{J}}_{\mathrm{T}} = \min_{v_t,\tau_t,\lambda_t,s_{t,i},\gamma_{t,i,k}} \sum_{t=1}^{T} \hat{J}_{N,t}(\varepsilon) \tag{118}$$

5 Case Study

The main aim of this research is to show benefits of participation of Behind the Meter (BTM) storage system in feasible electricity market as well as improving the self-consumption and demand side management. In this regard, different scenarios defined, and different optimization approach have been implemented. It is important to take into account that almost no real data for BTM storage is available since all of them are private sector and these data are confidential [152]. On the other hand, by increasing of installation of roof top PV panels and BTM storage, changing the market structure such as FERC Order. 755 [45] and frequent adaptation of market regulation such as FERC Order. 841 [76] the ancillary services and energy price trend has been changed and it is not stable yet. These two challenges bring difficulty to find and choose proper cases. Nevertheless, in this research a household user with roof top PV and battery storage system in California has been chosen as case study. The main reason to choose California region is this region has one of the most BTM storage installation and the same time the its market regulation is the most advanced and adopted for renewable generators and energy storage systems. Moreover, in all case scenarios, data from year 2016 has been used for scheduling and market data from year 2017 used for test and feasibility tests. Solar irradiance data for Los Angeles area has been collected from PHOTOVOLTAIC GEOGRAPHICAL INFORMATION SYSTEM (PVGIS) [153] (Figure 5-1).

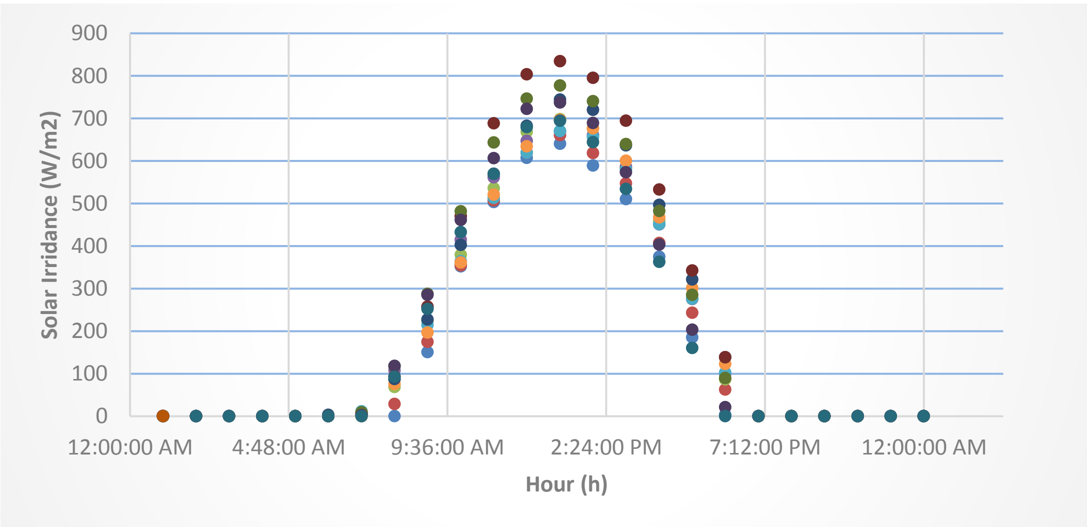


Figure 5-1 – Monthly Solar Irradiance of Los Angeles region

Due to seasonal change in Time of Use (ToU) tariff and PV production, all scenarios have been calculated separately for Winter and Summer season. The sizing of PV and battery bank is based on a sizing model in [154]. The parameters of this system are listed in Table 5. The maximum power delivered on each flow is defined as 5 kW which is the limitation of invertor.

The mono-crystalline silicon (mc-Si) has been considered as PV type and its output power follows the equation (119) where Irr_t is solar irradiance at each moment [155]. Load profile has been considered as typical residential load [141] and it will change based on seasonal ratio [156].

$$P_t^{PV} = 0.000898 \times Irr_t - 0.0138 \tag{119}$$

Nominal Battery Capacity	30 kWh
Battery Charge Efficiency	85%
Battery Discharge Efficiency	95%
Initial State of Charge	16 kWh
Minimum SoC	15%
Maximum SoC	90%
PV array's capacity	5 kW

Table 5 – Parameters of Hybrid PV-Battery system

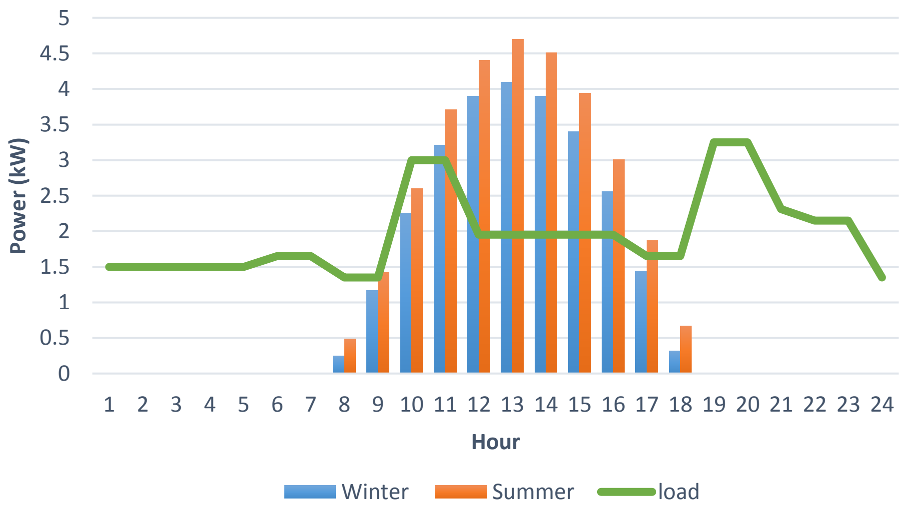


Figure 5-2 – Seasonal PV Production Power output and Load

5.1 Demand Side Management

In the first case scenario, the behind the meter battery with rooftop PV panels used for demand side management. In this case, just surplus energy from PV and battery export to grid and battery packs do not participate in any market. For both Winter and Summer time optimization run to minimize the total cost based on objective function (65). In addition to load profile and PV production for each season, the energy tariff for weekday from online data centre of [33] have been used separately. The contract ratio for selling energy to the grid considered as 85%. In all utilities, Winter period is between November to end of April (8 months) and Summer is defined from June to end of September (4 months).

For second stage of this scenario, the uncertainties of load and PV production up to 20% of each hour and based on described probability distribution in section 4.1.2 have been added and new value for each power flow scheduling have been revised respectively. In order to have more precise scheduling and better comparison with the other cases, uncertainties will determine every 15 min and new optimization with MPC will perform based on 15min time interval (instead of each hour).

In this case, load profile and PV production after adding uncertainties will change as Figure 5-3.

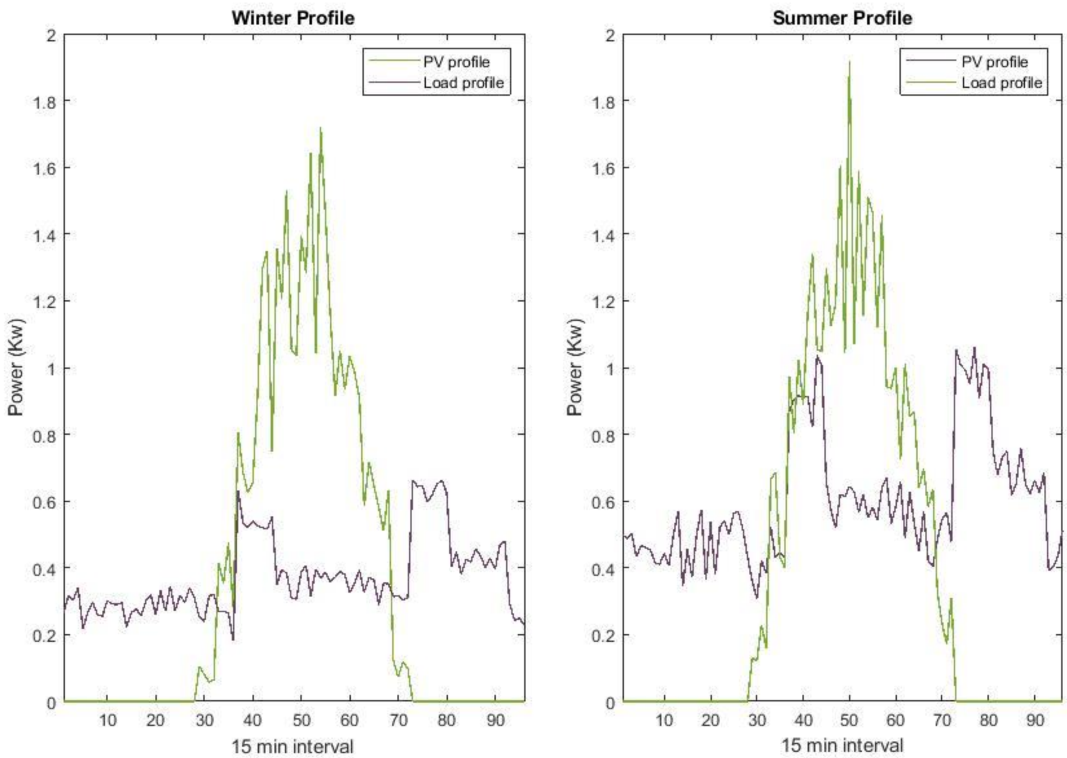


Figure 5-3 – PV and Load profile with uncertainties in Winter and Summer

5.2 Electricity Market and DSM

In this section, instead of just optimal scheduling the BESS with respect to demand side load profile, it has been participated in feasible electricity markets that have been explained in sub-section 1.1.7.2 and formulated in sub-section . In order to have comprehensive comparison all assumptions in section 5.1 is also valid for this section including further assumptions related to market and optimization methods which will described in this section. Base on CAISO tariff [34] and FERC Order. [76] battery energy storages are valid to participate in ancillary services including spinning reserve (as a fast response generator), regulation up and regulating down. Also, traditionally, they could bid for retail energy market as well. It is important to take into account that during participation in ancillary services we have double payment both for their capacity commitment and energy delivery. For ISO retail energy market, Local Marginal Price must be use as reference for energy price.

As the market price range for winter and summer time has different level and the main purpose is to have comparison with solely DSM case, here also separate simulation for winter and summer time performed. The general procedure in this case is that, first in DA interval a whole day schedule of battery with respect to load profile, solar generation, LMP and ancillary services price and calling signal for markets will be clear. For ancillary services, there is no available and full day market to participate and each service provider must follow the market request signal from ISO. In this research, we assumed that these markets are calling 8 times per day and at the same time which is the worth case scenario. For regulation market, as discussed earlier, in general service providers must follow the AGC signal and they also will be paid based on accuracy of their performance. However, in our case as we are working with BTM batteries and the total capacity is low, for sake of simplicity we neglect this payment.

After DA interval, pre-schedule of batteries has been determined and the committed values for DA market have been fixed. In the second stage, based on remained capacity of battery, new forecasting values for demand profile and PV production as well new signals for real-time markets, new optimization will be run for each hour (instead of whole day) and based on 15 min interval which is the RT market signalling interval. To add and update the battery SoC based on DA values and proceeding hours, MPC algorithm has been developed. In practice, service providers must pay penalty for any deviation from confirmed values in DA and real-time dispatch. The penalty ratio depends on contract and service type and there is no clear information available. However, it must consider that up to valumn which scheduled in DA will pay based on DA price and the extra amount will treat based on RT price. This fact has been shown in formula (96). Thus, in this research BESS is forced to follow the DA schedule as priority.

Moreover, in this section three different optimization approaches for dealing with market price uncertainties (which didn’t exist in previous section) including deterministic, robust and data-driven distributionally robust optimization (DRO) run separately. All market data have been collected from CAISO online data centre [33] for year 2016 and 2017. In this way for all case scenarios, first the scheduled values based on data from 2016 train and then based on data from 2017 will be test. In addition, in order to have more realistic case, since predicting full data is not possible, only limited number of days selected as useful data.

5.2.1 Deterministic Optimization solution

Problem formulation for deterministic optimization have been explained in section 4.2 as base case scenario. In this formulation, we assumed the market price for each season is equal to seasonal average of price of each market. The main problem with deterministic approach is that it doesn't consider the fluctuation of prices however, the formulation and optimization is the simple and fast. In Figure 5-4 - Figure 5-7 comparison of average prices for DA interval in each market between winter and summer, full seasonal data and selected data has been shown. The same in Figure 5-8 - Figure 5-11 for RT interval. For full data figures for both DA and RT check the Appendix A.

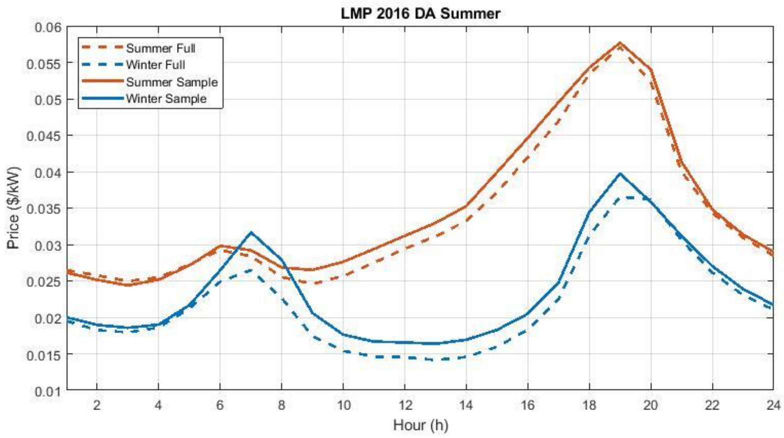


Figure 5-4 - LMP seasonal DA average price in 2016

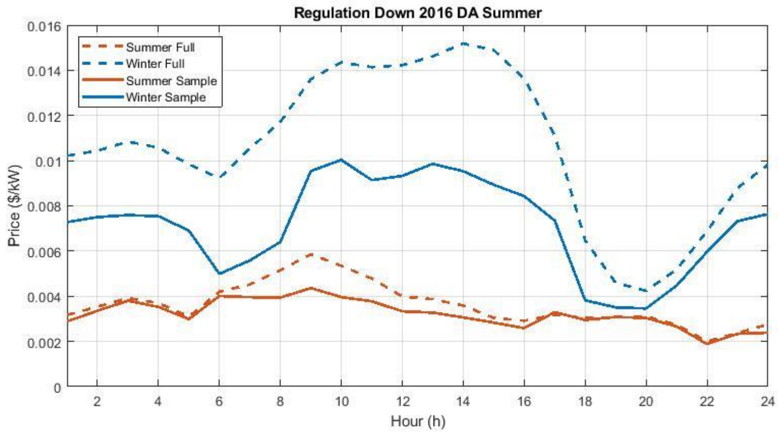


Figure 5-5 – Regulation Down DA seasonal average price in 2016

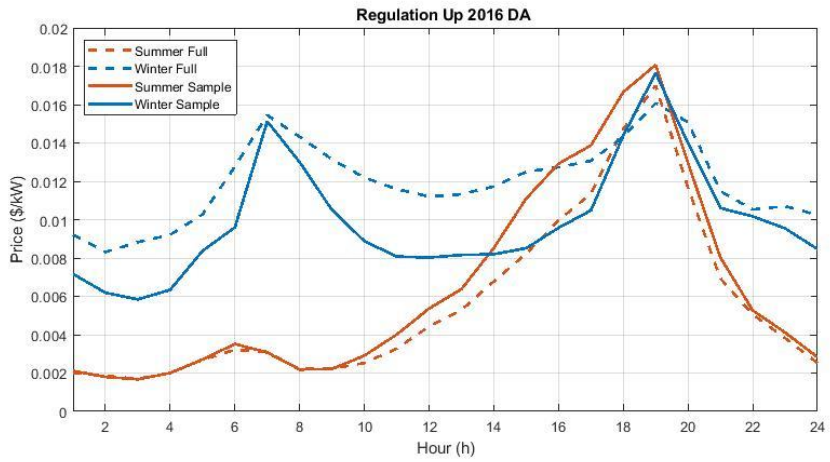


Figure 5-6 - Regulation Up DA seasonal average price in 2016

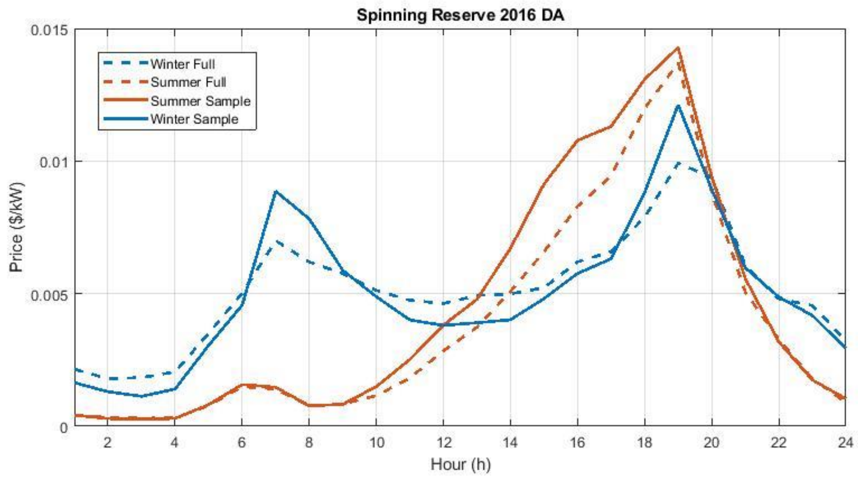


Figure 5-7 – Spinning Reserve DA seasonal average price in 2016

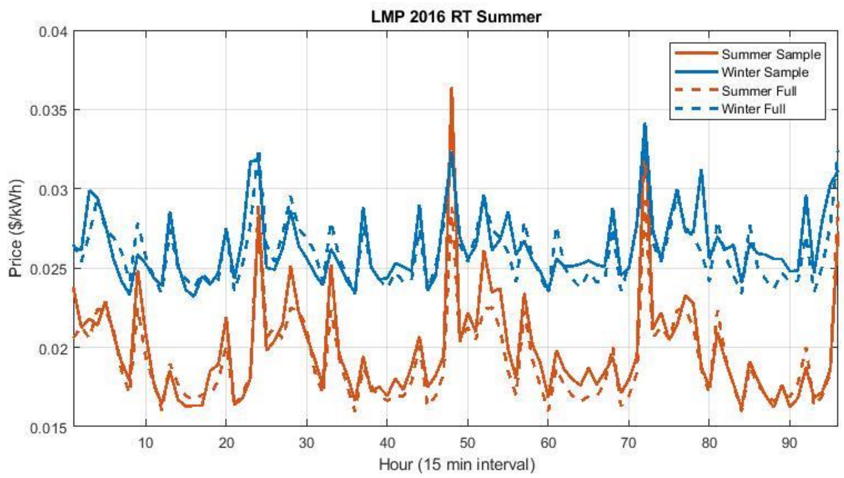


Figure 5-8 - LMP RT seasonal average price in 2016

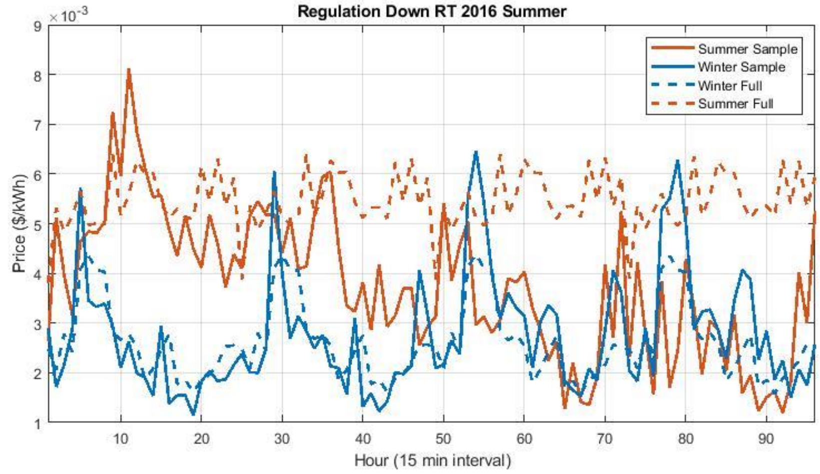


Figure 5-9- Regulation Down RT seasonal average price in 2016

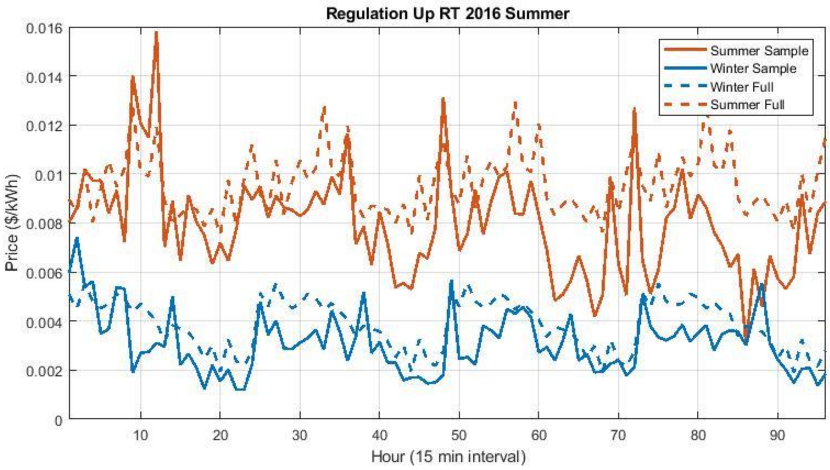


Figure 5-10- Regulation UP RT seasonal average price in 2016

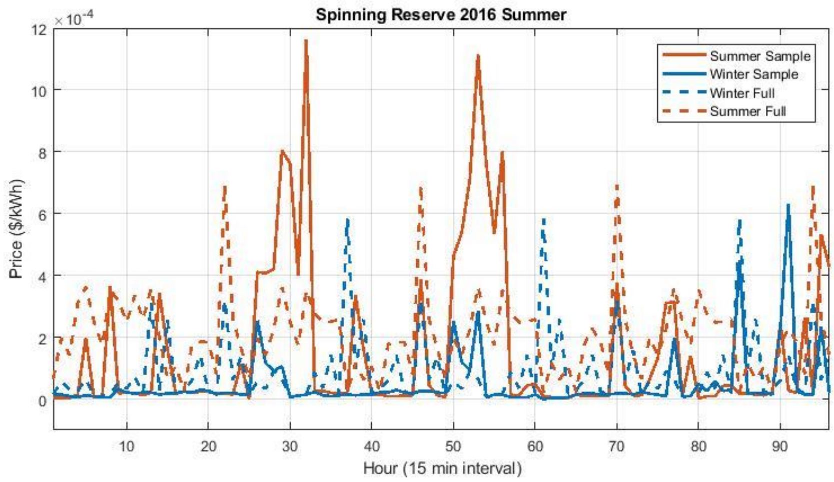


Figure 5-11- Spinning Reserve RT seasonal average price in 2016

5.2.2 Robust Optimization solution

As already explained in section 4.2.1.1, in this research in line with [157] the confidence gap for worth case realization of the market prices considered. In this way, we assumed that confidence gap for all market at each instance $\Delta\pi_t^{()}$ both for day ahead and real time interval is equal to 80%. To implement this approach, from selected data the average of minimum 20% data have been considered as worth solution. The rest of procedure is the same as deterministic approach which explained in previous section.

5.2.3 Data-Driven Distributionally Robust Optimization solution

In DRO programming, instead of using fixed uncertainty set, we need to develop as ambiguity set. Thus, in this research as explain in section 4.2.1.2, Wasserstein probability distance solution has been chosen to construct ambiguity set. In order to implement DRO in equations (117) and (118), we need to consider following assumptions:

- The number of selected samples for each season is 30 days.
- The full polytope uncertainty set is $\Xi := \{\pi \in \mathbb{R}^m : C\pi \leq d\}$, in our problem, for each market in each interval, we have individual uncertainty set. For sake of simplicity, we consider $C = 1$ and d equal to maximum of collected data for each market.
- confidence level of CVaR α, the radius of Wasserstein ball ε and risk aversion value ζ. Here α and ε are assumed as 0.001 and ζ = 0.9.

Note: it is very critical point that there is a trade-off between final cost value and the robustness of problem against price uncertainties. The conservativeness of the optimization is controlled by adjusting confidence level of CVaR α, the radius of Wasserstein ball ε and risk aversion value ζ.

6 Simulation and Results

As mentioned in previous chapter, all market data has been collected from CAISO online website [33] from year 2016. From wintertime and summertime 30 random data in each season from workdays selected for scheduling. Then after scheduling in DA and RT interval, the feasibility of solution proved by data from 2017.

All simulation has been conducted with CVX integrated in MATLAB. MOSEK [158] has been chosen as solver for mixed-integer linear optimization problem. The environment is a desktop with Intel Core™ i5-2430 M, 2.4 GHz CPU and 8 GB RAM.

In the first step of this section the scheduling results based on different scenarios have been shown and then in final sub-section the general comparison has been done.

6.1 Demand Side Management Results

In this case, we don’t participate in any market, the only purpose is to improve self-consumption of PV with battery energy storage and the only revenue comes from export the surplus energy of PV/Battery to grid with 80% of buying price. In this way, as it is shown in Figure 6-1 and Figure 6-2, in summer season DA scheduling battery is used between hour 18:00-21:00 to meet the load and it charged in early morning and midnight from grid. The rest of load covered by PV during day and consumer must buy the remained from grid. In RT revise after adding uncertainties, the battery charge more from PV in daytime instead of fully charge by grid. However, load curtailment is almost the same.

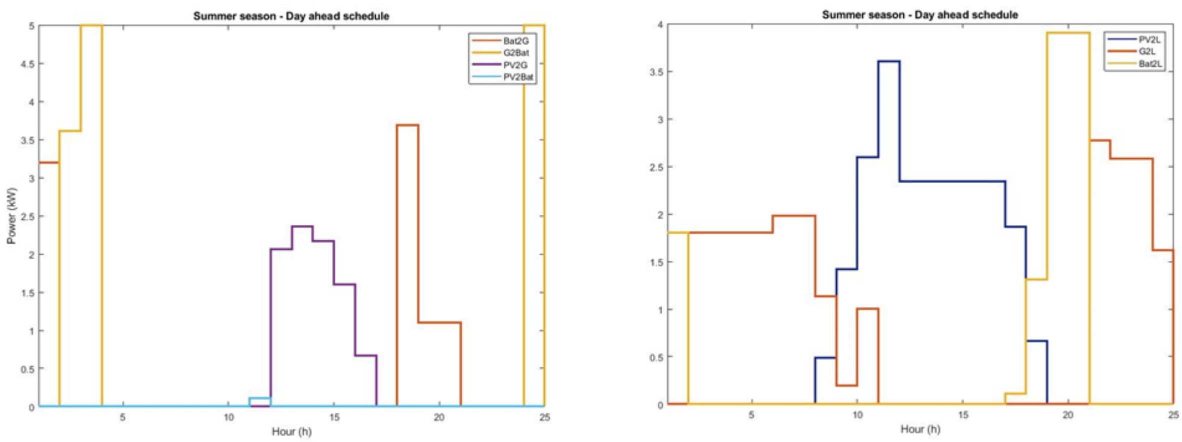


Figure 6-1 - DA Battery Schedule in Summer DSM

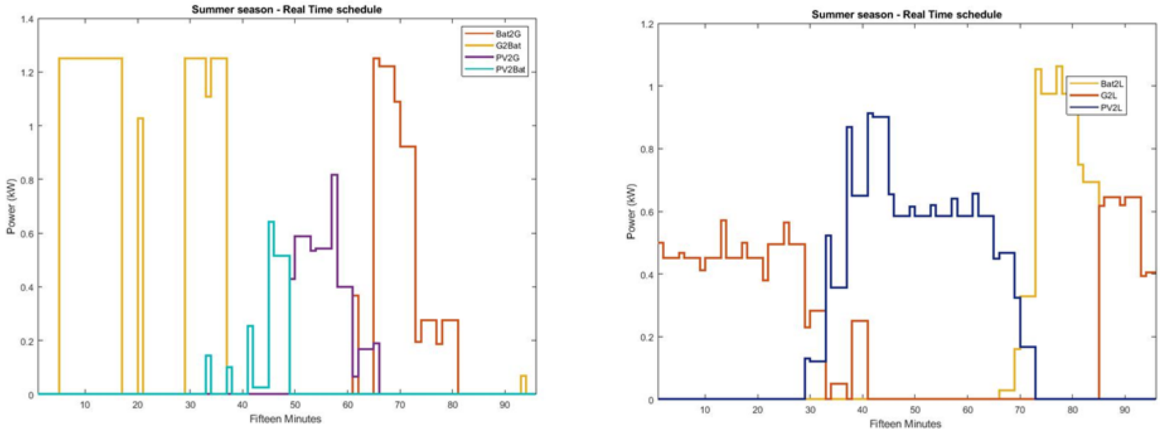


Figure 6-2 - RT Battery Schedule in Summer DSM

In winter season, the behaviour of battery is slightly different compared with summer. The main different is that not only battery meet the load in evening time, but also it covers the load in midnight and early morning for short period. The second different is that it will charge all during daytime both from PV and grid. In general, these differences come from lower load demand and lower energy cost in daytime compare with summer season. These power flows are illustrated in Figure 6-3 and Figure 6-4.

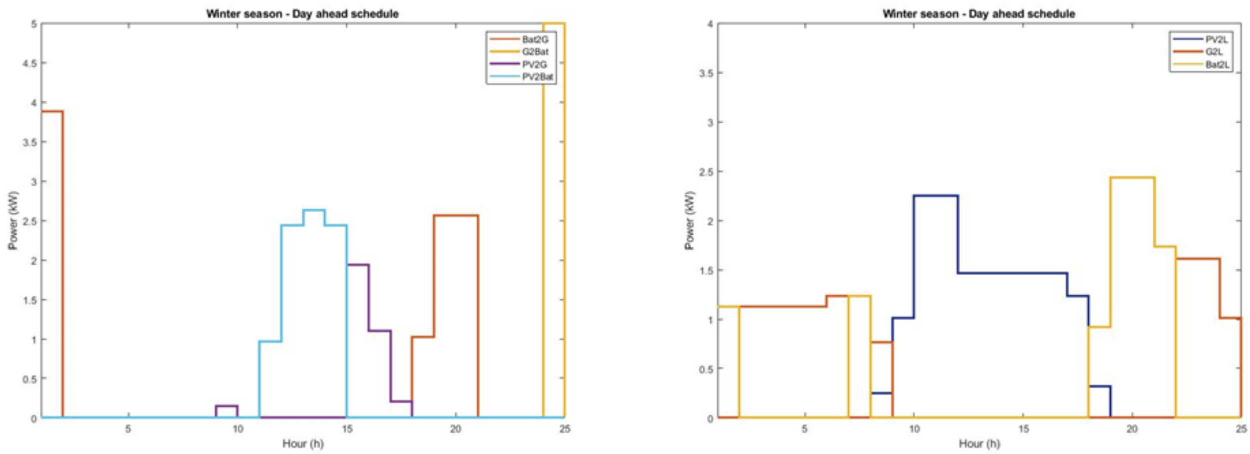


Figure 6-3 - DA Battery Schedule in Winter DSM

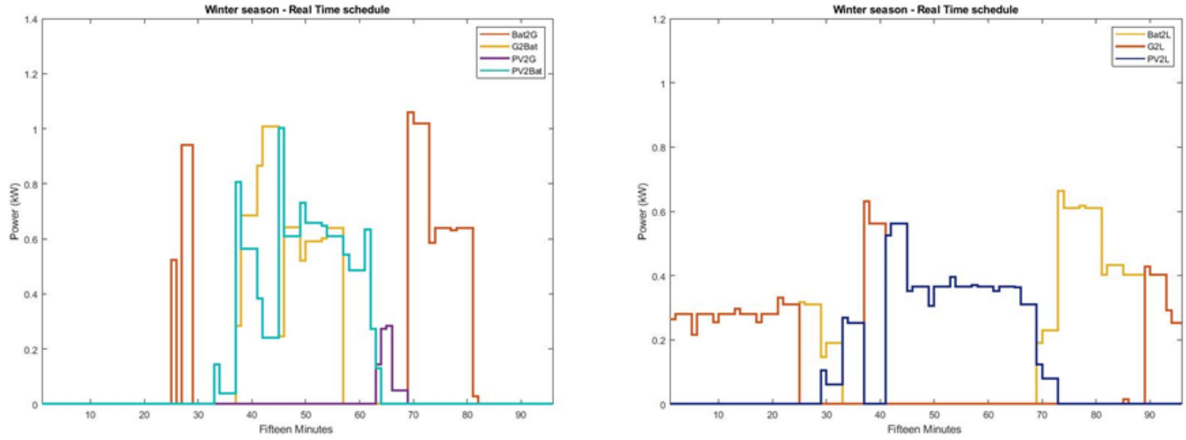


Figure 6-4- RT Battery Schedule in Winter DSM

To sum up, general comparison between summer and winter season in case of PV-battery system without participating in any market shown that in wintertime battery system are more active and have more contribution, however, in both case in most of hours in day battery doesn't participate at all.

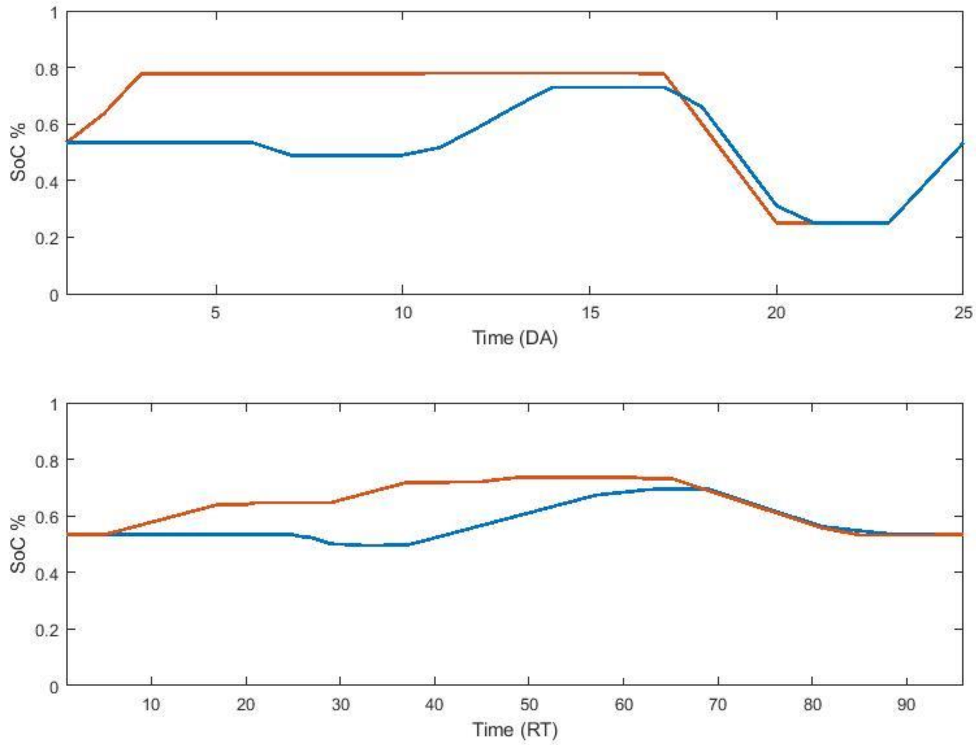


Figure 6-5 – State of Charge in DSM

6.2 DSM and Market participation Results

In this section, not only demand side management but also participating in market considered. Three main approach for two season and in DA and RT interval simulated and power flows, market volume and SoCs plotted and explained.

6.2.1 Deterministic optimization

In this method, both for winter and summer battery doesn't support load at all and just participate in market. In this solution, battery participate in regulation down as much as possible and it just participate in energy market solely in one hour. The same as spinning reserve. In this way, it saves more energy for regulation market without any extra charge from grid.

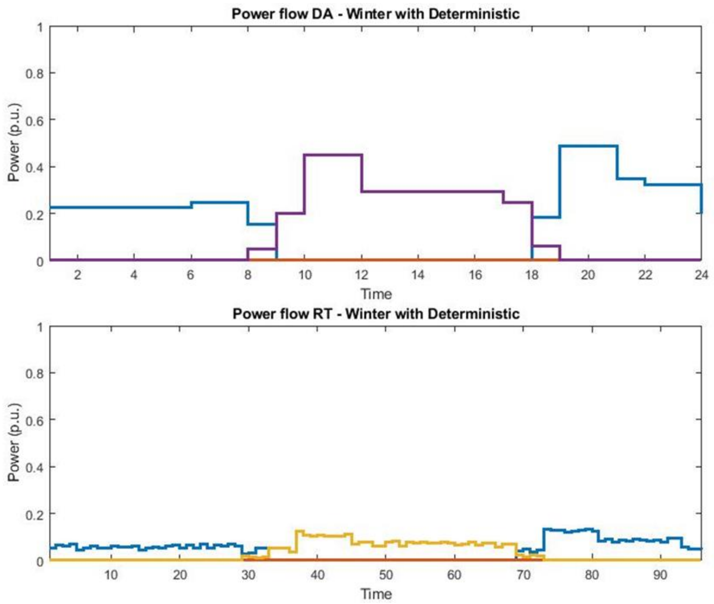


Figure 6-6 – DA and RT schedule with deterministic optimization in Winter

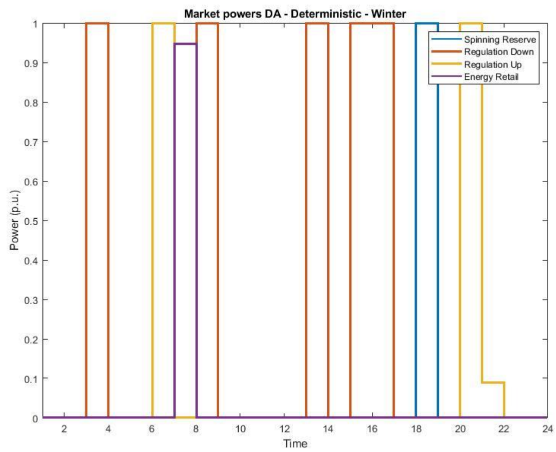


Figure 6-7- Market values participation values with deterministic optimization in Winter

On the other hand, load profile is covered fully with PV and grid which is too costly and in case of rejecting the bids of DA market it is too risky solution and not robust at all. The main different between winter and summer schedule is that in summertime it participates more in energy market and very few in load. These results have been shown in Figure 6-6 till Figure 6-10.

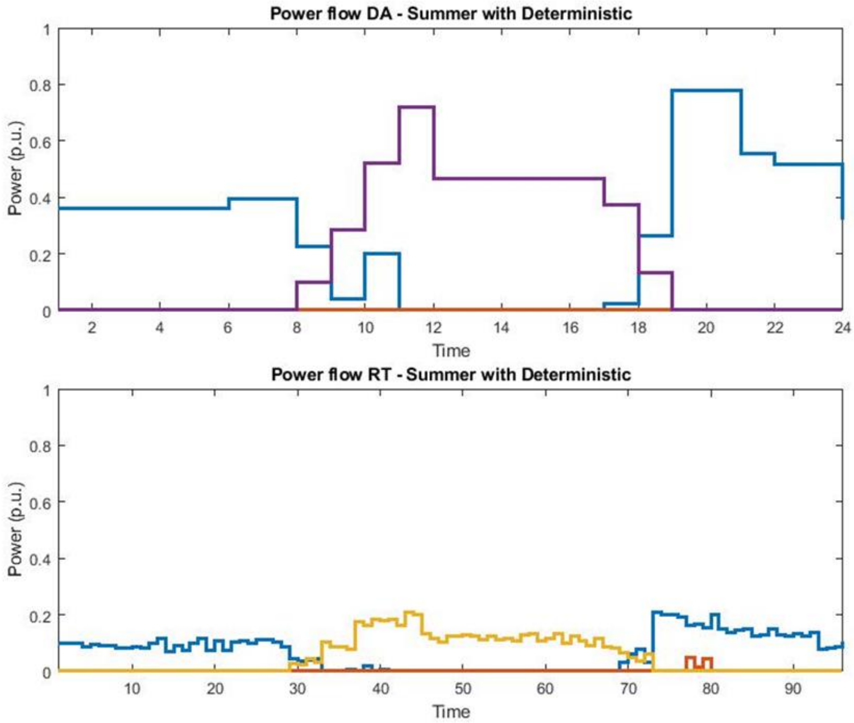


Figure 6-8- DA and RT schedule with deterministic optimization in Summer

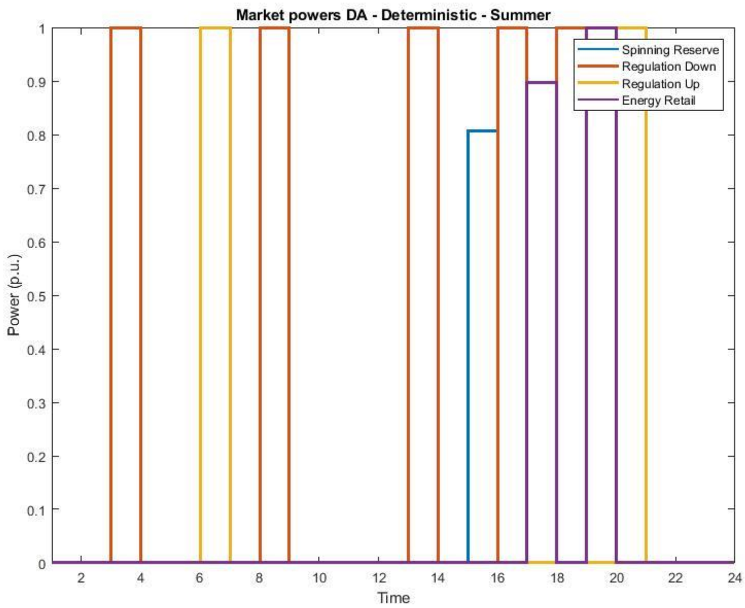


Figure 6-9- Market values participation values with deterministic optimization in Summer

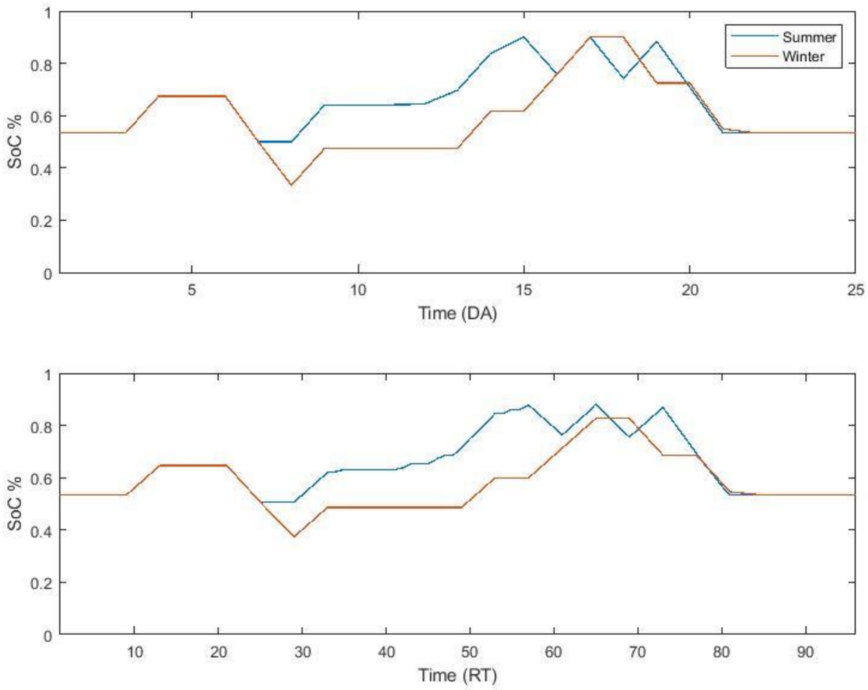


Figure 6-10- State of Charge with Deterministic Optimization in winter and summer both DA (top) and RT (bottom)

6.2.2 Robust optimization

In robust optimization approach, unlike deterministic approach, the main focus of battery is to cover the load profile and increase the self-consumption. In this way robust is more similar to basic case of DSM. However, the main different is to participate in regulation down market instead of buying energy directly from grid. In this way, battery can serve more load not only in evening time but also in hours before PV production. Meantime, as in this approach worth case scenarios are considered, the market price would be quite low and this the reason that battery won't participate in any market as much as possible. In this approach, summer and winter schedule are close and the only different is that in summer due to higher production of PV, battery has more flexibility in participating in market. But in general, this robust optimization is too conservative against market price and less active in market. These results have been shown in Figure 6-11 till Figure 6-15.

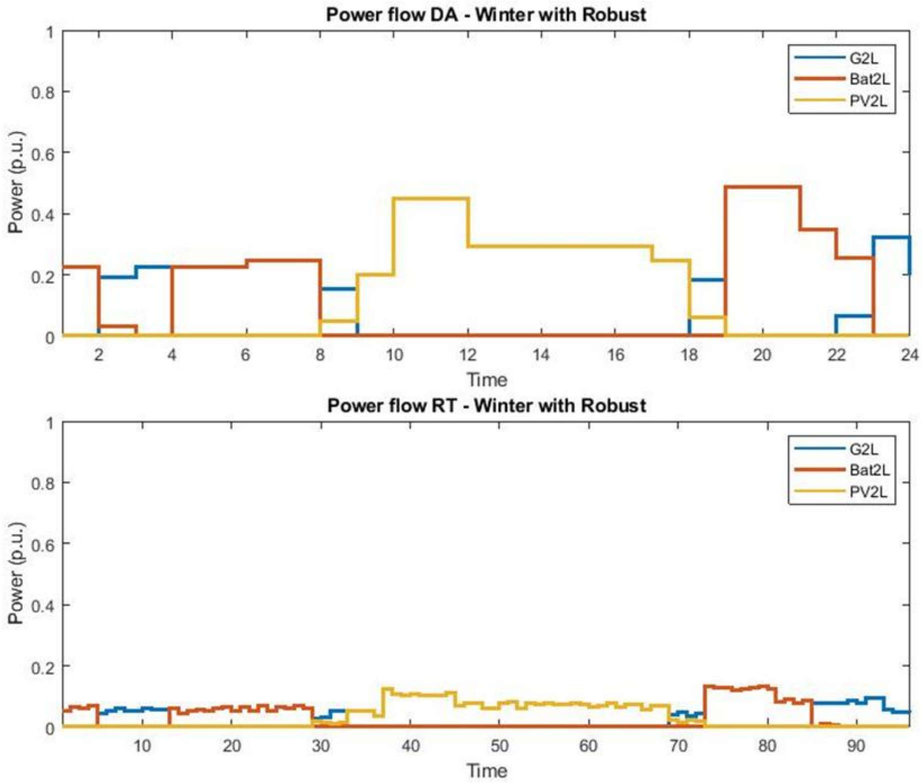


Figure 6-11- DA and RT schedule with robust optimization in Winter

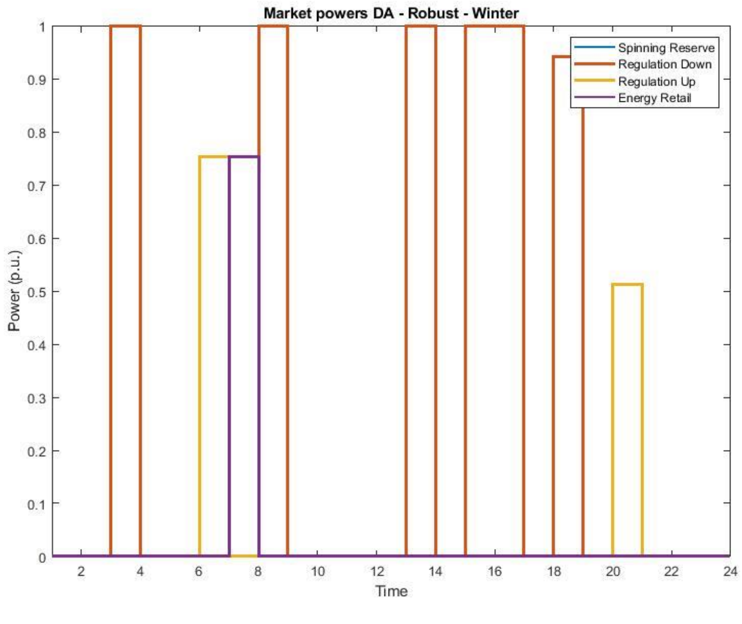


Figure 6-12- Market values participation values with robust optimization in Winter

-

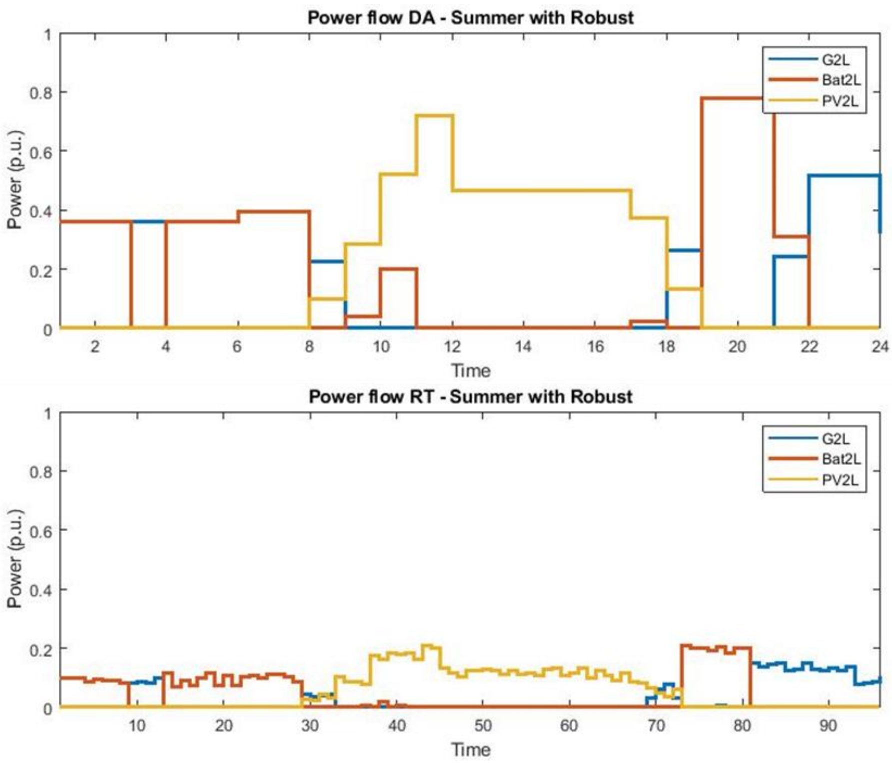


Figure 6-13- DA and RT schedule with robust optimization in Summer

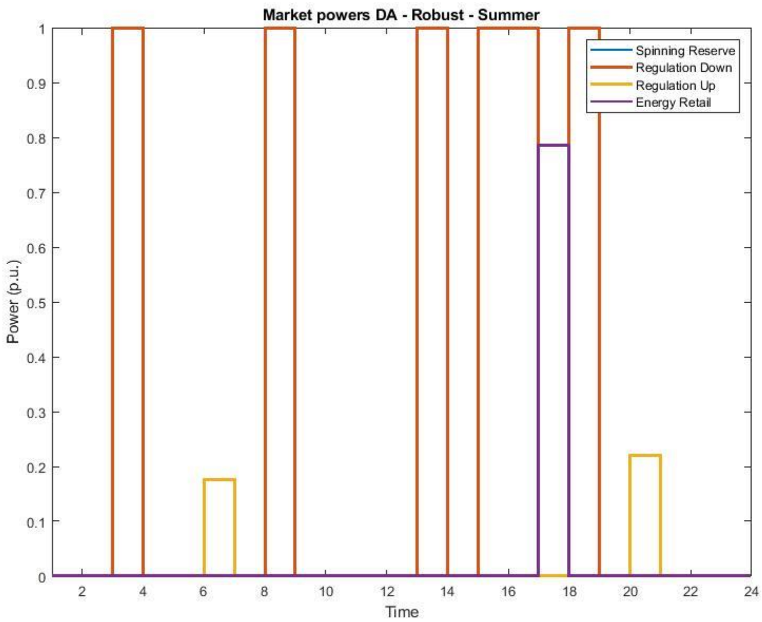


Figure 6-14- Market values participation values with robust optimization in Summer

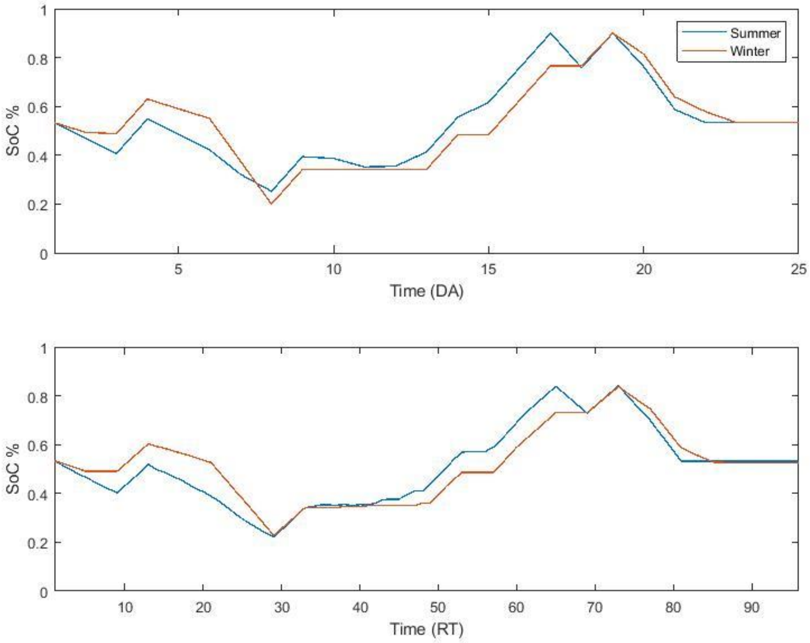


Figure 6-15- State of Charge with Robust Optimization in winter and summer both DA (top) and RT (bottom)

6.2.3 DRO

As discussed in previous chapters, DRO approach is robust and at mean time immune against over-conservative. This conclusion is completely obvious form scheduling results. As discussed in deterministic and robust approach, in one of them battery won't participate in load serving at all and the other it participates as much as possible. In this DRO, battery covers the load both in morning and evening (in morning less than robust). In addition, it also covers the load in midnight as well. In market side, the same as other approaches, it participates mostly in regulation down. However, by considering the uncertainties of energy market it partly participates in energy market additionally in different time interval. This behaviour makes approach more comprehensive compare to other approaches. In this way, we can use the battery in most hours of day. Take into account, that in our research we didn't set any constraints for battery life cycle, thus it would transfer as much energy as it is able. These results have been illustrated in Figure 6-16 till Figure 6-20.

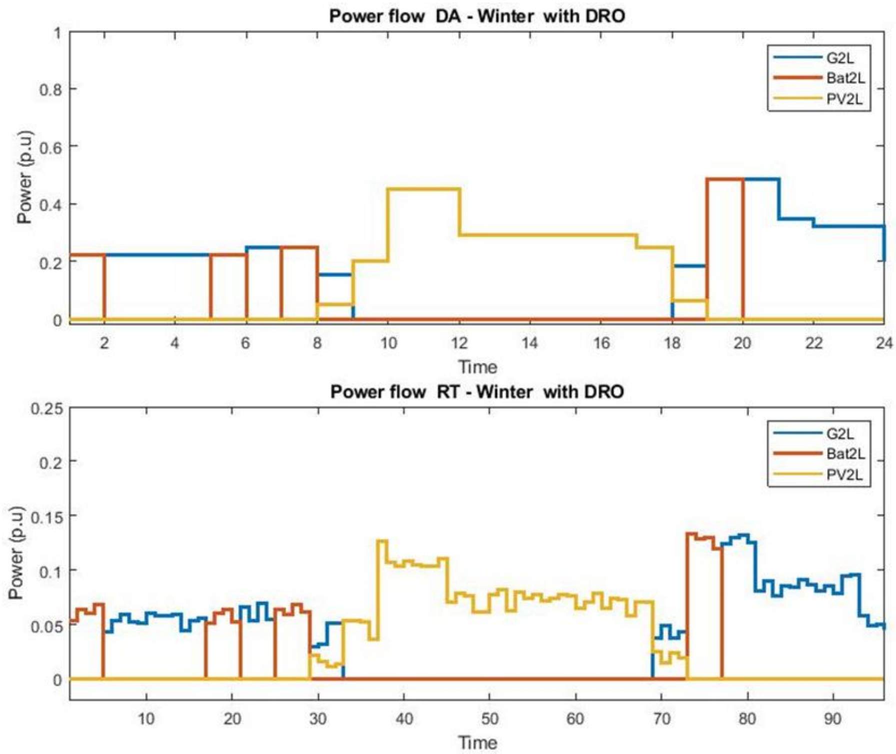


Figure 6-16- DA and RT schedule with DRO optimization in Winter

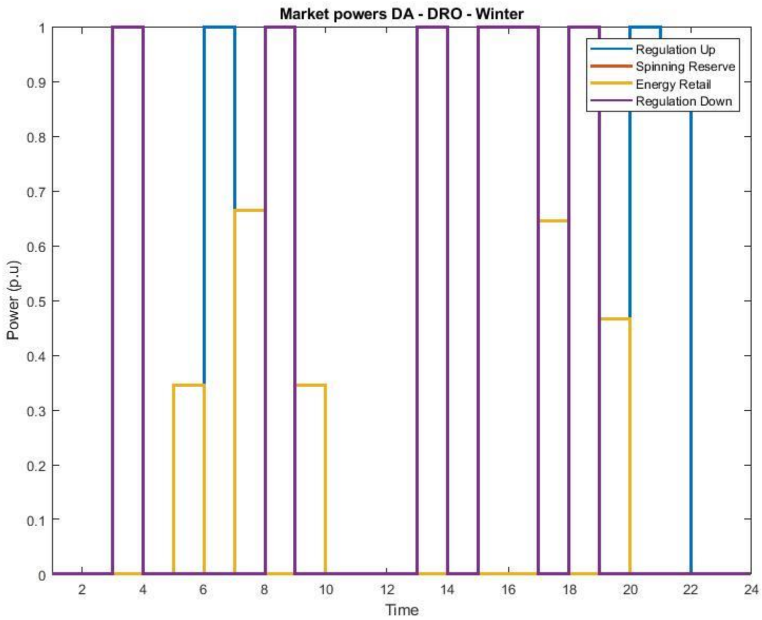


Figure 6-17- Market values participation values with DRO optimization in Winter

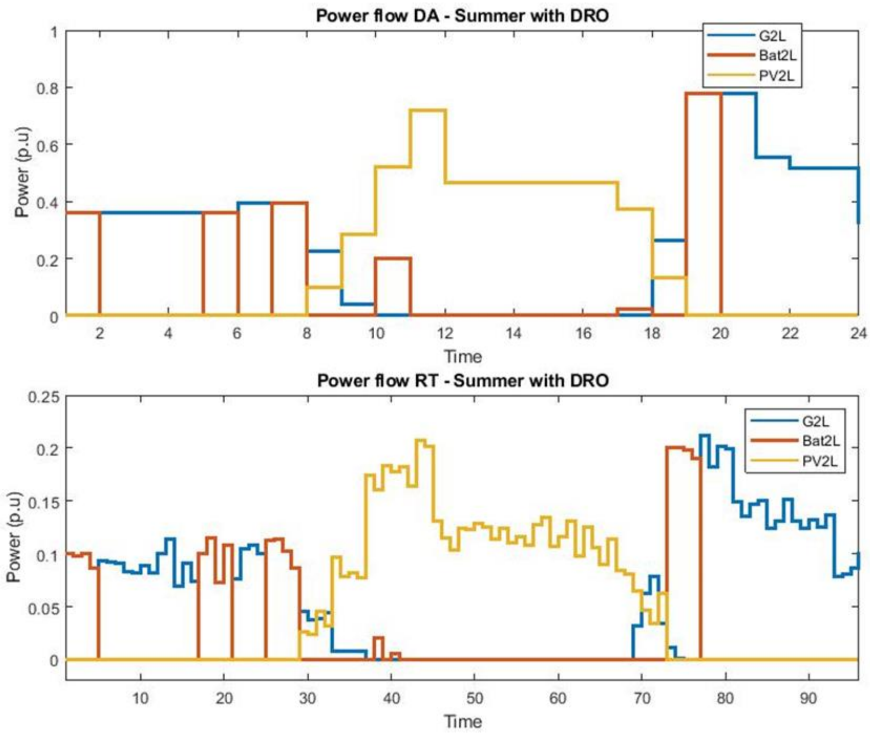


Figure 6-18- DA and RT schedule with DRO optimization in Summer

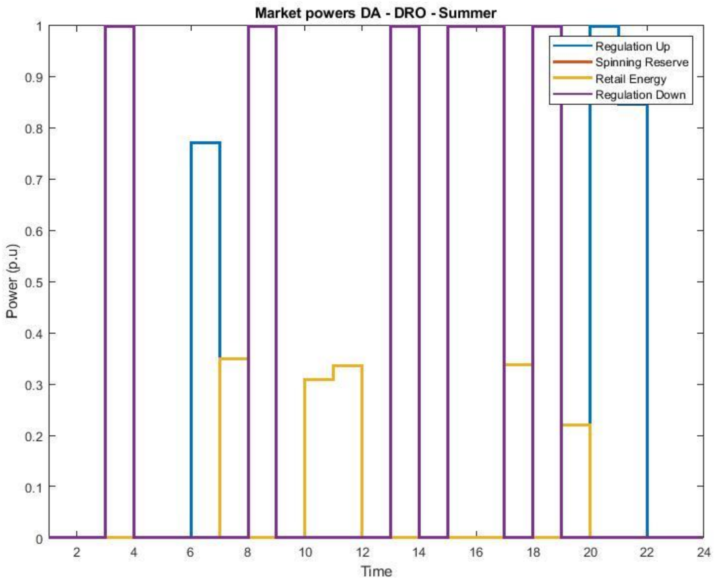


Figure 6-19- Market values participation values with DRO optimization in Summer

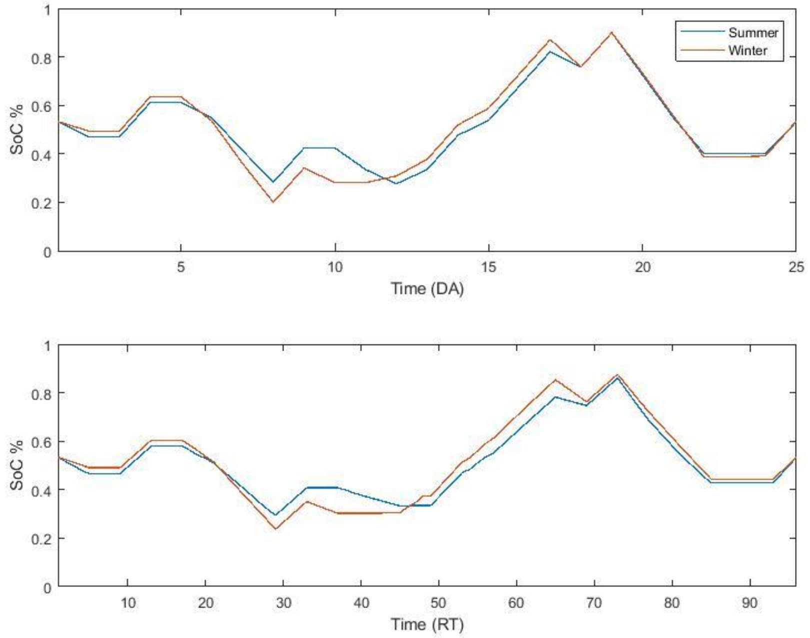


Figure 6-20- State of Charge with DRO Optimization in winter and summer both DA (top) and RT (bottom)

6.3 General Comparative Results

The main aim of this research is to minimize the cost of whole system of hybrid PV-Battery by participating in electricity markets. In this section, the economical perspective of problem has been studied in dept. In order to have more comprehensive results, we used real market data other than training data (year 2016) as test data (year 2017) to check the feasibility and profitability of our solution. In this regard, for each season two month selected. For winter January and February, and in summer June and July selected. In the first step, the total revenue including all costs for demand and battery charging and all incomes form market calculated. The results are summarized in Table 6.

	No market	**Deterministic**	**RO**	**DRO**
Winter	-$45.85	-$26.41	-$30.41	-$17.35
Summer	-$77.13	-$29.41	-$41.52	-$22.72

Table 6 - Total Revenue in two months in winter and summer with different optimization approach

The first important conclusion is that beside the optimization approach, participating in market along with DSM has better result. Then, it shows that DRO work better than other approaches in both seasons. DRO could reduce around 62% and 70% of costs in winter and summer respectively. On the other hand, analysing total daily revenue of winter (Figure 6-21) shows almost the same trend for all approaches, however, RO and deterministic are too close except few days which made final differences. Also, all cases have better result in all days as expected before.

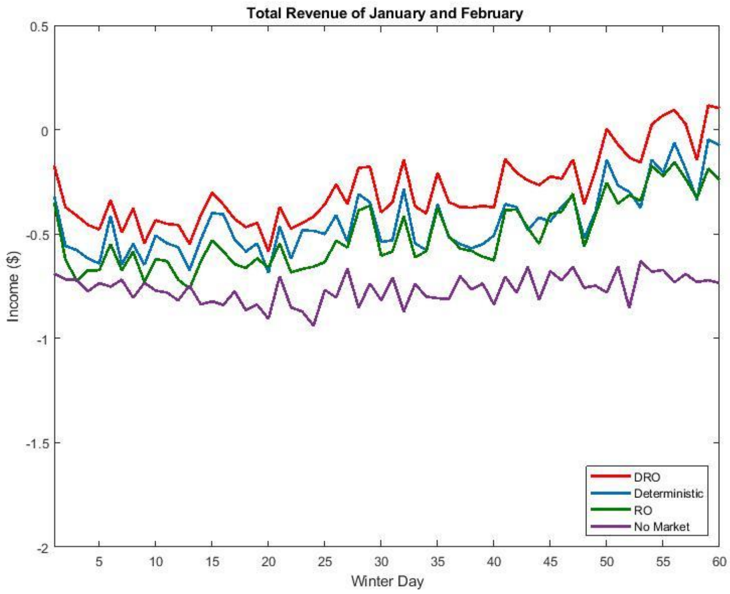


Figure 6-21- Total daily revenue of January and February 2017

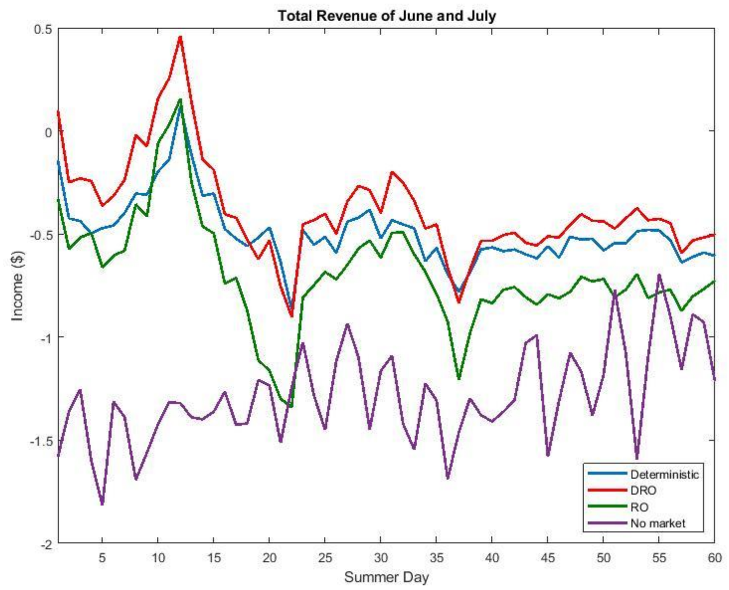


Figure 6-22- Total daily revenue of June and July 2017

In summer season (Figure 6-22), the results have more fluctuation due higher value of market prices and higher market uncertainties. In this figure, unlike winter results, in few days the deterministic outcome is better that DRO and it is due to robustness factor of DRO method. Also, it shows that robust method in few days is even worth than basic scenario which is the result of over-conservative of this method. For Further understanding of root cause of these differences between different approaches, segmented cost revenue of each season is also studied.

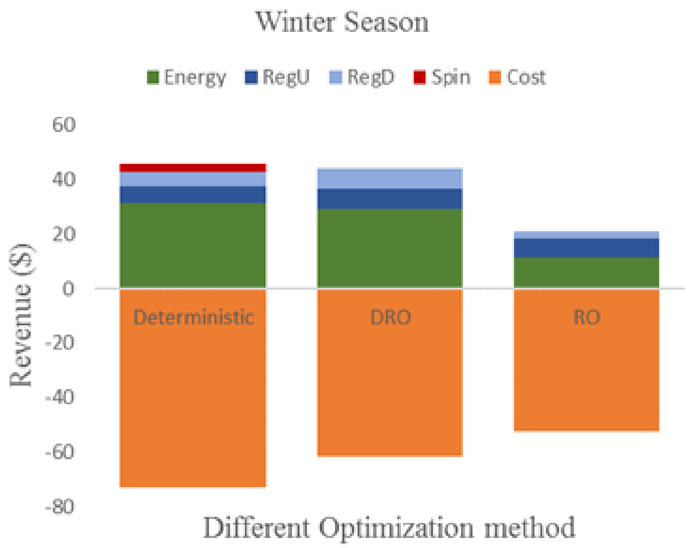


Figure 6-23- Segmented total revenue based on different market profit and importing energy costs for winter

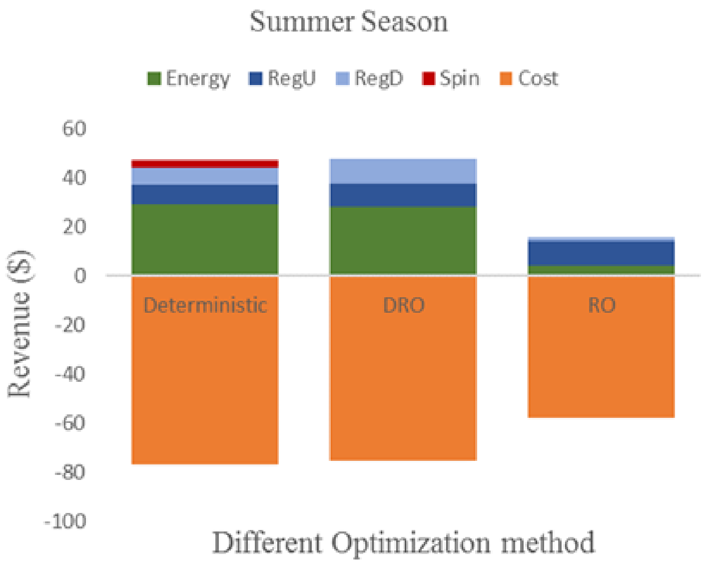


Figure 6-24- Segmented total revenue based on different market profit and importing energy costs for summer

The segmented analysis of markets revenue shows that energy market has a highest income and after that as expected regulation market is the best option. It is important to remind that ancillary services are called for limited times per day, however, in similar case regulation service market could be more profitable than solely energy market. The second point regarding Figure 6-23 is that only in deterministic method battery will participate in spinning reserve and in other approaches they won't. This result comes from low price and high uncertainty of spinning reserve market in comparison with other markets. The final conclusion from these figures is that in deterministic method in spite of higher income, the final outcome is worth due to high demand cost which is solved in DRO by better scheduling and managing of the battery.

Note that in these figures the operational cost due to battery charging and discharging didn't include. This operational cost has critical role in final profitability of market and limits the overall overuse of battery and prevent aging of the battery.

7 Conclusion

Traditionally, in order to improve the intermittency of renewable energy sources and improve the reliability and profitability of these sources different storage system have been used. Battery energy storage systems (BESS) are a good candidate for join PV panels due to their fast response and improvement of technology. However, the high capital cost of BESS is still one of the biggest challenges. In the recent years, by improvement of smart grids and revision in market's regulations new opportunities have been introduced for BESS for further profits. On the other hand, in conventional managing of batteries in demand side, these assets just used for few hours in days and in rest of day remained intact which means the full capacity of batteries didn't use. In this regard, recent regulations suggest additional revenue specifically for behind the meter's batteries (BTM) to not only support PV and load curtailment but also participate in wholesale energy markets. The main aim of this research was to investigate the profitability of BTM battery assets joint with roof top PV panels, participating both in demand side management and possible electricity markets.

The first step toward enhancing battery assets revenue was a comprehensive literature on potential solutions for batteries in order to provide services and make additional profit. In this regard, battery assets based on installation locations divided to three main group. First, those assets which are connected directly to transmission network. The second group are installed in distribution network (usually with distributed generators) and the last one those are installed behind meters. The first two groups can provide different services for ISO/RTOs and utilities. Mostly the main concern in these services are reliability and security of grid. On the other hand, the main goal of behind meters' batteries are supporting households and decrease the demand cost and energy import from grid. The interesting point about last group is that based on new regulations, specifically in California region, these assets are allowed to participate in same services as first two groups, which means that BTM batteries not only have the conventional usage but also they have great opportunities to increase the overall profit of the system.

In this second step, the general concepts and regulations of electricity market had been reviewed. The main focus of this research was in California electricity market which is under supervision of CAISO. Meanwhile, for better understanding of different markets potential other regions in U.S. as well as Italy reviewed. In CAISO market, battery assets are allowed to participate in wholesale energy markets including ancillary services and energy retail markets. These markets are designed and ran in different time interval including Day-ahead market, Real-time (hour- ahead) and real time dispatch (energy imbalance market). In this research, we only focus on DA and RT markets. The ancillary services in CAISO is including spinning reserve, regulation Up and regulation down services which are capacity markets in DA and participants will be paid for power commitment. At mean time, in RT these markets run again but they are real time energy dispatch. The interesting point regarding ancillary services is that in case of calling in DA committed capacity in RT they will be paid also for energy delivery which is extra revenue for assets.

In order to compare European market and specifically Italian one with CAISO, with respect to BTM batteries, the lack of capacity market is obvious. In Italian market the capacity market as explained in literature review is still limited to pilot projects, however, in CAISO not only it used the benefits of capacity market for couple years but in addition they introduced the supplementary regulations such as pay as performance to have more supportive market for battery assets. The second different between Italian markets and California market is that although in Italy the quantity and quality of household meters is almost the same (or even better) than California, however, lack of proper progress and consideration in term of regulation for BTM assets prevent them to participate in market. However, in CAISO, there is still some doubts and barriers for these assets to participate in markets such as price energy used for battery charging or clear requirement and specification for batteries which are under discussion by different committee.

The proposed problem of simultaneous managing of demand side and participating in market challenged by different types of uncertainties which are must take into account. In general, three types of uncertainties are influence in our problem. The first two groups are related to market and the last one is belonged to consumer side. During DA and RT interval market, each service provider must participate in bidding process and based on volume and proposed price its bids might be awarded fully or partly (in some cases maybe fully reject). This uncertainty of awarded ratio is the first type of uncertainties that we are facing in this problem. Unfortunately, since the awarded values for each services provider is confidential, there is no accurate data available to predict the best behavior of market, however, in our problem as we are focusing on BTM batteries and low capacity, we assumed that fixed amount of DA bids and all RT bids will be accepted in market which due to the fact that these assets are price takers could be close to reality. The second type of uncertainties are the market prices. Traditionally in literature different forecasting methods has been proposed to deal with this problem, however, due to lack of existing data and recent changes in markets behavior due to massive installation of distributed generators, the proposed methods are not useful enough. On the other hand, the optimization methods such stochastic programming has been used which are following determined probability distribution. These methods are also challenged by inaccurate PD and heavy calculations.

To deal with this type of uncertainties, a novel data-driven distributionally robust optimization solution has been proposed. In this method, instead of using fixed uncertainty set, it uses the ambiguity sets which include all possible uncertainties. In addition, in this method the solution is robust against highly fluctuations and at mean time we can tune the conservativeness of the solution. To implement the DRO optimization method, we used the idea of Conditional Value at Risk (CVaR) and in this way, we could handle the uncertainties of all markets together. The last challenge and last uncertainty type back to consumer side, which are PV production intermittency and load profile fluctuation. In literature, many forecasting methods had been introduced for this type of uncertainty, however, in this research we introduced the model predictive control over one-hour prediction time horizon. In this solution, the prescheduled values along with updated values for PV and load will be revised for remained hour of day. At mean time, the RT markets are added to system and in case of availability of battery capacity it can participate in this market as well.

To show the profitability and feasibility of proposed solution, this method has been compared with different scenarios. The first scenario is the PV joint battery system only managing demand side. In this case battery is just used for improving self-consumption and decreasing demand cost and it doesn’t have any direct income. In the second scenarios beside DRO solution, conventional deterministic and robust optimization also used to compare different optimization approach solutions.

The general optimization has been trained based on real market data in year 2016 from California region and the outcome has been tested based on 2017. In each method, the optimization performed based on winter and summer season to have more accurate results. The results show that participating in market could decrease the overall cost around at least 34% in winter and 47% in summer season. In addition, our DRO solution could improve this reduction to 62% in winter and 70% in summer season. The second outcome is that by participating in markets, we can explore from battery in more hours/day instead of just evening hours for load covering. In addition, the detailed study on different approach scheduling shows the improvement of battery usage in term of dealing with market uncertainties and participating in demand side.

The future work for this research would be analyzing this methodology for different scale and market structure by considering power grid constraints and battery lifetime cycles. In addition, the DRO method is challenged by different parameters which must be tuned based on collected data set. Next possible study could be proposed revised DRO solution to have adoptive parameters based on available date set.

8 References

[1] "Solar Industry Research Data," Solar Energy Industries Association, Aguest 2019. [Online]. Available: https://www.seia.org/solar-industry-research-data.

[2] "Utility-scale battery storage to reach 12 GW, $8.44 billion by 2024," PV magazine, 17 SEPTEMBER 2015. [Online]. Available: https://www.pv-magazine.com/2015/09/17/utility-scale-battery-storage-to-reach-12-gw-8-44-billion-by-2024_100021149/.

[3] "After record year, U.S. energy storage forecasted to break 1 GW capacity mark in 2019," Industry Dive, 2019. [Online]. Available: https://www.utilitydive.com/news/after-record-year-us-energy-storage-forecasted-to-break-1-gw-capacity-ma/415081/.

[4] California ISO, "California Road Map - Advancing And Maximizing The Value Of Energy Storage Technology," CAISO, December 2014.

[5] J. Taft and A. Becker-Dippmann, Grid Architecture, U.S. Department of Energy, January 2015.

[6] "Key Players," North American Electric Reliability Corporation, July 2019. [Online]. Available: https://www.nerc.com/AboutNERC/keyplayers/Pages/default.aspx.

[7] "NORTHEAST RECYCLING COUNCIL," NERC, July 2019. [Online]. Available: https://nerc.org/.

[8] M. Villareal and I. Fergusson, "The North American Free Trade Agreement (NAFTA)," in *Washington, D.C.: Congressional Research Service.*, 2015.

[9] G. Horlick and C. Schuchhardt, "NAFTA Provisions and the Electricity Sector," in *Commission for Environmental Cooperation of North America*, Montreal, 2002.

[10] V. A. B. J. J. H. Elizabeth Anne Moler, "ORDER NO. 888," FEDERAL ENERGY REGULATORY COMMISSION (FERC), April 24, 1996.

[11] " Order No. 859 - Revisions to the Filing Process for Commission Forms," FEDERAL ENERGY REGULATORY COMMISSION, June 20, 2019.

[12] "Open Access Transmission Tariff (OATT) Reform," FEDERAL ENERGY REGULATORY COMMISSION, 25 September 2018. [Online]. Available: https://www.ferc.gov/industries/electric/indus-act/oatt-reform.asp.

[13] "Electric Reliability Council of Texas," ERCOT, 2019. [Online]. Available: http://www.ercot.com/.

[14] O. Workshop, "ERCOT Market Training," [Online]. Available: http://www.ercot.com/content/wcm/training_courses/107/ordc_workshop.pdf.

[15] ERCOT, "Module 2: Day-Ahead Operations," January 2010. [Online]. Available: http://www.ercot.com/content/wcm/training_courses/58/GEN101_M2_Jan2010.pdf.

[16] I. N. E. Inc., "Overview of New England's Wholesale Electricity Markets and Market Oversight," 15 May 2013. [Online]. Available: https://www.iso-ne.com/pubs/spcl_rpts/2013/markets_overview_051513_final.pdf.

[17] "ISO New England," 2019. [Online]. Available: https://www.iso-ne.com/.

[18] R. Benbow, "2018-2019 Winter Readiness," 18 October 2018. [Online]. Available: https://www.ferc.gov/CalendarFiles/20181018104634-Benbow,%20MISO%20Presentation.pdf.

[19] MISO, "Market Reports," July 2019. [Online]. Available: https://www.misoenergy.org/markets-and-operations/real-time--market-data/market-reports/#t=10&p=0&s=MarketReportPublished&sd=desc.

[20] "Business Practices Manuals," MISO, July 2019. [Online]. Available: https://www.misoenergy.org/legal/business-practice-manuals/.

[21] P. LeeVanSchaick, "Highlights of the 2018 State of the Market Report for the NYISO Markets," 13 May 2019. [Online]. Available:

https://www.nyiso.com/documents/20142/6426548/2018%20NYISO%20SOM%20Report%20Presentation_for%20BIC.pdf/20600fe4-2967-532c-d6ec-382416e83abc.
[22] R. Walawalkar, “Electric Energy Storage. Opportunities and Challenges in New York,” NYSERDA, 2005.
[23] “NYISO's wholesale electricity markets,” NYISO, July 2019. [Online]. Available: https://www.nyiso.com/markets.
[24] N. S. Services, “Market Participants User’s Guide,” December 2018. [Online]. Available: https://www.nyiso.com/documents/20142/3625950/mpug.pdf/.
[25] “PJM Manual 11: Energy & Ancillary Services Market Operations, Revision: 87,” March 23 2017. [Online]. Available: http://bit.ly/2EV6Cu7.
[26] P. -. M. S. D. Department, “PJM Manual 28: Operating Agreement Accounting - Revision: 82,” July 2019. [Online]. Available: https://www.pjm.com/~/media/documents/manuals/m28.ashx.
[27] D.-A. a. R.-T. M. Operations, “PJM Manual 11: Energy & Ancillary Services Market Operations,” 30 May 2019. [Online]. Available: https://www.pjm.com/~/media/documents/manuals/m11.ashx.
[28] “Ancillary Services,” PJM, July 2019. [Online]. Available: https://www.pjm.com/markets-and-operations/ancillary-services.aspx.
[29] “GLOSSARY,” SPP, July 2019. [Online]. Available: https://www.spp.org/glossary/.
[30] S. P. P. (SPP), “Energy Imbalance System Market Training,” February 2010. [Online]. Available: http://www2.econ.iastate.edu/tesfatsi/SPPMarketTrainingModule.26Feb2010.pdf.
[31] S. M. Design, “Market Protocols SPP Integrated Marketplace - Revision 34a,” December 2010. [Online]. Available: https://www.spp.org/documents/31676/integrated%20marketplace%20protocols%2034a.pdf. [Accessed July 2019].
[32] “Southwest Power Pool: State of the Market 2017,” SPP, July 2019. [Online]. Available: https://www.elp.com/Electric-Light-Power-Newsletter/articles/2018/05/southwest-power-pool-state-of-the-market-2017.html.
[33] “California ISO Open Access Same-time Information System (OASIS),” CAISO, [Online]. Available: http://oasis.caiso.com/mrioasis/logon.do.
[34] “Tariff - Fifth Replacement FERC,” California Independent System Operator Corporation Electric,, 2019. [Online]. Available: http://www.caiso.com/Documents/ConformedTariff-asof-Mar1-2019.pdf.
[35] D. D. -. CAISO, “Business Practice Manual for Market Operations - Version 54,” 30 October 2017. [Online]. Available: https://bpmcm.caiso.com/BPM%20Document%20Library/Market%20Operations/BPM_for_Market%20Operations_V54_redline.pdf.
[36] S. M. -. CAISO, “Business Practice Manual for Definitions & Acronyms - Version 7,” 4 February 2019. [Online]. Available: https://bpmcm.caiso.com/BPM%20Document%20Library/Definitions%20and%20Acronyms/Definitions%20and%20Acronyms%20BPM%20Version%2017_Redline.pdf.
[37] Federal Energy Regulatory Commission, “Glossary,” 15 March 2016. [Online]. Available: http://bit.ly/2ALPJkP.
[38] E. Ela, M. Milligan and B. Kirby, “Operating Reserves and Variable Generation,” National Renewable Energy Laboratory , August 2011.
[39] Y. G. Rebours, D. S. Kirschen, M. Trotignon and S. Rossignol, “A Survey of Frequency and Voltage Control Ancillary Services—Part I: Technical Features,” *IEEE Transactions on Power Systems*, vol. 22, no. 1, pp. 350 - 357, Feb. 2007.
[40] Y. G. Rebours, D. S. Kirschen, M. Trotignon and S. Rossignol, “A Survey of Frequency and Voltage Control Ancillary Services—Part II: Economic Features,” *IEEE Transactions on Power Systems*, vol. 22, no. 1, pp. 358-366, Feb. 2007.

[41] J. F. Ellison, L. S. Tesfatsion, V. W. Loose and R. H. Byrne, "Project Report: A Survey of Operating Reserve Markets in U.S ISO/RTO-managed Electric Energy Regions," Sandia National Laboratorie, September 2012.

[42] California Independent System Operator Corporation, "Appendix K - California ISO," 1 July 2018. [Online]. Available: http://bit.ly/2QegIuq.

[43] California ISO, "Spinning Reserve and Non-Spinning Reserve," 31 Jan 2006. [Online]. Available: http://bit.ly/2ALiNbV.

[44] California ISO, "Department of Market Monitoring 2017 Annual Market Issues and Performance Report Posted, Web Conference Call June 14, 2018," 11 June 2018. [Online]. Available: http://bit.ly/2P6s6w1.

[45] Federal Energy Regualtory Commission, "FERC order 755," 20 October 2011. [Online]. Available: http://bit.ly/2QhOhvz.

[46] California ISO, 20 September 2012. [Online]. Available: http://bit.ly/2PGhYtl.

[47] California ISO, "Market Design Report Order 755," 31 July 2014. [Online]. Available: http://bit.ly/2QjQ0AP.

[48] A. Sadeghi-Mobarakeh and H. Mohsenian-Rad, "Optimal Bidding in Performance-Based Regulation Markets: An MPEC Analysis With System Dynamics," *IEEE Transactions on Power Systems* , vol. 32, no. 2, pp. 1282 - 1292, March 2017 .

[49] "Western Energy Imbalance Market," California Independent System Operator, 2019. [Online]. Available: https://www.westerneim.com/Pages/About/default.aspx.

[50] I. J. (. Pérez-Arriaga, Regulation of the Power Sector, London: Springer-Verlag , 2013.

[51] "Electric System - Terna spa," 2019. [Online]. Available: https://www.terna.it/en/electric-system.

[52] "Gestore Mercati Energetici," GME, 2019. [Online]. Available: https://www.mercatoelettrico.org/En/Default.aspx.

[53] Terna, "Nuovo MSD 2010," 2010. [Online]. Available: http://download.terna.it/terna/0000/0135/22.PDF.

[54] Terna, " MSD 2011 – Integrazione MI-MSD," [Online]. Available: http://download.terna.it/terna/0000/0135/27.PDF.

[55] Terna, "Codice di trasmissione dispacciamento, sviluppo e sicurezza della rete," 8 July 2013. [Online]. Available: http://download.terna.it/terna/0000/0107/31.pdf.

[56] A. Agrillo, M. d. Verme, P. Liberatore, D. Lipari, V. Maio, V. Surace and L. Benedetti, "rapporto "Energia da fonti rinnovabili in Italia - 2017" - Gse," December 2018. [Online]. Available: https://www.gse.it/.../Rapporti%20statistici/Rapporto%20Statistico%20FER%202017.pdf.

[57] T. E. U. Committee, "The EU's Target for Renewable Energy:20% by 2020," 24 October 2009. [Online]. Available: https://publications.parliament.uk/pa/ld200708/ldselect/ldeucom/175/175.pdf.

[58] K. d. Bergh and E. Delarue, "Cycling of conventional power plants: Technical limits and actual costs," *sciencedirect: Energy Conversion and Management,* vol. 97, pp. 70-77, June 2015.

[59] T. S. E. GRUPPO, "PIANO DI SVILUPPO," TERNA, 2019. [Online]. Available: http://download.terna.it/terna/0000/1188/36.PDF.

[60] "Deliberazione 393/2015/R/eel, Riforma organica della regolazione del servizio di dispacciamento dell'energua elettrica e conseguente attivazione del progetto interdirezionale RDE," AEEGSI, July 2015.

[61] "Documento per la consultazione 298/2016/R/eel, Prima fase della riforma del mercato per il servizio di dispacciamento: aperture alla domanda, alle fonti rinnovabili non programmabili e alla generazione distribuita," AEEGSI, June 2016.

[62] "Deliberazione 300/2017/R/eel, Prima apertura del MSD alla domanda elettrica ed alle unità di produzione anche da fonti rinnovanili non già abilitate nonchè ai sistemi di accumulo, istituzione di progetti pilota in vista della costituzione del TIDE coerent," AEEGSI, May 2017.

[63] "Partecipazione della domanda al MSD, Progetto pilota ai sensi della delibera," Terna, May 2017.

[64] “Deliberazione 372/2017/R/eel, Approvazione del regolamento, predisposto da Terna S.p.A. ai sensi della deliberazione 300/2017/R/eel, relativo al progetto pilota per la partecipazione della domanda al MSD, modifiche alla deliberazione dell’Autorità 300/201,” AEEGSI, May 2017.
[65] “Regolamento recante le modalità per la creazione, qualificazione e gestione di unità virtuali di produzione abilitate al MSD,” Terna, September 2017.
[66] “Deliberazione 583/2017/R/eel, Approvazione del regolamento, predisposto da Terna S.p.A. ai sensi della deliberazione 300/2017/R/eel, relativo al progetto pilota per la partecipazione della generazione distribuita, come UVAP, al MSD,” AEEGSI, August 2017.
[67] ARERA, “Testo integrato del dispacciamento elettrico (TIDE) - Orientamenti complessivi,” 25 luglio 2019. [Online]. Available: https://www.arera.it/it/schedetecniche/19/322-19st.htm.
[68] F. E. R. COMMISSION, “FERC Order No. 890,” 16 February 2007. [Online]. Available: https://www.ferc.gov/whats-new/comm-meet/2007/021507/E-1.pdf.
[69] A. Sakti, A. Botterud and F. O’Sullivan, “Review of wholesale markets and regulations for advanced energy storage services in the United States: Current status and path forward,” *Energy Policy,* vol. 120, pp. 569-579, September 2018.
[70] California ISO, “Non-Generator Resource Regulation Energy Management Project Implementation Plan – Version 2.1,” 13 March 2012. [Online]. Available: http://bit.ly/2D3bKx1.
[71] “Energy storage and distributed energy resources,” California Independent System Operator, Sep 2019. [Online]. Available: http://www.caiso.com/informed/Pages/StakeholderProcesses/EnergyStorage_DistributedEnergyResources.aspx#Phase1.
[72] C. ISO, “Energy Storage and Distributed Energy Resources (ESDER) - Revised Draft Final Proposal,” 23 December 2015. [Online]. Available: http://www.caiso.com/Documents/RevisedDraftFinalProposal-EnergyStorageDistributedEnergyResources.pdf.
[73] M. &. I. P. -. C. ISO, “Energy Storage and Distributed Energy Resources Phase 2,” 8 June 2017. [Online]. Available: http://www.caiso.com/Documents/DraftFinalProposal-EnergyStorage_DistributedEnergyResourcesPhase2.pdf.
[74] M. &. I. P. -. C. ISO, “Energy Storage and Distributed Energy Resources Phase 3,” 11 July 2018. [Online]. Available: http://www.caiso.com/Documents/DraftFinalProposal-EnergyStorage-DistributedEnergyResourcesPhase3.pdf.
[75] M. &. I. P. -. C. ISO, “Energy Storage and Distributed Energy Resources Phase 4 - Straw Proposal,” 26 April 2019. [Online]. Available: http://www.caiso.com/Documents/StrawProposal-EnergyStorageandDistributedEnergyResourcesPhase4.pdf.
[76] Federal Energy Regualtory Commission, “Order No. 841 - Federal Energy Regulatory Commission,” 15 February 2018. [Online]. Available: http://bit.ly/2JByncW.
[77] H. Chen, T. N. Cong, W. Yang, C. Tan, Y. liang Li and Y. Ding, “Progress in electrical energy storage system: A critical review,” *Progress in Natural Science,* vol. 19, no. 3, pp. 291-312, 10 March 2009.
[78] X. Luo, J. Wang, M. Dooner and J. Clarke, “Overview of current development in electrical energy storage technologies and the application potential in power system operation,” *Applied Energy,* vol. 137, pp. 511-536, 1 January 2015.
[79] E. e. s. p. team, “Electrical Energy Storage: White paper,” December 2011. [Online]. Available: https://www.iec.ch/whitepaper/pdf/iecWP-energystorage-LR-en.pdf.
[80] F. Figueiredo and P. Flynn, “Using diurnal power price to configure pumped storage,” *IEEE Transactions on Energy Conversion,* vol. 21, no. 3, Sept. 2006.
[81] R. Madlener and J. Latz, “Economics of centralized and decentralized compressed air energy storage for enhanced grid integration of wind power,” *Applied Energy,* vol. 101, pp. 299-309, January 2013.
[82] Z. Long and Q. Zhiping, “Review of Flywheel Energy Storage System,” in *Proceedings of ISES*

World Congress , 2007.

[83] R. Peña-Alzola, R. Sebastián, J. Quesada and A. Colmenar, “Review of flywheel based energy storage systems,” in *International Conference on Power Engineering, Energy and Electrical Drives,* Malaga, Spain, 2011.

[84] J. Song, Y. Wang and C.C.Wan, “Review of gel-type polymer electrolytes for lithium-ion batteries,” *Journal of Power Sources,* vol. 77, no. 2, pp. 183-197, February 1999 .

[85] U. D. o. E. O. o. E. E. &. R. ENERGY, “Fuel Cells,” July 2019. [Online]. Available: https://www.energy.gov/eere/fuelcells/fuel-cells.

[86] S. Mekhilef, R. Saidur and A. Safari, “Comparative study of different fuel cell technologies,” *Renewable and Sustainable Energy Reviews,* vol. 16, no. 1, pp. 981-989, January 2012.

[87] F. Díaz-González, A. Sumper, O. Gomis-Bellmunt and R. Villafáfila-Robles, “A review of energy storage technologies for wind power applications,” *Renewable and Sustainable Energy Reviews,* vol. 16, no. 4, pp. 2154-2171, May 2012.

[88] M. H. Ali and B. Wu, “An Overview of SMES Applications in Power and Energy Systems,” *IEEE Transactions on Sustainable Energy,* vol. 1, no. 1, April 2010.

[89] S. Kuravi, J. Trahan, D. Y. Goswami, M. M.Rahman and E. K.Stefanakos, “Thermal energy storage technologies and systems for concentrating solar power plants,” *Progress in Energy and Combustion Science,* vol. 39, no. 4, pp. 285-319, August 2013.

[90] B. Saha and K. Goebel, “Modeling Li-ion Battery Capacity Depletion in a Particle Filtering Framework,” in *Annual Conference of the Prognostics and Health Management Society*, 2009.

[91] N. Omar, P. V. d. Bossche, T. Coosemans and J. V. Mierlo, “Peukert Revisited—Critical Appraisal and Need for Modification for Lithium-Ion Batteries,” *Energies,* vol. 6, no. 11, pp. 5625-5641, 2013.

[92] Rocky Mountain Institue, “The conomics of battery energy storage,” October 2015. [Online]. Available: http://bit.ly/2PdP1pm.

[93] A. Ben-Tal, L. E. Ghaoui and A. Nemirovski, Robust Optimization, Princeton Series in Applied Mathematics, 2009.

[94] P. MohajerinEsfahani and D. Kuhn, “Data-driven distributionally robust optimization using the Wasserstein metric: performance guarantees and tractable reformulations,” *Mathematical Programming,* vol. 171, no. 1–2, p. 115–166, September 2018.

[95] J. C. Spall, “STOCHASTIC OPTIMIZATION,” in *Handbook of Computational Statistics: Concepts and Methods (2nd ed.) (J. Gentle, W. Härdle, and Y. Mori, eds.),* Springer, 2012, pp. 173-201.

[96] L. A. Hannah, “Stochastic Optimization,” *International Encyclopedia of the Social & Behavioral Sciences,* pp. 473-481, April 4, 2014.

[97] M. H.Alrefaei and S. Andradóttir, “A modification of the stochastic ruler method for discrete stochastic optimization,” *European Journal of Operational Research,* vol. 133, no. 1, pp. 160-182, 16 August 2001.

[98] L. Shi and S. O´lafsson, “Nested Partitions Method for Stochastic Optimization,” *Methodology And Computing In Applied Probability,* vol. 2, no. 3, p. 271–291, September 2000 .

[99] S. M. Robinson, “Analysis of Sample-Path Optimization,” *Mathematics of Operation Research,* vol. 21, no. 3, Agu 1996.

[100] A. J. Kleywegt, A. Shapiro and T. Homem-de-Mello, “The Sample Average Approximation Method for Stochastic Discrete Optimization,” *SIAM Journal on Optimization,* vol. 12, no. 2, July 2006.

[101] Y. W. A. Shapiro, “Convergence Analysis of Stochastic Algorithms,” *Mathematics of Operations Research,* vol. 21, no. 3, Aug 1996.

[102] G. Gürkan, A. Y. Özge and S. M. Robinson, “Sample-path solution of stochastic variational inequalities,” *Mathematical Programming,* vol. 84, no. 2, p. 313–333, February 1999.

[103] J. R. Birge and F. Louveaux, Introduction to stochastic programming, Springer Science &

Business Media, 2011.

[104] A. Shapiro, T. Homem-de-Mello and J. Kim, "Conditioning of convex piecewise linear stochastic programs," *Mathematical Programming,* vol. 94, no. 1, p. 1–19, December 2002.

[105] H. Hashemi-Dezaki, M. Hamzeh, H. Askarian-Abyaneh and H. Haeri-Khiavi, "Risk management of smart grids based on managed charging of PHEVs and vehicle-to-grid strategy using Monte Carlo simulation," *Energy Conversion and Management,* vol. 100, pp. 262-276, August 2015.

[106] S. S. Reddy, V. Sandeep and C.-M. Jung, "Review of stochastic optimization methods for smart grid," *Frontiers in Energy - Springer,* vol. 11, no. 2, p. 197–209, June 2017.

[107] N. Alguacil and A. Conejo, "Multiperiod optimal power flow using Benders decomposition," *IEEE Transactions on Power Systems,* vol. 15, no. 1, Feb. 2000.

[108] A. Papavasiliou and S. S. Oren, "Multiarea Stochastic Unit Commitment for High Wind Penetration in a Transmission Constrained Network," *Operations Research* , vol. 61, no. 3, May 2013.

[109] J. Wang, M. Shahidehpour and Z. Li, "Security-Constrained Unit Commitment With Volatile Wind Power Generation," *IEEE Transactions on Power Systems,* vol. 23, no. 3, Aug. 2008.

[110] L. Wu, M. Shahidehpour and T. Li, "Stochastic Security-Constrained Unit Commitment," *IEEE Transactions on Power Systems,* vol. 22, no. 2, May 2007.

[111] J. Wang, A. Botterud, V. Miranda, C. Monteiro and G. Sheble, "Impact of wind power forecasting on unit commitment and dispatch," in *Proc. 8th Int. Workshop Large-Scale Integration of Wind Power into Power Systems*, 2009.

[112] A. L. Soyster, "Technical Note—Convex Programming with Set-Inclusive Constraints and Applications to Inexact Linear Programming," *Operations Research,* vol. 21, no. 5, Sep 1973.

[113] A. N. A. Ben-Tal, "Robust Convex Optimization," *Mathematics of Operation Research,* vol. 23, no. 4, pp. 769-1024, November 1998.

[114] A. Ben-Tal and A. Nemirovski, "Robust solutions of uncertain linear programs," *Operations Research Letters,* vol. 25, no. 1, pp. 1-13, August 1999.

[115] A. Ben-Tal and A. Nemirovski, "Robust solutions of Linear Programming problems contaminated with uncertain data," *Mathematical Programming,* vol. 88, no. 3, p. 411–424 , September 2000.

[116] L. EI-Ghaoui and H. Lebret, "Robust solutions to least-square problems to uncertain data matrices," *Sima Journal on Matrix Analysis and Applications 18* , pp. 1035-1064, 1997.

[117] M. S. Dimitris Bertsimas, "The Price of Robustness," *Operations Research,* vol. 52, no. 1, Feb 2004.

[118] Y. Guan and J. Wang, "Uncertainty Sets for Robust Unit Commitment," *IEEE Transactions on Power Systems,* vol. 29, no. 3, May 2014.

[119] D. Bertsimas, E. Litvinov, X. A. Sun, J. Zhao and T. Zheng, "Adaptive Robust Optimization for the Security Constrained Unit Commitment Problem," *IEEE Transactions on Power Systems,* vol. 28, no. 1, pp. 52-63, Feb. 2013.

[120] L. Zhao and B. Zeng, "Robust unit commitment problem with demand response and wind energy," in *2012 IEEE Power and Energy Society General Meeting*, San Diego, CA, USA, 2012.

[121] A. Nemirovski and A. Shapiro, "Convex Approximations of Chance Constrained Programs," *SIAM Journal on Optimization,* vol. 17, no. 4, p. 969–996, 2007.

[122] W. Chen, M. Sim, J. Sun and C.-P. Teo, "From CVaR to Uncertainty Set: Implications in Joint Chance-Constrained Optimization," *Operations Research* , vol. 58, no. 2, Oct 2009.

[123] D. Bertsimas and D. B. Brown, "Constructing Uncertainty Sets for Robust Linear Optimization," *Operations Research* , vol. 57, no. 6, Apr 2009.

[124] Z. Chen, L. Wu and Y. Fu, "Real-Time Price-Based Demand Response Management for Residential Appliances via Stochastic Optimization and Robust Optimization," *IEEE Transactions on Smart Grid,* vol. 3, no. 4, Dec. 2012.

[125] J. E. Smith and R. L. Winkler, "The Optimizer's Curse: Skepticism and Postdecision Surprise in Decision Analysis," *Management Science,* vol. 52, no. 3, Mar 2006.

[126] D. Bertsimas, E. Litvinov, X. A. Sun, J. Zhao and T. Zheng, "Adaptive Robust Optimization for the Security Constrained Unit Commitment Problem," *IEEE Transactions on Power Systems,* vol. 28, no. 1, Feb. 2013.

[127] H. E. Scarf, " A min-max solution of an inventory problem," *RAND CORP SANTA MONICA CALIF,* June 1957.

[128] P. Mohajerin-Esfahani and D. Kuhn, "Data-driven distributionally robust optimization using the Wasserstein metric: performance guarantees and tractable reformulations," *Mathematical Programming,* vol. 171, no. 1-2, Sep 2018.

[129] E. Delage and Y. Ye, "Distributionally Robust Optimization Under Moment Uncertainty with Application to Data-Driven Problems," *Operations Research,* vol. 58, no. 3, Jan 2010.

[130] W. Wiesemann, D. Kuhn and M. Sim, "Distributionally Robust Convex Optimization," *Operations Research,* vol. 62, no. 6, Oct 2014.

[131] W. Wei, F. Liu and S. Mei, "Distributionally Robust Co-Optimization of Energy and Reserve Dispatch," *IEEE Transactions on Sustainable Energy,* vol. 7, no. 1, Jan. 2016.

[132] Y. Zhang, S. Shen and J. L. Mathieu, "Distributionally Robust Chance-Constrained Optimal Power Flow With Uncertain Renewables and Uncertain Reserves Provided by Loads," *IEEE Transactions on Power Systems* , vol. 32, no. 2, March 2017.

[133] Z. Wang, Q. Bian, H. Xin and D. Gan, "A Distributionally Robust Co-Ordinated Reserve Scheduling Model Considering CVaR-Based Wind Power Reserve Requirements," *IEEE Transactions on Sustainable Energy* , vol. 7, no. 2, April 2016.

[134] Z. Wang, P. W. Glynn and Y. Ye, "Likelihood robust optimization for data-driven," *Computational Management Science,* vol. 13, no. 2, April 2016.

[135] E. Erdoğan and G. Iyengar, "Ambiguous chance constrained problems and robust optimization," *Mathematical Programming,* vol. 107, no. 1-2, p. 37–61, June 2006.

[136] Z. Hu and L. J. Hong, "Kullback-Leibler divergence constrained distributionally robust optimization," *Optimization Online,* 2013.

[137] D. Wozabal, "A framework for optimization under ambiguity," *Annals of Operations Research,* vol. 193, no. 1, p. 21–47, March 2012.

[138] Y. Guo, K. Baker, E. Dall'Anese, Z. Hu and T. H. Summers, "Data-Based Distributionally Robust Stochastic Optimal Power Flow—Part I: Methodologies," *IEEE Transactions on Power Systems* , vol. 34, no. 2, March 2019 .

[139] L. Yao, X. Wang, C. Duan, J. Guo, X. Wu and Y. Zhang, "Data-driven distributionally robust reserve and energy scheduling over Wasserstein balls," *IET Generation, Transmission & Distribution,* vol. 12, no. 1, Jan 2018.

[140] A. Shapiro, "Distributionally Robust Stochastic Programming," *SIAM Journal on Optimization,* vol. 27, no. 4, Oct 2017.

[141] Z. Wu, H. Tazvinga and X. Xia, "Demand side management of photovoltaic-battery hybrid system," *Applied Energy,* vol. 148, pp. 294-304, 15 June 2015.

[142] I. Ranaweera and O.-M. Midtgård, "Optimization of operational cost for a grid-supporting PV system with battery storage," *Renewable Energy,* vol. 88, pp. 262-272, April 2016.

[143] A. J. K. a. B. W. Nottrott, "Energy dispatch schedule optimization and cost benefit analysis for grid-connected, photovoltaic-battery storage systems," *Renewable Energy* , vol. 55, p. 2013, 230-240..

[144] M. Janina, K.-P. Kairies, D. Magnor, M. Leuthold, M. Bost, S. Gährs, E. Szczechowicz, M. Cramer and D. U. Sauer, "Analysis of the maximal possible grid relief from PV-peak-power impacts by using storage systems for increased self-consumption," *Applied Energy* , vol. 137, pp. 567-575, 2015.

[145] I. Atzeni, L. G. Ordóñez, G. Scutari, D. P. Palomar and J. R. Fonollosa, "Demand-Side Management via Distributed Energy Generation and Storage Optimization," *IEEE Transactions on Smart Grid* , vol. 4, no. 2, pp. 866 - 876, June 2013 .

[146] G. He, Q. Chen, C. Kang, P. Pinson and Q. Xia, “Optimal Bidding Strategy of Battery Storage in Power Markets Considering Performance-Based Regulation and Battery Cycle Life,” *IEEE Transactions on Smart Grid,* vol. 7, no. 5, pp. 2359 - 2367, Sept. 2016.

[147] Y. V. Makarov, P. V. Etingov, J. Ma, Z. Huang and K. Subbarao, “Incorporating Uncertainty of Wind Power Generation Forecast Into Power System Operation, Dispatch, and Unit Commitment Procedures,” *IEEE Transactions on Sustainable Energy,* vol. 2, no. 4, pp. 433 - 442, Oct. 2011 .

[148] N. Y. I. S. Operator, “Market Participants User’s Guide,” 2018. [Online]. Available: https://www.nyiso.com/documents/20142/3625950/mpug.pdf/. [Accessed 2019].

[149] R. Walawalkar, J. Apt and R. Mancini, “Economics of electric energy storage for energy arbitrage and regulation in New York,” *Energy Policy,* vol. 35, no. 4, pp. 2558-2568, April 2007 .

[150] R. T. Rockafellar and S. Uryasev, “Optimization of Conditional Value-at-Risk,” *Journal of Risk,* pp. 21-42, 2000.

[151] R. T. Rockafellar and S. Uryasev, “Optimization of conditional value-at-risk,” *Journal of risk,* vol. 2, pp. 21-42, April 2000.

[152] M. Fisher, J. Apt and J. F. Whitacre, “Can flow batteries scale in the behind-the-meter commercial and industrial market? A techno-economic comparison of storage technologies in California,” *Journal of Power Sources,* vol. 420, pp. 1-8, April 2019.

[153] “PHOTOVOLTAIC GEOGRAPHICAL INFORMATION SYSTEM,” European Commission, July 2019. [Online]. Available: https://re.jrc.ec.europa.eu/pvg_tools/en/tools.html.

[154] T. HoveI and H. Tazvinga, “A techno-economic model for optimising component sizing and energy dispatch strategy for PV-diesel-battery hybrid power systems,” *Journal of Energy in Southern Africa,* vol. 23, no. 4, 2012.

[155] M. S. Buday, “Measuring irradiance, temperature and angle of incidence effects on photovoltaic modules in Auburn Hills, Michigan,” University of Michigan, Agust 2011.

[156] S. Senemar, M. Rastegar, M. Dabbaghjamanesh and N. D. Hatziargyriou, “Dynamic Structural Sizing of Residential Energy Hubs,” *IEEE Transactions on Sustainable Energy ,* June 2019.

[157] M. Kazemi, H. Zareipour, N. Amjady, W. D. Rosehart and M. Ehsan, “Operation Scheduling of Battery Storage Systems in Joint Energy and Ancillary Services Markets,” *IEEE Transactions on Sustainable Energy ,* vol. 8, no. 4, pp. 1726 - 1735, Oct. 2017.

[158] “MOSEK Optimization Toolbox for MATLAB. Version 9.0.104,” MOSEK ApS, Agu 2019.

[159] D. Frankel and A. Wagner, “Battery storage: The next disruptive technology in the power sector,” mckinsey & company, June 2017.

[160] H. Akhavan-Hejazi and H. Mohsenian-Rad, “Optimal Operation of Independent Storage Systems in Energy and Reserve Markets With High Wind Penetration,” *IEEE Transactions on Smart Grid,* vol. 5, no. 2, March 2014 .

[161] Z. Wang, A. Negash and D. S. Kirschen, “Optimal scheduling of energy storage under forecast uncertainties,” *IET Generation, Transmission & Distribution,* vol. 11, no. 17, p. 4220 – 4226, 30 November 2017.

[162] H. Mohsenian-Rad, “Optimal Bidding, Scheduling, and Deployment of Battery Systems in California Day-Ahead Energy Market,” *IEEE Transactions on Power Systems,* vol. 31, no. 1, Jan. 2016.

[163] T. Zhao and Z. Ding, “Cooperative Optimal Control of Battery Energy Storage System Under Wind Uncertainties in a Microgrid,” *IEEE Transactions on Power Systems,* vol. 33, no. 2, March 2018.

[164] J. M. Eyer, P. C. Butler and J. J. J. Iannucci, “Estimating electricity storage power rating and discharge duration for utility transmission and distribution deferral :a study for the DOE energy storage program.,” U.S. Department of Energy Office of Scientific and Technical Information, November 2005.

[165] G. Carpinelli, F. Mottola, D. Proto and A. Russo, “Optimal allocation of dispersed generators, capacitors and distributed energy storage systems in distribution networks,” in *Modern Electric*

Power Systems, Wroclaw, Poland, 2010 .

[166] A. Nottrott, J. Kleissl and B. Washom, "Energy dispatch schedule optimization and cost benefit analysis for grid-connected, photovoltaic-battery storage systems," *Renewable Energy,* vol. 55, p. 2013, 230-240..

[167] E. L.Ratnam, S. R.Weller and C. M.Kellett, "An optimization-based approach to scheduling residential battery storage with solar PV: Assessing customer benefit," *Renewable Energy,* vol. 75, pp. 123-134, March 2015.

[168] V. Pradhan, V. S. K. M. Balijepalli and S. A. Khaparde, "An Effective Model for Demand Response Management Systems of Residential Electricity Consumers," *IEEE Systems Journal,* vol. 10, no. 2, June 2016.

[169] J. Mitra and M. R. Vallem, "Determination of Storage Required to Meet Reliability Guarantees on Island-Capable Microgrids With Intermittent Sources," *IEEE Transactions on Power Systems,* vol. 27, no. 4, pp. 2360-2367, Nov. 2012.

[170] J. Mitra, "Reliability-Based Sizing of Backup Storage," *IEEE Transactions on Power Systems,* vol. 25, no. 2, pp. 1198 - 1199, May 2010.

[171] M. Fisher, J. Apt and J. F.Whitacre, "Can flow batteries scale in the behind-the-meter commercial and industrial market? A techno-economic comparison of storage technologies in California," *Journal of Power Sources,* vol. 420, pp. 1-8, April 2019.

[172] A. Alqurashi, A. H.Etemadi and A. Khodaei, "Treatment of uncertainty for next generation power systems: State-of-the-art in stochastic optimization," *Electric Power Systems Research,* pp. 233-245, December 2016.

[173] Q. P. Zheng, J. Wang and A. L. Liu, "Stochastic Optimization for Unit Commitment—A Review," *: IEEE Transactions on Power Systems* , vol. 30, no. 4, July 2015.

[174] G. Liu, Y. Xu and K. Tomsovic, "Bidding Strategy for Microgrid in Day-Ahead Market Based on Hybrid Stochastic/Robust Optimization," *IEEE Transactions on Smart Grid,* vol. 7, no. 1, Jan. 2016.

[175] P. Malysz, S. Sirouspour and A. Emadi, "An Optimal Energy Storage Control Strategy for Grid-connected Microgrids," *IEEE Transactions on Smart Grid,* vol. 5, no. 4, pp. 1785 - 1796, July 2014.

[176] H. Alharbi and K. Bhattacharya, "Stochastic Optimal Planning of Battery Energy Storage Systems for Isolated Microgrids," *IEEE Transactions on Sustainable Energy* , vol. 9, no. 1, Jan. 2018.

[177] W. Su, J. Wang and J. Roh, "Stochastic Energy Scheduling in Microgrids With Intermittent Renewable Energy Resources," *IEEE Transactions on Smart Grid,* vol. 5, no. 4, pp. 1876 - 1883, July 2014.

[178] S. I. Vagropoulos and A. G. Bakirtzis, "Optimal Bidding Strategy for Electric Vehicle Aggregators in Electricity Markets," *IEEE Transactions on Power Systems,* vol. 28, no. 4, Nov. 2013.

List of Figures

List of Tables

List of Abbreviation

CAISO	California Independent System Operator
BESS	Battery Energy Storage System
TSO	Transmission System Operator
EU	European Union
DAM	Day-ahead Market
IM	Intra-day Market
MSD	Ancillary Services Market (*Mercato del Servizio di Dispacciamento*)
RT	Real-Time market
SMP	System Marginal Price
PAB	Pay as Bids
MSE	Ministry of Economic Development (*Ministero dello Sviluppo Economico*)
ARERA	the Italian Regulatory Authority for Energy, Networks and Environment (Autorità di Regolazione per Energia Reti e Ambiente)
GSE	*Gestore dei Servizi Energetici*
GME	*Gestore dei Mercati Energetici*
AU	Single Buyer (*Acquirente Unico*)
AGCM	Antitrust Authority (*Autorità Garante della Concorrenza e del Mercato*)
IPEX	Italian Power Exchange
MPE	Spot Electricity Market (*Mercato a Pronti*)
MTE	Forward Electricity Market (*Mercato a Termine*)
PUN	National Single Price (*Prezzo Unico Nazionale*)
NERC	North American Electric Reliability Corporation
FERC	Federal Energy Regulatory Commission
RUC	Reliability Unit Commitment
RTBM	Real-Time Balancing Market
DAEM	Day-Ahead Energy Market
RTEM	Real-Time Energy Market
DASRM	Day-Ahead Scheduling Reserve Market
RMCP	regulation market clearing price
RMPCP	regulation market performance clearing price
RMCCP	regulation market capability clearing price
NGR	Non-Generator Resources
ESDER	Energy storage and distributed energy resources

Nomenclature

Indices and Sets

t	Time index.
$Spin$	Subscribe for Spinning Reserve.
$RegU$	Subscribe for Regulation Up.
$RegD$	Subscribe for Regulation Down.
E	Subscribe for Energy Market.
D	Subscribe for Demand.
PV	Subscribe for Photovoltaic.
$\mathbb{V}$	Set of decision variables.
v	Subscribe for decision variables.
π	Subscribe for uncertain variables (price).
T	Set of time.
L	Subscribe for Load.
ch	Subscribe for Charge.
dch	Subscribe for Discharge.
$Perf$	Superscript for regulation performance.
$mile$	Superscript for regulation mileage.
t_{end}	Last time interval
$PV2L$	Subscribe for delivered from PV to Load.
$PV2Bat$	Subscribe for delivered from PV to battery.
$Bat2L$	Subscribe for delivered from battery to Load.
$Bat2G$	Subscribe for delivered from battery to grid.
$G2Bat$	Subscribe for delivered from grid to battery.
$G2L$	Subscribe for delivered from grid to Load.
DA	Subscribe for day-ahead market.
RT	Subscribe for real-time market.
Op	Subscribe for Operational cost.
Im	Subscribe for Import energy from grid.
Ex	Subscribe for Import energy to grid.

ξ	Subscribe for uncertainty.
Ξ	Uncertainty set.
N	Number of training data set.
$\hat{\mathcal{P}}_N$	Ambiguity set.
$\mathbb{Q}$	Probability distribution.
$\hat{()}$	Index for training data-set.

Parameters and Constants

$\pi_t^{(.)}$	Market price at time t	[$/kWh]
ρ_t	Energy price at time t.	[$/kWh]
$\eta^{(.)}$	Charging/discharging efficiency of battery.	-
P_{Max}	Nominal capacity of inverter	kW
$Cap_t^{(.)}$	Nominal capacity at time t.	kW
$l^{(.)}$	Penalty rate for energy deviation.	[$/kWh]
$\vartheta^{(.)}$	Energy deviation threshold.	-
ε	Confidence level of Wasserstein ball	-
α	Confidence level of CVaR.	-
ζ	Investor’s risk-aversion.	-

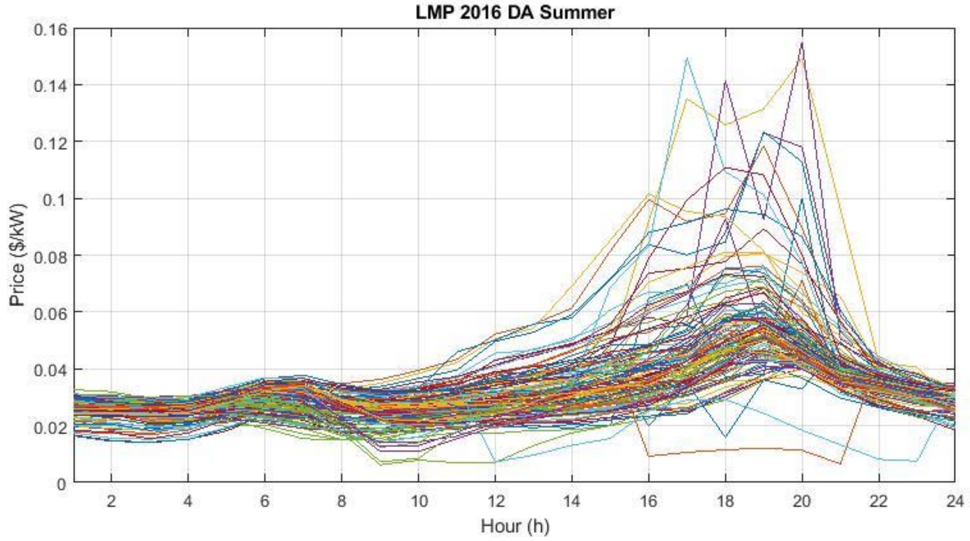
Variables

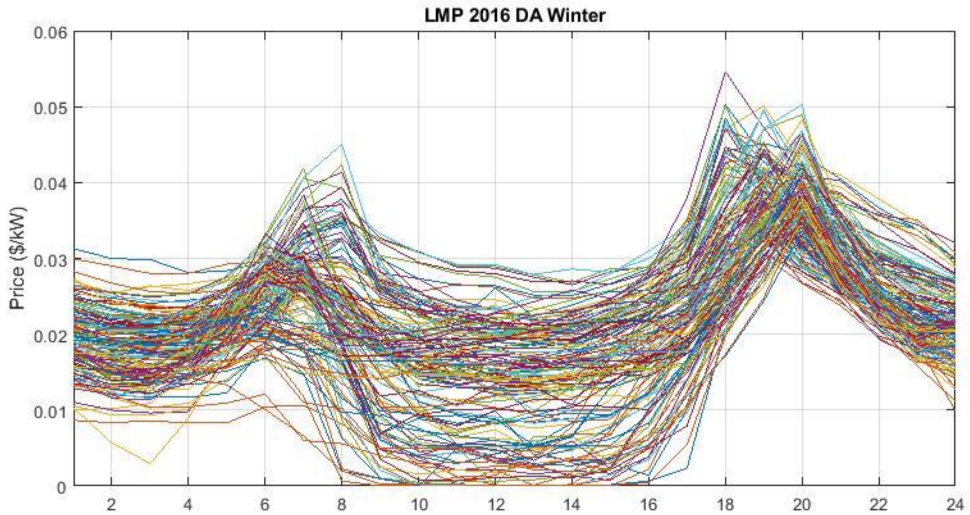
$R_t^{(.)}$	Market Revenue at time t.	$
C_t^{Op}	Operational Cost at time t.	$
C_t^{D}	Demand Cost at time t.	$
SoC_t	State of Charge of Battery at time t.	kWh
$P_t^{(.)}$	Capacity offered in market.	kW
$Perf_t^{Reg}$	Performance Payment for regulation market.	$
m_t	Regulation Mileage Multiplier at time t.	-
acc_t	accuracy of Performance response at time t.	kW/kWh
M_t	Binary variable for Charging/Discharging mode.	-
$E_t^{(.)}$	Total energy exchange at time t.	kWh
$\Delta E_t^{(.)}$	Energy deviation from day-ahead at time t.	kWh

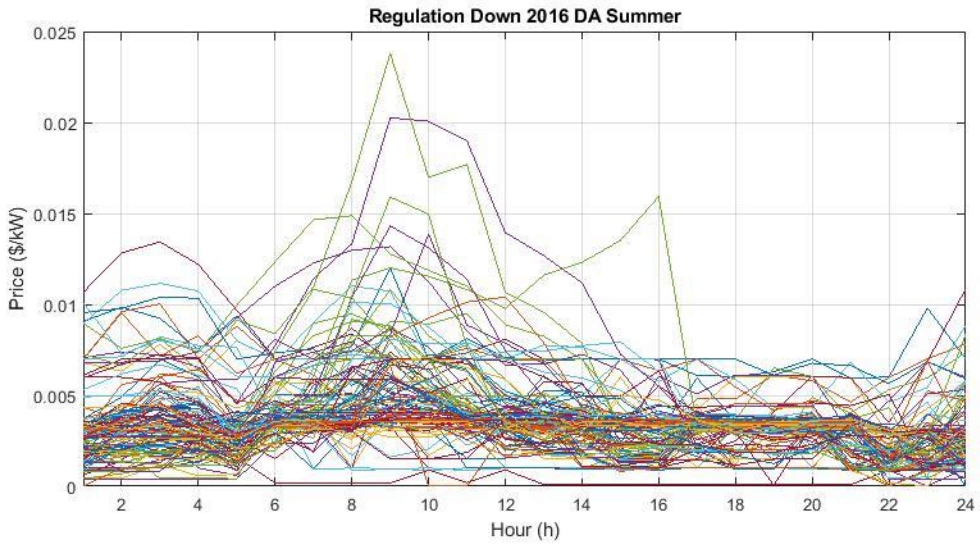
$U_t^{(.)}$	Penalty for energy deviation [$].	$

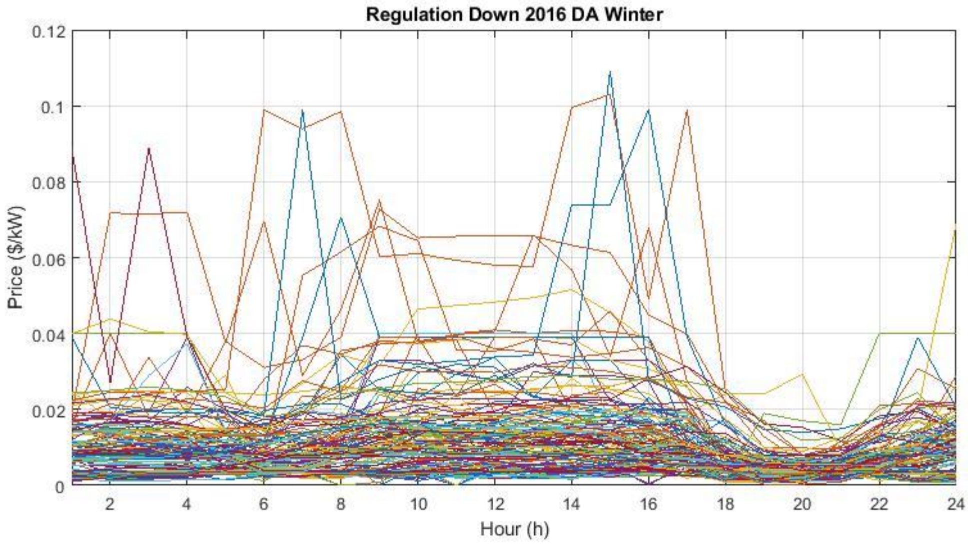
Appendix A – Market Data 2016

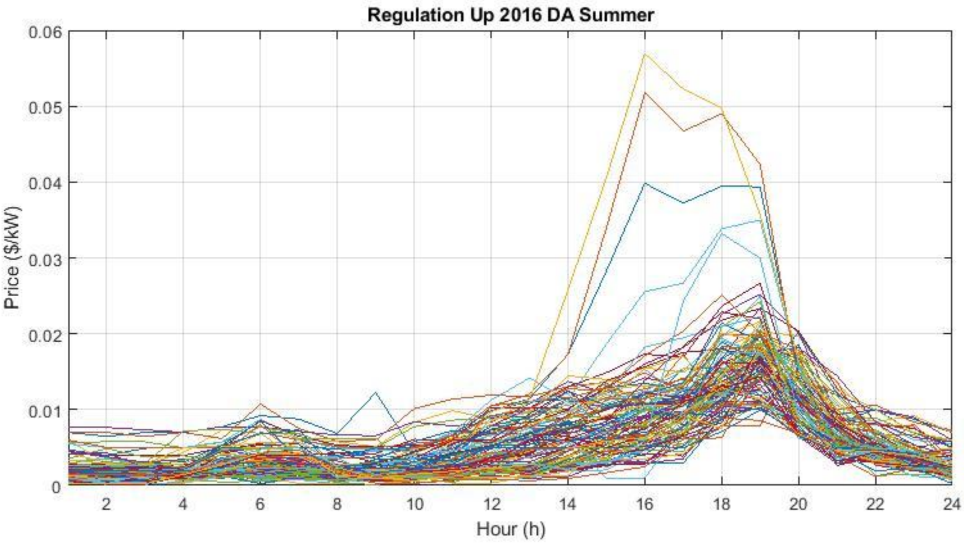
Full seasonal market data in day-ahead and real-time interval:

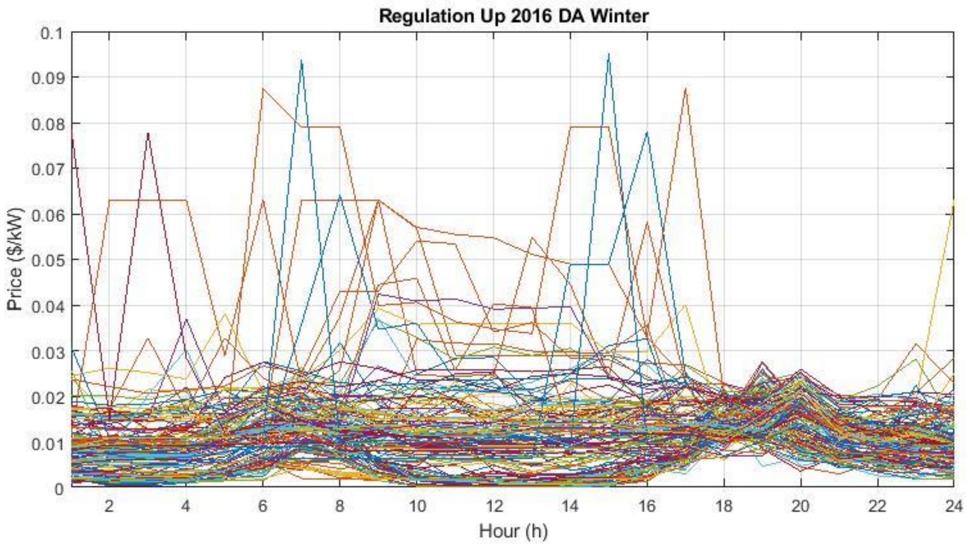


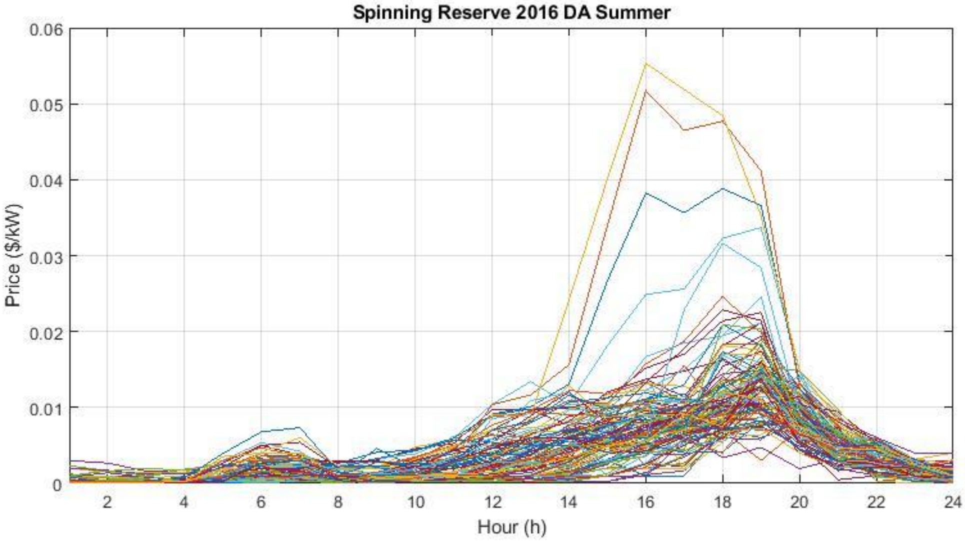


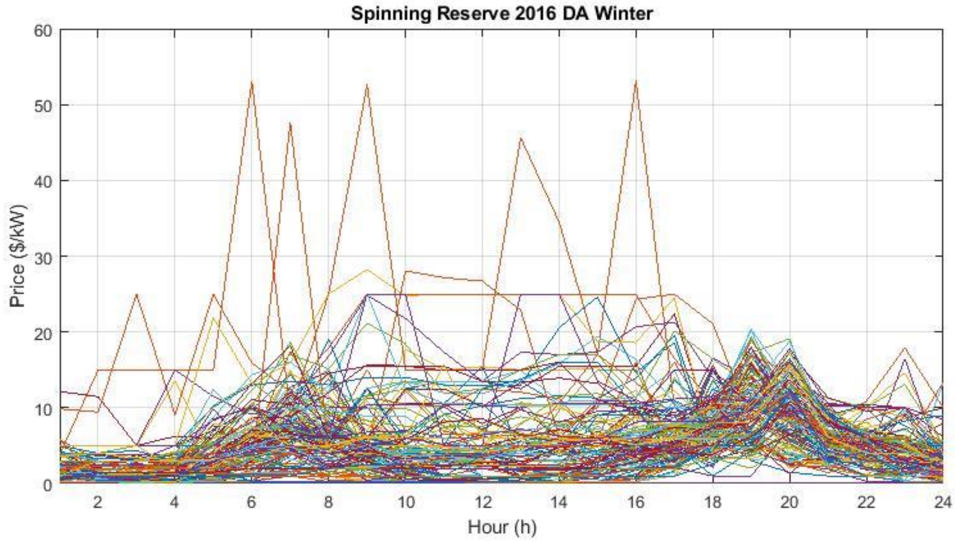


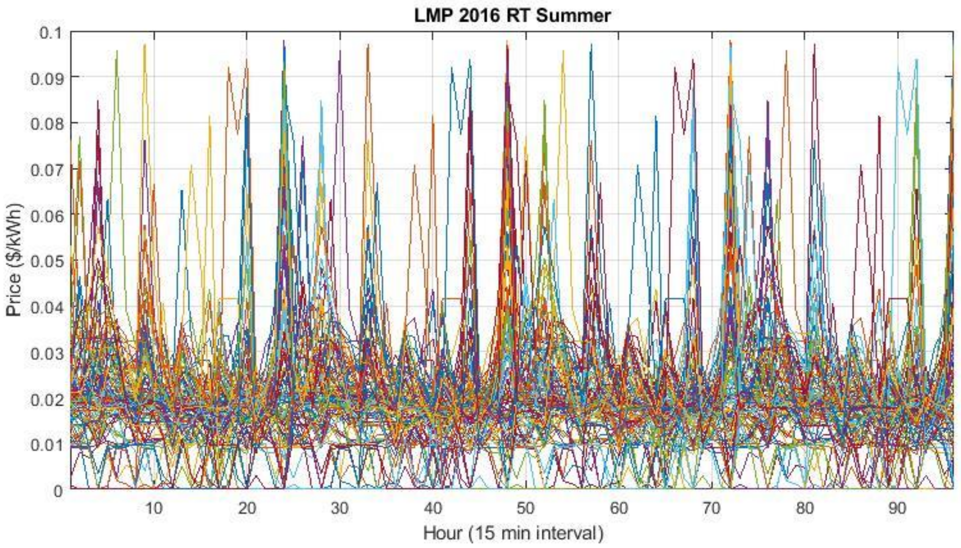

Regulation Down 2016 DA Winter
Price ($/kW)
Hour (h)
0.12
0.1
0.08
0.06
0.04
0.02
0
2
4
6
8
10
12
14
16
18
20
22
24

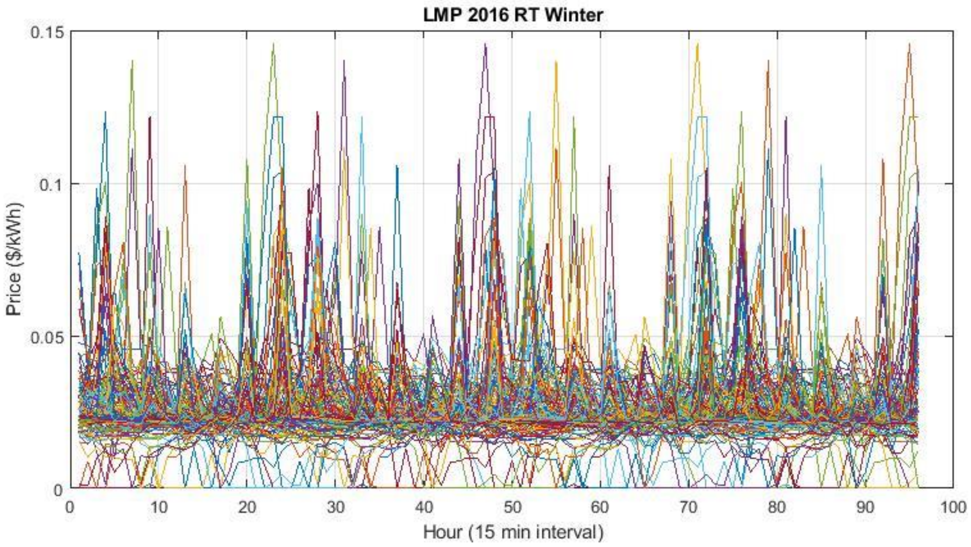

Regulation Up 2016 DA Summer
Price ($/kW)
Hour (h)
0.06
0.05
0.04
0.03
0.02
0.01
0
2
4
6
8
10
12
14
16
18
20
22
24

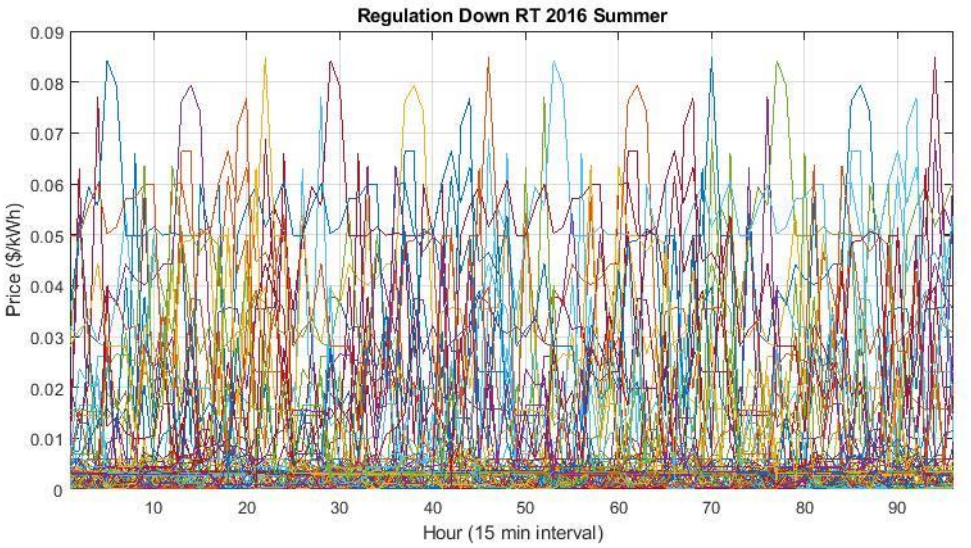

Regulation Up 2016 DA Winter
Price ($/kW)
Hour (h)
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
2
4
6
8
10
12
14
16
18
20
22
24

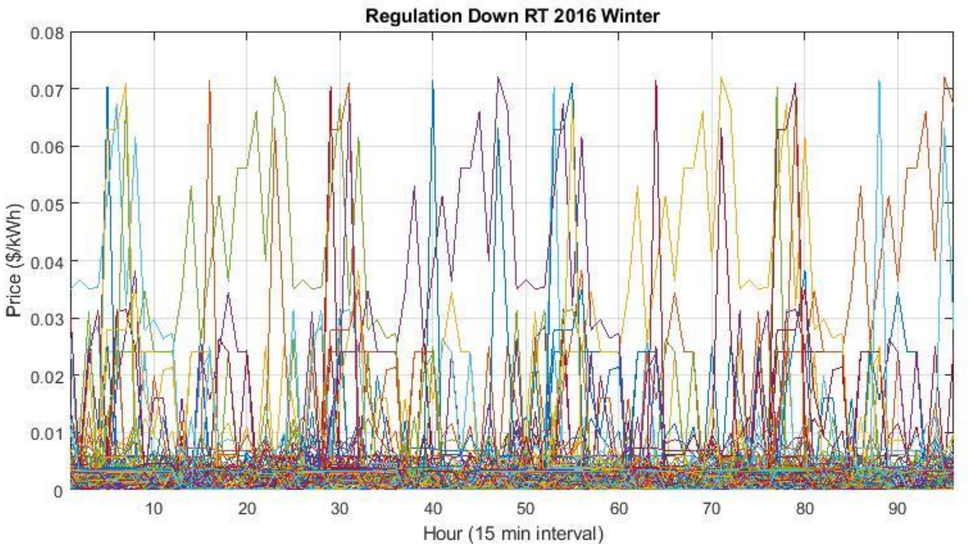

Spinning Reserve 2016 DA Summer
Price ($/kW)
Hour (h)

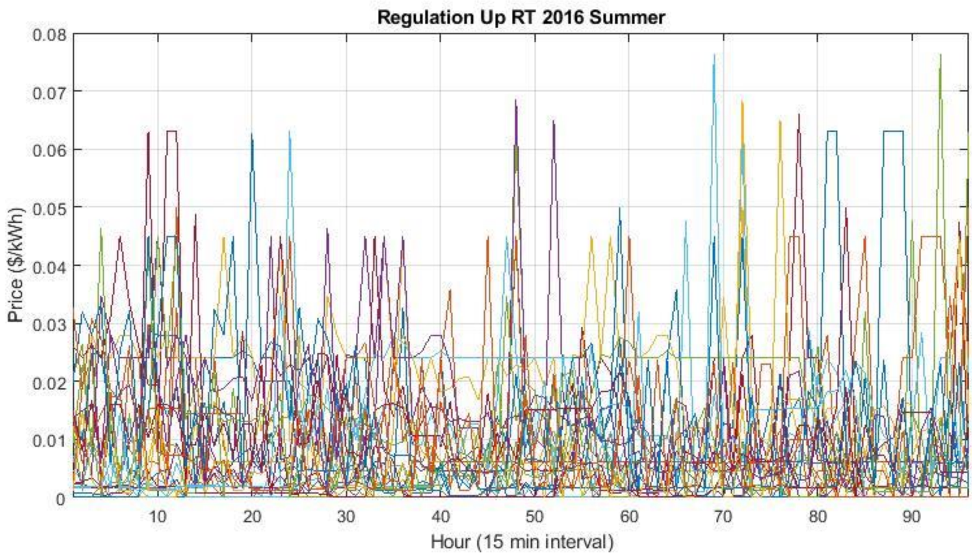

Spinning Reserve 2016 DA Winter
Price ($/kW)
Hour (h)

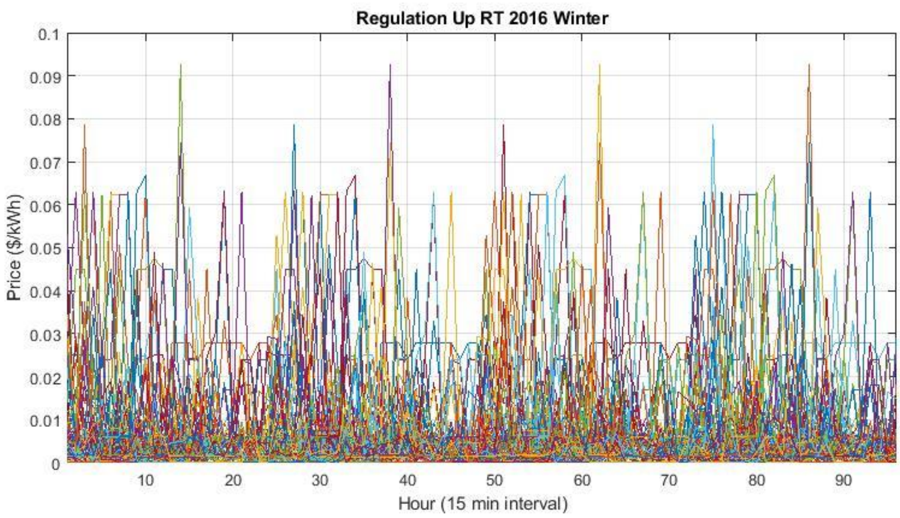

LMP 2016 RT Summer
Price ($/kWh)
Hour (15 min interval)

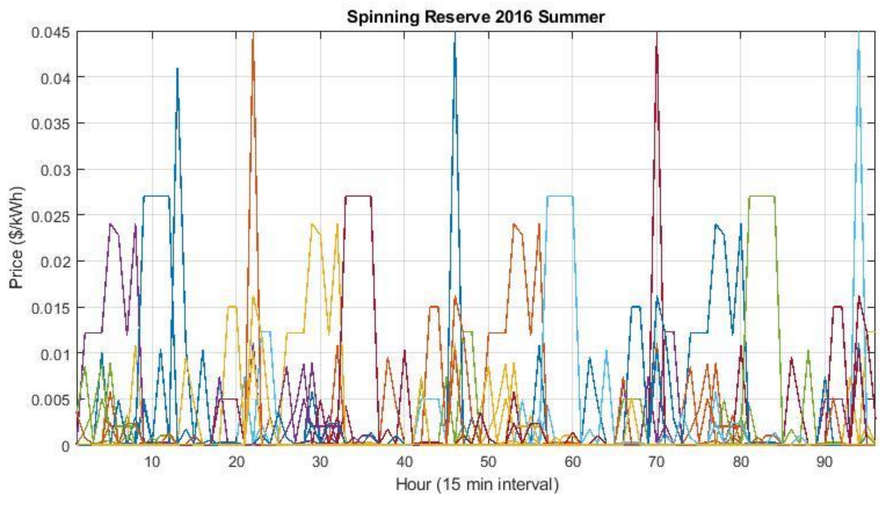

LMP 2016 RT Winter
Price ($/kWh)
Hour (15 min interval)

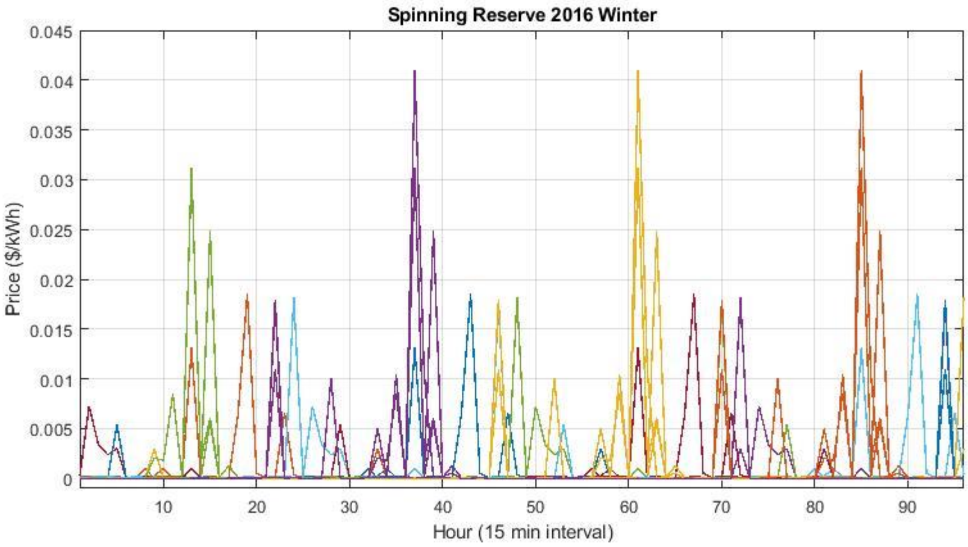

Regulation Down RT 2016 Summer
Price ($/kWh)
Hour (15 min interval)


Regulation Down RT 2016 Winter
Price ($/kWh)
Hour (15 min interval)


Regulation Up RT 2016 Summer
Price ($/kWh)
Hour (15 min interval)


Regulation Up RT 2016 Winter
Price ($/kWh)
Hour (15 min interval)


Spinning Reserve 2016 Summer
Price ($/kWh)
Hour (15 min interval)


Spinning Reserve 2016 Winter
Price ($/kWh)
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
10
20
30
40
50
60
70
80
90
Hour (15 min interval)

Appendix B – Demand side management Matlab Codes

```
[Cap_PV_win,Cap_PV_sum,Cap_L_sum,Cap_L_w
in] = LoadPVprofile();


display('demand and solar Profile
added')
% %% Battery and other variable defining
Eta_Ch = 0.85 ;                          %
Charging Efficiency of the Battery
Eta_D = 0.95 ;
% Discharging Efficiency of the Battery
BAT_CAP = 30; % Nominal Energy Capacity
Battery kWh

SOC_Max = BAT_CAP*0.9 ;
SOC_Min = BAT_CAP*0.2 ;
SOC_0 = 16;
Cap_Max = 5 ;                         % The
Maximum allowble power flow KW -
inverter limits
c_op = 0.005  ;
%($/kWh) Operation Cost Coefficient
 [~, ~, raw] = xlsread('E:\Polimi
courses\Thesis\UC Riverside\Final
Codes\DATA.xlsx','TOU','A2:G25');
data = reshape([raw{:}],size(raw));
SDGE_win = data(:,2);
SDGE_sum = data(:,3);
Edison_win = data(:,4);
Edison_sum = data(:,5);
PGE_win = data(:,6);
PGE_sum = data(:,7);
clearvars data raw;
Pr_buy = SDGE_sum;%PGE_win;
    clear Cap_G2Bat_sum
    clear Cap_G2L_sum
    clear Cap_Bat2G_sum
    clear Cap_PV2L_sum
    clear Cap_PV2Bat_sum
    clear Cap_Bat2L_sum
    clear Cap_PV2G_sum
    clear M_SUM
    clear cost_demand_sum
    clear income_sum
    clear cost_op_sum
    clear cost_sum
    clear Soc_sum
    clear SOC_sum
    clear OBJ_sum
    clear Cap_charge_sum
    clear Cap_discharge_sum
cvx_begin
    variable Cap_G2Bat_sum(25)
nonnegative
    variable Cap_G2L_sum(25) nonnegative
    variable Cap_Bat2G_sum(25)
nonnegative
    variable Cap_PV2L_sum(25)
nonnegative
    variable Cap_PV2Bat_sum(25)
nonnegative
    variable Cap_Bat2L_sum(25)
nonnegative
    variable Cap_PV2G_sum(25)
nonnegative
    variable M_sum(24) binary
 for k = 1:25
    if k < 25
   cost_demand_sum(k,1) =
Mean_LMP_da_SUM_low(k) .*
(Cap_G2Bat_sum(k)+ Cap_G2L_sum(k));
   income_sum(k,1)        =  0.85*
Mean_LMP_da_SUM_low(k) .*
(Cap_PV2G_sum(k)+Cap_Bat2G_sum(k));
   cost_op_sum(k,1)      = c_op
.*(Cap_Bat2L_sum(k)+Cap_Bat2G_sum(k)+Cap
_G2Bat_sum(k)+Cap_PV2Bat_sum(k));
   cost_sum(k,1)   =
cost_demand_sum(k,1)+ cost_op_sum(k,1) -
income_sum(k,1);
   Cap_charge_sum(k,1)    =
Cap_G2Bat_sum(k) + Cap_PV2Bat_sum(k);
   Cap_discharge_sum(k,1)  =
Cap_Bat2L_sum(k) + Cap_Bat2G_sum(k);

if k==1
Soc_sum(k,1) = SOC_0 + Cap_PV2G_sum(1);
else
   Soc_sum(k,1) = (Eta_Ch
.*(Cap_PV2Bat_sum(k) +
Cap_G2Bat_sum(k)))-
((Cap_Bat2L_sum(k)+Cap_Bat2G_sum(k))./Et
a_D);
end
SOC_sum(k,1) = sum(Soc_sum);
else
     Soc_sum(k,1) = (Eta_Ch
.*(Cap_PV2Bat_sum(k-1) +
Cap_G2Bat_sum(k-1)))-((Cap_Bat2L_sum(k-
1)+Cap_Bat2G_sum(k-1))./Eta_D);
     SOC_sum(k,1) = sum(Soc_sum);
    end
 end
OBJ_sum = sum(cost_sum);
minimize(OBJ_sum)

   subject to
   SOC_sum(1) == SOC_0;% for initial
state
   SOC_sum(25)  >= SOC_sum(1) ;

  for k = 1:24
    Cap_PV2L_sum(k)+ Cap_Bat2L_sum(k) +
Cap_G2L_sum(k) ==Cap_L_sum(k);
    SOC_Min <= SOC_sum(k)   <= SOC_Max ;
    Cap_PV2G_sum(k) + Cap_PV2Bat_sum(k)
+ Cap_PV2L_sum(k) <= Cap_PV_sum(k);
      0<= Cap_charge_sum(k)<= Cap_Max *
M_sum(k);
```

```
    0<= Cap_discharge_sum(k)<= Cap_Max *
(1-M_sum(k));
  end
  cvx_end
  display('DA optimization for DA Done
!!!')
for day = 1:120; %the selected day
       Pr_buy_sample_sum  =
LMP_da_sum_test(:,day) ;
  for k =1:24
   cost_demand_da_sum(k,day) =
Pr_buy_sample_sum(k) .*
(Cap_G2Bat_sum(k)+ Cap_G2L_sum(k));
   income_da_sum(k,day)       = 0.85*
Pr_buy_sample_sum(k) .*
(Cap_PV2G_sum(k)+Cap_Bat2G_sum(k));
   cost_op_da_sum(k,day)      = c_op
.*(Cap_Bat2L_sum(k)+Cap_Bat2G_sum(k)+Cap
_G2Bat_sum(k)+Cap_PV2Bat_sum(k));
   cost_da_sum(k,day)         = -
cost_demand_da_sum(k,day)-
cost_op_da_sum(k,day) +
income_da_sum(k,day);

  end
  Cost_da_sum(day,1) =
sum(cost_da_sum(:,day));
  end
  Cost_T_da_sum = sum(Cost_da_sum)

for i=1:24
    for k=1:4

        Cap_L_sum_RT(4*(i-1)+k,1)=
Cap_L_sum(i)/4;
        Cap_PV_sum_RT(4*(i-1)+k,1)=
Cap_PV_sum(i)/4;
        Pr_buy_RT(4*(i-1)+k,1)=
Pr_buy(i)/4;
    end
end
[W_PV_sum,W_Load_sum] =
Uncertainty(Cap_PV_sum_RT,Cap_L_sum_RT);


 display("PV and Load Disterbance
added")


Hour = 1;


  N=24;


  X_rt = zeros(96,1);


  while Hour <= 24

    clear Cap_G2Bat_sum_rt
    clear Cap_G2L_sum_rt
    clear Cap_Bat2G_sum_rt
    clear Cap_PV2L_sum_rt
    clear Cap_PV2Bat_sum_rt
    clear Cap_Bat2L_sum_rt
    clear Cap_PV2G_sum_rt
    clear M_SUM_rt
    clear cost_demand_sum_rt
    clear income_sum_rt
    clear cost_op_sum_rt
    clear cost_sum_rt
    clear Soc_sum_rt
    clear SOC_sum_rt
    clear OBJ_sum_rt
    clear Cap_charge_sum_rt
    clear Cap_discharge_sum_rt

cvx_begin
    variable Cap_G2Bat_sum_rt(4*N)
nonnegative
    variable Cap_G2L_sum_rt(4*N)
nonnegative
    variable Cap_Bat2G_sum_rt(4*N)
nonnegative
    variable Cap_PV2L_sum_rt(4*N)
nonnegative
    variable Cap_PV2Bat_sum_rt(4*N)
nonnegative
    variable Cap_Bat2L_sum_rt(4*N)
nonnegative
    variable Cap_PV2G_sum_rt(4*N)
nonnegative
    variable M_sum_rt(4*N) binary
 for k = 1:4*N+1
        if k <= 4*N
            if k<=1
                X_rt(4*(Hour-1)+k,1) =
1;
            end
   cost_demand_sum_rt(k,1) =
Mean_LMP_DA_SUM_low(4*(Hour-1)+k) .*
(Cap_G2Bat_sum_rt(k)+
Cap_G2L_sum_rt(k));
   income_sum_rt(k,1) =  0.85*
Mean_LMP_DA_SUM_low(4*(Hour-1)+k) .*
(Cap_PV2G_sum_rt(k)+Cap_Bat2G_sum_rt(k))
;
   cost_op_sum_rt(k,1) =   c_op
.*(Cap_Bat2L_sum_rt(k)+Cap_Bat2G_sum_rt(
k));
   cost_sum_rt(k,1) =
cost_demand_sum_rt(k,1)+
cost_op_sum_rt(k,1) -
income_sum_rt(k,1);
   Cap_charge_sum_rt(k,1) =
Cap_G2Bat_sum_rt(k) +
Cap_PV2Bat_sum_rt(k);
   Cap_discharge_sum_rt(k,1) =
Cap_Bat2L_sum_rt(k) +
Cap_Bat2G_sum_rt(k);
   Soc_sum_rt(k,1) = (Eta_Ch
.*(Cap_PV2Bat_sum_rt(k) +
Cap_G2Bat_sum_rt(k)))./4-
((Cap_Bat2L_sum_rt(k)+Cap_Bat2G_sum_rt(k
))./Eta_D)./4;

   if Hour ==1
        if k==1
        SOC_sum_rt(k,1) = SOC_0 +
Cap_PV2G_sum_rt(1);
        else
        SOC_sum_rt(k,1) = SOC_0 +
sum(Soc_sum_rt(1:k-1));
        end
   else
        if k==1
         SOC_sum_rt(k,1) =
SOC_sum_rtS(4*(Hour-1),1)+
Soc_sum_rtS(4*(Hour-1),1)+
Cap_PV2G_sum_rt(1)*0;
        else
         SOC_sum_rt(k,1) =
SOC_sum_rtS(4*(Hour-1),1)+
Soc_sum_rtS(4*(Hour-1),1)+
sum(Soc_sum_rt(1:k-1));
        end
   end
```

```
          else
             if Hour ==1
                SOC_sum_rt(k,1) = SOC_0 +
Cap_PV2G_sum_rt(1);
             else
                SOC_sum_rt(k,1) =
SOC_sum_rtS(4*(Hour-1),1)+
Soc_sum_rtS(4*(Hour-1),1)+
sum(Soc_sum_rt(1:k-1));
             end
          end
 end

 OBJ_sum_rt = sum(cost_sum_rt);
 minimize(OBJ_sum_rt)

   subject to
   if Hour==1
   SOC_sum_rt(1) == SOC_0;% for initial
state
   end
   SOC_sum_rt(4*N+1)  >= SOC_0 ;

  for k = 1:4*N
    Cap_PV2L_sum_rt(k)+
Cap_Bat2L_sum_rt(k) + Cap_G2L_sum_rt(k)
== Cap_L_sum_RT(4*(Hour-
1)+k)+X_rt(4*(Hour-
1)+k)*W_Load_sum(4*(Hour-1)+k);
    SOC_Min <= SOC_sum_rt(k)  <= SOC_Max
;
    Cap_PV2G_sum_rt(k) +
Cap_PV2Bat_sum_rt(k) +
Cap_PV2L_sum_rt(k) ==
Cap_PV_sum_RT(4*(Hour-
1)+k)+X_rt(4*(Hour-
1)+k)*W_PV_sum(4*(Hour-1)+k);
    0<= Cap_charge_sum_rt(k)<= Cap_Max *
M_sum_rt(k)/4;
    0<= Cap_discharge_sum_rt(k)<=
Cap_Max * (1-M_sum_rt(k))/4;
  end
    cvx_end

  for k=1:4
      Soc_sum_rtS(4*(Hour-1)+k,1) =
Soc_sum_rt(k);
      SOC_sum_rtS(4*(Hour-1)+k,1) =
SOC_sum_rt(k);
      SOCC_sum_rtS(4*(Hour-1)+k,1) =
SOC_sum_rtS(4*(Hour-1)+k,1)/BAT_CAP;
      Cap_G2Bat_sum_rtS(4*(Hour-1)+k,1)
= Cap_G2Bat_sum_rt(k);
      Cap_G2L_sum_rtS(4*(Hour-1)+k,1) =
Cap_G2L_sum_rt(k);
      Cap_Bat2G_sum_rtS(4*(Hour-1)+k,1)
=  Cap_Bat2G_sum_rt(k);
      Cap_PV2L_sum_rtS(4*(Hour-1)+k,1) =
Cap_PV2L_sum_rt(k);
      Cap_PV2Bat_sum_rtS(4*(Hour-1)+k,1)
=  Cap_PV2Bat_sum_rt(k);
      Cap_Bat2L_sum_rtS(4*(Hour-1)+k,1)
= Cap_Bat2L_sum_rt(k);
      Cap_PV2G_sum_rtS(4*(Hour-1)+k,1) =
Cap_PV2G_sum_rt(k);
      M_sum_rtS(4*(Hour-1)+k,1) =
M_sum_rt(k);

  end
  N = N-1;
  Hour = Hour+1;
  end
  SOCC_DSM_sum_rt = SOC_sum_rtS/BAT_CAP;
```

```
    display('RT Optimization for DSM
done!!!')
for day = 1:120; %the selected day
       Pr_buy_sample_sum  =
LMP_rt_sum_test(:,day) ;
  for k =1:96
   cost_demand_rt_sum(k,day) =
Pr_buy_sample_sum(k) .*
(Cap_G2Bat_sum_rtS(k)+
Cap_G2L_sum_rtS(k));
   income_rt_sum(k,day)      = 0.85*
Pr_buy_sample_sum(k) .*
(Cap_PV2G_sum_rtS(k)+Cap_Bat2G_sum_rtS(k
));
   cost_op_rt_sum(k,day)     = c_op*1.3
.*(Cap_Bat2L_sum_rtS(k)+Cap_Bat2G_sum_rt
S(k)+Cap_G2Bat_sum_rtS(k)+Cap_PV2Bat_sum
_rtS(k));
   cost_rt_sum(k,day)        = -
cost_demand_rt_sum(k,day)-
cost_op_rt_sum(k,day) +
income_rt_sum(k,day);

  end
  Cost_rt_sum(day,1) =
sum(cost_rt_sum(:,day));
  end
  Cost_T_rt_sum = sum(Cost_rt_sum)



clear Cap_G2Bat_win
    clear Cap_G2L_win
    clear Cap_Bat2G_win
    clear Cap_PV2L_win
    clear Cap_PV2Bat_win
    clear Cap_Bat2L_win
    clear Cap_PV2G_win
    clear M_win
    clear cost_demand_win
    clear income_win
    clear cost_op_win
    clear cost_win
    clear Soc_win
    clear SOC_win
    clear OBJ_win
    clear Cap_charge_win
    clear Cap_discharge_win
cvx_begin
    variable Cap_G2Bat_win(25)
nonnegative
    variable Cap_G2L_win(25) nonnegative
    variable Cap_Bat2G_win(25)
nonnegative
    variable Cap_PV2L_win(25)
nonnegative
    variable Cap_PV2Bat_win(25)
nonnegative
    variable Cap_Bat2L_win(25)
nonnegative
    variable Cap_PV2G_win(25)
nonnegative
    variable M_win(24) binary
 for k = 1:25
    if k < 25
   cost_demand_win(k,1) =
Mean_LMP_da_WIN_low(k) .*
(Cap_G2Bat_win(k)+ Cap_G2L_win(k));
   income_win(k,1)       =  0.85*
Mean_LMP_da_WIN_low(k) .*
(Cap_PV2G_win(k)+Cap_Bat2G_win(k));
   cost_op_win(k,1)       = c_op
.*(Cap_Bat2L_win(k)+Cap_Bat2G_win(k)+Cap
_G2Bat_win(k)+Cap_PV2Bat_win(k));
```

```
   cost_win(k,1)   =
cost_demand_win(k,1)+ cost_op_win(k,1) -
income_win(k,1);
   Cap_charge_win(k,1)   =
Cap_G2Bat_win(k) + Cap_PV2Bat_win(k);
   Cap_discharge_win(k,1) =
Cap_Bat2L_win(k) + Cap_Bat2G_win(k);

if k==1
Soc_win(k,1) = SOC_0 + Cap_PV2G_win(1);
else
   Soc_win(k,1) = (Eta_Ch
.*(Cap_PV2Bat_win(k) +
Cap_G2Bat_win(k)))-
((Cap_Bat2L_win(k)+Cap_Bat2G_win(k))./Et
a_D);
end
SOC_win(k,1) = sum(Soc_win);
else
     Soc_win(k,1) = (Eta_Ch
.*(Cap_PV2Bat_win(k-1) +
Cap_G2Bat_win(k-1)))-((Cap_Bat2L_win(k-
1)+Cap_Bat2G_win(k-1))./Eta_D);
     SOC_win(k,1) = sum(Soc_win);
    end
 end
OBJ_win = sum(cost_win);
minimize(OBJ_win)

   subject to
   SOC_win(1) == SOC_0;% for initial
state
   SOC_win(25)  >= SOC_win(1) ;

  for k = 1:24
    Cap_PV2L_win(k)+ Cap_Bat2L_win(k) +
Cap_G2L_win(k) ==Cap_L_win(k);
    SOC_Min <= SOC_win(k)  <= SOC_Max ;
    Cap_PV2G_win(k) + Cap_PV2Bat_win(k)
+ Cap_PV2L_win(k) <= Cap_PV_win(k);
    0<= Cap_charge_win(k)<= Cap_Max *
M_win(k);
    0<= Cap_discharge_win(k)<= Cap_Max *
(1-M_win(k));
  end
  cvx_end

  display('DA optimization for DA Done
!!!')
for day = 1:120; %the selected day
       Pr_buy_sample_win   =
LMP_da_win_test(:,day) ;
  for k =1:24
   cost_demand_da_win(k,day) =
Pr_buy_sample_win(k) .*
(Cap_G2Bat_win(k)+ Cap_G2L_win(k));
   income_da_win(k,day)       = 0.85*
Pr_buy_sample_win(k) .*
(Cap_PV2G_win(k)+Cap_Bat2G_win(k));
   cost_op_da_win(k,day)      = c_op
.*(Cap_Bat2L_win(k)+Cap_Bat2G_win(k)+Cap
_G2Bat_win(k)+Cap_PV2Bat_win(k));
   cost_da_win(k,day)         = -
cost_demand_da_win(k,day)-
cost_op_da_win(k,day) +
income_da_win(k,day);

  end
  Cost_da_win(day,1) =
sum(cost_da_win(:,day));
  end
  Cost_T_da_win = sum(Cost_da_win)

for i=1:24
    for k=1:4

        Cap_L_win_RT(4*(i-1)+k,1)=
Cap_L_win(i)/4;
        Cap_PV_win_RT(4*(i-1)+k,1)=
Cap_PV_win(i)/4;
        Pr_buy_RT(4*(i-1)+k,1)=
Pr_buy(i)/4;
end
  end
  Hour = 1;


  N=24;


  X_rt = zeros(96,1);


  while Hour <= 24

    clear Cap_G2Bat_win_rt
    clear Cap_G2L_win_rt
    clear Cap_Bat2G_win_rt
    clear Cap_PV2L_win_rt
    clear Cap_PV2Bat_win_rt
    clear Cap_Bat2L_win_rt
    clear Cap_PV2G_win_rt
    clear M_win_rt
    clear cost_demand_win_rt
    clear income_win_rt
    clear cost_op_win_rt
    clear cost_win_rt
    clear Soc_win_rt
    clear SOC_win_rt
    clear OBJ_win_rt
    clear Cap_charge_win_rt
    clear Cap_discharge_win_rt

cvx_begin
    variable Cap_G2Bat_win_rt(4*N)
nonnegative
    variable Cap_G2L_win_rt(4*N)
nonnegative
    variable Cap_Bat2G_win_rt(4*N)
nonnegative
    variable Cap_PV2L_win_rt(4*N)
nonnegative
    variable Cap_PV2Bat_win_rt(4*N)
nonnegative
    variable Cap_Bat2L_win_rt(4*N)
nonnegative
    variable Cap_PV2G_win_rt(4*N)
nonnegative
    variable M_win_rt(4*N) binary
 for k = 1:4*N+1
        if k <= 4*N
            if k<=1
                X_rt(4*(Hour-1)+k,1) =
1;
            end
   cost_demand_win_rt(k,1) =
Mean_LMP_DA_WIN_low(4*(Hour-1)+k) .*
(Cap_G2Bat_win_rt(k)+
Cap_G2L_win_rt(k));
   income_win_rt(k,1) =  0.85*
Mean_LMP_DA_WIN_low(4*(Hour-1)+k) .*
(Cap_PV2G_win_rt(k)+Cap_Bat2G_win_rt(k))
;
   cost_op_win_rt(k,1) =   c_op
.*(Cap_Bat2L_win_rt(k)+Cap_Bat2G_win_rt(
k));
   cost_win_rt(k,1) =
cost_demand_win_rt(k,1)+
```

```
cost_op_win_rt(k,1) -
income_win_rt(k,1);
   Cap_charge_win_rt(k,1) =
Cap_G2Bat_win_rt(k) +
Cap_PV2Bat_win_rt(k);
   Cap_discharge_win_rt(k,1) =
Cap_Bat2L_win_rt(k) +
Cap_Bat2G_win_rt(k);
   Soc_win_rt(k,1) = (Eta_Ch
.*(Cap_PV2Bat_win_rt(k) +
Cap_G2Bat_win_rt(k)))./4-
((Cap_Bat2L_win_rt(k)+Cap_Bat2G_win_rt(k
))./Eta_D)./4;

   if Hour ==1
        if k==1
        SOC_win_rt(k,1) = SOC_0 +
Cap_PV2G_win_rt(1);
        else
        SOC_win_rt(k,1) = SOC_0 +
sum(Soc_win_rt(1:k-1));
        end
   else
        if k==1
         SOC_win_rt(k,1) =
SOC_win_rtS(4*(Hour-1),1)+
Soc_win_rtS(4*(Hour-1),1)+
Cap_PV2G_win_rt(1)*0;
        else
         SOC_win_rt(k,1) =
SOC_win_rtS(4*(Hour-1),1)+
Soc_win_rtS(4*(Hour-1),1)+
sum(Soc_win_rt(1:k-1));
        end
   end

         else
            if Hour ==1
               SOC_win_rt(k,1) = SOC_0 +
Cap_PV2G_win_rt(1);
            else
               SOC_win_rt(k,1) =
SOC_win_rtS(4*(Hour-1),1)+
Soc_win_rtS(4*(Hour-1),1)+
sum(Soc_win_rt(1:k-1));
            end
         end
 end

 OBJ_win_rt = sum(cost_win_rt);
 minimize(OBJ_win_rt)

   subject to
   if Hour==1
   SOC_win_rt(1) == SOC_0;% for initial
state
   end
   SOC_win_rt(4*N+1)  >= SOC_0 ;

  for k = 1:4*N
    Cap_PV2L_win_rt(k)+
Cap_Bat2L_win_rt(k) + Cap_G2L_win_rt(k)
== Cap_L_win_RT(4*(Hour-
1)+k)+X_rt(4*(Hour-
1)+k)*W_Load_win(4*(Hour-1)+k);
    SOC_Min <= SOC_win_rt(k)  <= SOC_Max
;
    Cap_PV2G_win_rt(k) +
Cap_PV2Bat_win_rt(k) +
Cap_PV2L_win_rt(k) ==
Cap_PV_win_RT(4*(Hour-
1)+k)+X_rt(4*(Hour-
1)+k)*W_PV_win(4*(Hour-1)+k);
    0<= Cap_charge_win_rt(k)<= Cap_Max *
M_win_rt(k)/4;
    0<= Cap_discharge_win_rt(k)<=
Cap_Max * (1-M_win_rt(k))/4;
  end
    cvx_end

  for k=1:4
      Soc_win_rtS(4*(Hour-1)+k,1) =
Soc_win_rt(k);
      SOC_win_rtS(4*(Hour-1)+k,1) =
SOC_win_rt(k);
      SOCC_win_rtS(4*(Hour-1)+k,1) =
SOC_win_rtS(4*(Hour-1)+k,1)/BAT_CAP;
      Cap_G2Bat_win_rtS(4*(Hour-1)+k,1)
= Cap_G2Bat_win_rt(k);
      Cap_G2L_win_rtS(4*(Hour-1)+k,1) =
Cap_G2L_win_rt(k);
      Cap_Bat2G_win_rtS(4*(Hour-1)+k,1)
=  Cap_Bat2G_win_rt(k);
      Cap_PV2L_win_rtS(4*(Hour-1)+k,1) =
Cap_PV2L_win_rt(k);
      Cap_PV2Bat_win_rtS(4*(Hour-1)+k,1)
=  Cap_PV2Bat_win_rt(k);
      Cap_Bat2L_win_rtS(4*(Hour-1)+k,1)
= Cap_Bat2L_win_rt(k);
      Cap_PV2G_win_rtS(4*(Hour-1)+k,1) =
Cap_PV2G_win_rt(k);
      M_win_rtS(4*(Hour-1)+k,1) =
M_win_rt(k);

  end
  N = N-1;
  Hour = Hour+1;
  end
  SOCC_DSM_win_rt = SOC_win_rtS/BAT_CAP;
    display('RT Optimization for DSM
done!!!')
 for day = 1:120; %the selected day
      Pr_buy_sample_win  =
LMP_rt_win_test(:,day) ;
  for k =1:96
   cost_demand_rt_win(k,day) =
Pr_buy_sample_win(k) .*
(Cap_G2Bat_win_rtS(k)+
Cap_G2L_win_rtS(k));
   income_rt_win(k,day)      = 0.85*
Pr_buy_sample_win(k) .*
(Cap_PV2G_win_rtS(k)+Cap_Bat2G_win_rtS(k
));
   cost_op_rt_win(k,day)     = c_op*1.8
.*(Cap_Bat2L_win_rtS(k)+Cap_Bat2G_win_rt
S(k)+Cap_G2Bat_win_rtS(k)+Cap_PV2Bat_win
_rtS(k));
   cost_rt_win(k,day)        = -
cost_demand_rt_win(k,day)-
cost_op_rt_win(k,day) +
income_rt_win(k,day);

  end
  Cost_rt_win(day,1) =
sum(cost_rt_win(:,day));
  end
  Cost_T_rt_win = sum(Cost_rt_win)
```

Appendix C – Market scheduling optimization Matlab Codes

```
clear all
clc
%% ADDING DA Market DATA over year
year = '2016DA';
[Spin_da_win,RegU_da_win,RegD_da_win,LMP_da_win,Spin_da_sum,RegU_da_sum,RegD_da_sum,LMP_da_sum]= MarketDA(year);
clear year
display('Train market data added')
%% Demand side Consumption and Solar production DATA
[Cap_PV_win,Cap_PV_sum,Cap_L_sum,Cap_L_win] = LoadPVprofile();
display('demand and solar Profile added')
%% TOU adding
[~, ~, raw] = xlsread('E:\Polimi courses\Thesis\UC Riverside\Final Codes\DATA.xlsx','TOU','A2:G25');
data = reshape([raw{:}],size(raw));
SDGE_win = data(:,2);
SDGE_sum = data(:,3);
Edison_win = data(:,4);
Edison_sum = data(:,5);
PGE_win = data(:,6);
PGE_sum = data(:,7);
clearvars data raw;

Pr_buy_WIN  =  Edison_win;
Pr_buy_SUM  =  Edison_sum;
display ('Time of use prices added')
 %% Calculation of revenue based on different Opt method -Test Data
year = '2017DA';
[Spin_da_win_test,RegU_da_win_test,RegD_da_win_test,LMP_da_win_test,Spin_da_sum_test,RegU_da_sum_test,RegD_da_sum_test,LMP_da_sum_test]= MarketDA(year);
clear year
display('Test market data added')
%% Test data Mean values
 for i = 1:24
       Mean_LMP_da_test_win(i,1)  = mean(LMP_da_win_test(i,:)); %Jan - May
       Mean_RegD_da_test_win(i,1) = mean(RegD_da_win_test(i,:));
       Mean_RegU_da_test_win(i,1) = mean(RegU_da_win_test(i,:));
       Mean_Spin_da_test_win(i,1) = mean(Spin_da_win_test(i,:));

       Mean_LMP_da_test_sum(i,1)  = mean(LMP_da_sum_test(i,:)) ;  %Jun-Sep
       Mean_RegD_da_test_sum(i,1) = mean(RegD_da_sum_test(i,:));
       Mean_RegU_da_test_sum(i,1) = mean(RegU_da_sum_test(i,:));
       Mean_Spin_da_test_sum(i,1) = mean(Spin_da_sum_test(i,:));
 end
 %% Battery and other variable defining
Eta_Ch = 0.85 ;                        % Charging Efficiency of the Battery
Eta_D = 0.95  ;                        % Discharging Efficiency of the Battery
BAT_CAP = 30  ;                        % Nominal Energy Capacity Battery kWh
SOC_Max = BAT_CAP*0.9 ;
SOC_Min = BAT_CAP*0.2 ;
SOC_0 = 16     ;
Cap_Max = 5    ;                       % The Maximum allowble power flow KW - inverter limits
c_op = 0.005   ;                       %($/kWh) Operation Cost Coefficient
%% Full data DA Mean values
for i= 1:24
LMP_da_sum_full(i,1)  = mean(LMP_da_sum(i,:)) ;
RegD_da_sum_full(i,1) = mean(RegD_da_sum(i,:));
RegU_da_sum_full(i,1) = mean(RegU_da_sum(i,:));
Spin_da_sum_full(i,1) = mean(Spin_da_sum(i,:));

LMP_da_win_full(i,1)  = mean(LMP_da_win(i,:)) ;
RegD_da_win_full(i,1) = mean(RegD_da_win(i,:));
RegU_da_win_full(i,1) = mean(RegU_da_win(i,:));
Spin_da_win_full(i,1) = mean(Spin_da_win(i,:));

end
%% Selection of Summer and Winter data for DRO (Excluding data from data pool) BIG DATA
   for i=1:24
      for k = 1:15
       LMP_da_SUM_low(i,4*(k-1)+1)= LMP_da_sum(i,2+(k-1)*7);
       LMP_da_SUM_low(i,4*(k-1)+2)= LMP_da_sum(i,3+(k-1)*7);
       LMP_da_SUM_low(i,4*(k-1)+3)= LMP_da_sum(i,4+(k-1)*7);
       LMP_da_SUM_low(i,4*(k-1)+4)= LMP_da_sum(i,5+(k-1)*7);
       Spin_da_SUM_low(i,4*(k-1)+1)= Spin_da_sum(i,2+(k-1)*7);
       Spin_da_SUM_low(i,4*(k-1)+2)= Spin_da_sum(i,3+(k-1)*7);
       Spin_da_SUM_low(i,4*(k-1)+3)= Spin_da_sum(i,4+(k-1)*7);
       Spin_da_SUM_low(i,4*(k-1)+4)= Spin_da_sum(i,5+(k-1)*7);
       RegU_da_SUM_low(i,4*(k-1)+1)= RegU_da_sum(i,2+(k-1)*7);
       RegU_da_SUM_low(i,4*(k-1)+2)= RegU_da_sum(i,3+(k-1)*7);
       RegU_da_SUM_low(i,4*(k-1)+3)= RegU_da_sum(i,4+(k-1)*7);
       RegU_da_SUM_low(i,4*(k-1)+4)= RegU_da_sum(i,5+(k-1)*7);
       RegD_da_SUM_low(i,4*(k-1)+1)= RegD_da_sum(i,2+(k-1)*7);
       RegD_da_SUM_low(i,4*(k-1)+2)= RegD_da_sum(i,3+(k-1)*7);
       RegD_da_SUM_low(i,4*(k-1)+3)= RegD_da_sum(i,4+(k-1)*7);
```

```
       RegD_da_SUM_low(i,4*(k-1)+4)=
RegD_da_sum(i,5+(k-1)*7);

       LMP_da_WIN_low(i,4*(k-1)+1)=
LMP_da_win(i,2+(k-1)*7);
       LMP_da_WIN_low(i,4*(k-1)+2)=
LMP_da_win(i,3+(k-1)*7);
       LMP_da_WIN_low(i,4*(k-1)+3)=
LMP_da_win(i,4+(k-1)*7);
       LMP_da_WIN_low(i,4*(k-1)+4)=
LMP_da_win(i,5+(k-1)*7);
       Spin_da_WIN_low(i,4*(k-1)+1)=
Spin_da_win(i,2+(k-1)*7);
       Spin_da_WIN_low(i,4*(k-1)+2)=
Spin_da_win(i,3+(k-1)*7);
       Spin_da_WIN_low(i,4*(k-1)+3)=
Spin_da_win(i,4+(k-1)*7);
       Spin_da_WIN_low(i,4*(k-1)+4)=
Spin_da_win(i,5+(k-1)*7);
       RegU_da_WIN_low(i,4*(k-1)+1)=
RegU_da_win(i,2+(k-1)*7);
       RegU_da_WIN_low(i,4*(k-1)+2)=
RegU_da_win(i,3+(k-1)*7);
       RegU_da_WIN_low(i,4*(k-1)+3)=
RegU_da_win(i,4+(k-1)*7);
       RegU_da_WIN_low(i,4*(k-1)+4)=
RegU_da_win(i,5+(k-1)*7);
       RegD_da_WIN_low(i,4*(k-1)+1)=
RegD_da_win(i,2+(k-1)*7);
       RegD_da_WIN_low(i,4*(k-1)+2)=
RegD_da_win(i,3+(k-1)*7);
       RegD_da_WIN_low(i,4*(k-1)+3)=
RegD_da_win(i,4+(k-1)*7);
       RegD_da_WIN_low(i,4*(k-1)+4)=
RegD_da_win(i,5+(k-1)*7);

    end

   Mean_LMP_da_SUM_low(i,1) =
mean(LMP_da_SUM_low(i,:));
   Mean_RegU_da_SUM_low(i,1)=
mean(RegU_da_SUM_low(i,:));
   Mean_RegD_da_SUM_low(i,1)=
mean(RegD_da_SUM_low(i,:));
   Mean_Spin_da_SUM_low(i,1)=
mean(Spin_da_SUM_low(i,:));

   Mean_LMP_da_WIN_low(i,1) =
mean(LMP_da_WIN_low(i,:));
   Mean_RegU_da_WIN_low(i,1)=
mean(RegU_da_WIN_low(i,:));
   Mean_RegD_da_WIN_low(i,1)=
mean(RegD_da_WIN_low(i,:));
   Mean_Spin_da_WIN_low(i,1)=
mean(Spin_da_WIN_low(i,:));
   end
   N_SUM_low  = size(LMP_da_SUM_low,2);
   N_WIN_low  = size(LMP_da_WIN_low,2);

   Max_LMP_da_SUM_low =
max(LMP_da_SUM_low,[],2);
   Max_RegU_da_SUM_low =
max(RegU_da_SUM_low,[],2);
   Max_RegD_da_SUM_low =
max(RegD_da_SUM_low,[],2);
   Max_Spin_da_SUM_low =
max(Spin_da_SUM_low,[],2);

   Max_LMP_da_WIN_low =
max(LMP_da_WIN_low,[],2);
   Max_RegU_da_WIN_low =
max(RegU_da_WIN_low,[],2);
   Max_RegD_da_WIN_low =
max(RegD_da_WIN_low,[],2);
   Max_Spin_da_WIN_low =
max(Spin_da_WIN_low,[],2);
   display ('data for DRO prepered')
   for i=1:24
      for k = 1:15
        LMP_da_SUM_low(i,2*(k-1)+1)=
LMP_da_sum(i,2+(k-1)*7);
        LMP_da_SUM_low(i,2*(k-1)+2)=
LMP_da_sum(i,3+(k-1)*7);
        Spin_da_SUM_low(i,2*(k-1)+1)=
Spin_da_sum(i,2+(k-1)*7);
        Spin_da_SUM_low(i,2*(k-1)+2)=
Spin_da_sum(i,3+(k-1)*7);
        RegU_da_SUM_low(i,2*(k-1)+1)=
RegU_da_sum(i,2+(k-1)*7);
        RegU_da_SUM_low(i,2*(k-1)+2)=
RegU_da_sum(i,3+(k-1)*7);
        RegD_da_SUM_low(i,2*(k-1)+1)=
RegD_da_sum(i,2+(k-1)*7);
        RegD_da_SUM_low(i,2*(k-1)+2)=
RegD_da_sum(i,3+(k-1)*7);

        LMP_da_WIN_low(i,2*(k-1)+1)=
LMP_da_win(i,5+(k-1)*7);
        LMP_da_WIN_low(i,2*(k-1)+2)=
LMP_da_win(i,6+(k-1)*7);
        Spin_da_WIN_low(i,2*(k-1)+1)=
Spin_da_win(i,5+(k-1)*7);
        Spin_da_WIN_low(i,2*(k-1)+2)=
Spin_da_win(i,6+(k-1)*7);
        RegU_da_WIN_low(i,2*(k-1)+1)=
RegU_da_win(i,5+(k-1)*7);
        RegU_da_WIN_low(i,2*(k-1)+2)=
RegU_da_win(i,6+(k-1)*7);
        RegD_da_WIN_low(i,2*(k-1)+1)=
RegD_da_win(i,5+(k-1)*7);
        RegD_da_WIN_low(i,2*(k-1)+2)=
RegD_da_win(i,6+(k-1)*7);
     end

   Mean_LMP_da_SUM_low(i,1) =
mean(LMP_da_SUM_low(i,:));
   Mean_RegU_da_SUM_low(i,1)=
mean(RegU_da_SUM_low(i,:));
   Mean_RegD_da_SUM_low(i,1)=
mean(RegD_da_SUM_low(i,:));
   Mean_Spin_da_SUM_low(i,1)=
mean(Spin_da_SUM_low(i,:));

   Mean_LMP_da_WIN_low(i,1) =
mean(LMP_da_WIN_low(i,:));
   Mean_RegU_da_WIN_low(i,1)=
mean(RegU_da_WIN_low(i,:));
   Mean_RegD_da_WIN_low(i,1)=
mean(RegD_da_WIN_low(i,:));
   Mean_Spin_da_WIN_low(i,1)=
mean(Spin_da_WIN_low(i,:));
   end
   N_SUM_low  = size(LMP_da_SUM_low,2);
   N_WIN_low  = size(LMP_da_WIN_low,2);

   Max_LMP_da_SUM_low =
max(LMP_da_SUM_low,[],2);
   Max_RegU_da_SUM_low =
max(RegU_da_SUM_low,[],2);
   Max_RegD_da_SUM_low =
max(RegD_da_SUM_low,[],2);
   Max_Spin_da_SUM_low =
max(Spin_da_SUM_low,[],2);

   Max_LMP_da_WIN_low =
max(LMP_da_WIN_low,[],2);
   Max_RegU_da_WIN_low =
max(RegU_da_WIN_low,[],2);
```

```
   Max_RegD_da_WIN_low =
max(RegD_da_WIN_low,[],2);
   Max_Spin_da_WIN_low =
max(Spin_da_WIN_low,[],2);
   display ('data for DRO prepered')

   %% Preparing data for Robust Creat
Minimum

  [Min_LMP_da_SUM_low]  =
MinimumDA(LMP_da_SUM_low,0.25);
  [Min_RegU_da_SUM_low] =
MinimumDA(RegU_da_SUM_low,0.25);
  [Min_RegD_da_SUM_low] =
MinimumDA(RegD_da_SUM_low,0.25);
  [Min_Spin_da_SUM_low] =
MinimumDA(Spin_da_SUM_low,0.25);

  [Min_LMP_da_WIN_low]  =
MinimumDA(LMP_da_WIN_low,0.25);
  [Min_RegU_da_WIN_low] =
MinimumDA(RegU_da_WIN_low,0.25);
  [Min_RegD_da_WIN_low] =
MinimumDA(RegD_da_WIN_low,0.25);
  [Min_Spin_da_WIN_low] =
MinimumDA(Spin_da_WIN_low,0.25);

display('Data for Robust optimizatin
prepared')

   %%
Tr_RS   = zeros(24,1);
Tr_RegU = zeros(24,1);
Tr_RegD = zeros(24,1);
Tr_E    = zeros(24,1);

AGC = randi([0,1],24,1);

Tr_RS(3,1)  = 1;
Tr_RS(6,1)  = 1;
Tr_RS(8,1)= 1;
Tr_RS(13,1)= 1;
Tr_RS(15,1)= 1;
Tr_RS(16,1)= 1;
Tr_RS(18,1)  = 1;
Tr_RS(20,1)=1;
Tr_RS(21,1)=1;
% Tr_RS(24,1)=1;

Tr_RegU(3,1)  = 1;
Tr_RegU(6,1)  = 1;
Tr_RegU(8,1)= 1;
Tr_RegU(13,1)=1;
Tr_RegU(15,1)=1;
Tr_RegU(16,1)=1;
Tr_RegU(18,1)=1;
Tr_RegU(20,1)=1;
Tr_RegU(21,1)=1;
%Tr_RegU(24,1)=1;

Tr_RegD(3,1)  = 1;
Tr_RegD(6,1)  = 1;
Tr_RegD(8,1)= 1;
Tr_RegD(13,1)=1;
Tr_RegD(15,1)=1;
Tr_RegD(16,1)=1;
Tr_RegD(18,1)=1;
Tr_RegD(20,1)=1;
Tr_RegD(21,1)=1;
% Tr_RegD(24,1)=1;
for k=1:24
   if AGC(k) ==1
       Tr_RegD(k,1)=0;
   else
```

```
       Tr_RegU(k,1)=0;
   end
end

%% Day ahead Optimization Case 1

tic

clear Cap_Discharge_DRO_SUM_low
clear cost_Charge_DRO_SUM_low
clear cost_Demand_DRO_SUM_low
clear income_Spin_DRO_SUM_low
clear Income_Spin_DRO_SUM_low
clear income_sell_DRO_SUM_low
clear INCOME_sell_DRO_SUM_low
clear income_E_DRO_SUM_low
clear Income_E_DRO_SUM_low
clear income_MilU_DRO_SUM_low
clear income_RegU_DRO_SUM_low
clear Income_RegU_DRO_SUM_low
clear cost_Charge_DRO_SUM_low
clear Cap_Charge_DRO_SUM_low
clear income_MilD_DRO_SUM_low
clear income_RegD_DRO_SUM_low
clear Income_RegD_DRO_SUM_low
clear income_Charging_DRO_SUM_low
clear income_Discharging_DRO_SUM_low
clear cost_OP_DRO_SUM_low
clear Soc_DRO_SUM_low
clear SOC_DRO_SUM_low
clear cost_DRO_SUM_low
clear COST_DRO_SUM_low
clear SOCC_DRO_SUM_low
clear lambda_Risk_SUM_low
clear S_Spin_SUM_low
clear S_LMP_SUM_low
clear S_RegU_SUM_low
clear S_RegD_SUM_low
clear S_Buy_SUM_low
clear Risk_CVaR_RegU_SUM_low
clear Risk_CVaR_RegD_SUM_low
clear Risk_CVaR_Spin_SUM_low
clear Risk_CVaR_LMP_SUM_low
clear Risk_CVaR_Buy_SUM_low
clear a1_Risk_SUM_low
clear ROO_Risk_SUM_low
clear a2_Risk_SUM_low
clear b1_Risk_SUM_low
clear b2_Risk_SUM_low
clear tou_Spin_SUM_low
clear tou_RegU_SUM_low
clear tou_RegD_SUM_low
clear tou_LMP_SUM_low
clear tou_Buy_SUM_low
clear gama1_Spin_SUM_low
clear gama2_Spin_SUM_low
clear gama1_RegU_SUM_low
clear gama2_RegU_SUM_low
clear gama1_RegD_SUM_low
clear gama2_RegD_SUM_low
clear gama1_LMP_SUM_low
clear gama2_LMP_SUM_low
clear gama1_Buy_SUM_low
clear gama2_Buy_SUM_low
clear a_RegU_DRO_SUM_low
clear a_Spin_DRO_SUM_low
clear a_LMP_DRO_SUM_low
clear a_RegD_DRO_SUM_low
clear a_Buy_DRO_SUM_low
clear a_Ex_ch_DRO_SUM_low
clear a_Ex_dch_DRO_SUM_low
clear Cap_Ex_ch_DRO_SUM_low
clear Cap_Ex_dch_DRO_SUM_low
```

```
clear cost_un_dch_DRO_SUM_low
clear cost_un_ch_DRO_SUM_low
clear a_ex_ch_DRO_SUM_low
clear a_ex_dch_DRO_SUM_low
clear Cap_Bat2L_DRO_SUM_low
clear a_Bat2L_DRO_SUM_low
clear a_G2Bat_DRO_SUM_low
clear a_PV2Bat_DRO_SUM_low
clear a_G2L_DRO_SUM_low
clear M_DRO_SUM_low
clear a_PV2L_DRO_SUM_low
cvx_begin

    variable Cap_G2Bat_DRO_SUM_low(24)
nonnegative
    variable Cap_RegD_DRO_SUM_low(24)
nonnegative
    variable Cap_PV2L_DRO_SUM_low(24)
nonnegative
    variable Cap_G2L_DRO_SUM_low(24)
nonnegative
    variable Cap_Bat2G_DRO_SUM_low(24)
nonnegative
    variable Cap_Bat2L_DRO_SUM_low(24)
nonnegative
    variable Cap_PV2Bat_DRO_SUM_low(24)
nonnegative
    variable Cap_RegU_DRO_SUM_low(24)
nonnegative
    variable Cap_Spin_DRO_SUM_low(24)
nonnegative
    variable Cap_Ex_ch_DRO_SUM_low(24)
nonnegative
    variable Cap_Ex_dch_DRO_SUM_low(24)
nonnegative
    variable M_DRO_SUM_low(24) binary
    variable lambda_Spin_SUM_low(24)
    variable lambda_LMP_SUM_low(24)
    variable lambda_RegU_SUM_low(24)
    variable lambda_RegD_SUM_low(24)
    variable lambda_Buy_SUM_low(24)
    variable
S_Spin_SUM_low(24,N_SUM_low)
    variable
S_RegU_SUM_low(24,N_SUM_low)
    variable
S_RegD_SUM_low(24,N_SUM_low)
    variable S_LMP_SUM_low(24,N_SUM_low)
    variable S_Buy_SUM_low(24,N_SUM_low)
    variable gama1_Spin_SUM_low(24)
    variable gama2_Spin_SUM_low(24)
    variable gama1_RegU_SUM_low(24)
    variable gama2_RegU_SUM_low(24)
    variable gama1_RegD_SUM_low(24)
    variable gama2_RegD_SUM_low(24)
    variable gama1_LMP_SUM_low(24)
    variable gama2_LMP_SUM_low(24)
    variable gama1_Buy_SUM_low(24)
    variable gama2_Buy_SUM_low(24)
    variable tou_Spin_SUM_low(N_SUM_low)
    variable tou_RegU_SUM_low(N_SUM_low)
    variable tou_RegD_SUM_low(N_SUM_low)
    variable tou_LMP_SUM_low(N_SUM_low)
    variable tou_Buy_SUM_low(N_SUM_low)

  for k = 1:25
      if k<25
    Cap_Charge_DRO_SUM_low(k,1) =
Cap_G2Bat_DRO_SUM_low(k)+Cap_PV2Bat_DRO_
SUM_low(k)+Cap_RegD_DRO_SUM_low(k);%+Cap
_Ex_ch_DRO_SUM_low(k);%+
    Cap_Discharge_DRO_SUM_low(k,1) =
Cap_Bat2G_DRO_SUM_low(k)+Cap_Spin_DRO_SU
M_low(k)+Cap_RegU_DRO_SUM_low(k)+Cap_Bat
2L_DRO_SUM_low(k);%+Cap_Ex_dch_DRO_SUM_l
ow(k);%+

   a_RegU_DRO_SUM_low(k,1)    =
Cap_RegU_DRO_SUM_low(k)/Cap_Max;
   a_RegD_DRO_SUM_low(k,1)    =
Cap_RegD_DRO_SUM_low(k)/Cap_Max;
   a_Spin_DRO_SUM_low(k,1)    =
Cap_Spin_DRO_SUM_low(k)/Cap_Max;
   a_LMP_DRO_SUM_low(k,1)      =
(Cap_Bat2G_DRO_SUM_low(k))/Cap_Max;%
   a_Buy_DRO_SUM_low(k,1)      =
Cap_G2Bat_DRO_SUM_low(k)/Cap_Max;
   a_ex_dch_DRO_SUM_low(k,1) =
Cap_Ex_dch_DRO_SUM_low(k)/Cap_Max;
   a_ex_ch_DRO_SUM_low(k,1)   =
Cap_Ex_ch_DRO_SUM_low(k)/Cap_Max;
   a_Bat2L_DRO_SUM_low(k,1)   =
Cap_Bat2L_DRO_SUM_low(k)/Cap_Max;
   a_G2Bat_DRO_SUM_low(k,1)   =
Cap_G2Bat_DRO_SUM_low(k)/Cap_Max;
   a_PV2Bat_DRO_SUM_low(k,1)  =
Cap_PV2Bat_DRO_SUM_low(k)/Cap_Max;
   a_G2L_DRO_SUM_low(k,1)      =
Cap_G2L_DRO_SUM_low(k)/Cap_Max;
   a_PV2L_DRO_SUM_low(k,1)      =
Cap_PV2L_DRO_SUM_low(k)/Cap_Max;
   cost_OP_DRO_SUM_low(k,1)  =  c_op
.*(a_PV2Bat_DRO_SUM_low(k)+
a_G2Bat_DRO_SUM_low(k) +
a_LMP_DRO_SUM_low(k)+a_Spin_DRO_SUM_low(
k)+a_RegD_DRO_SUM_low(k)+a_RegU_DRO_SUM_
low(k)) ; % Cost operation

    cost_un_dch_DRO_SUM_low(k,1)   =
Cap_Ex_dch_DRO_SUM_low(k)* 0;
    cost_un_ch_DRO_SUM_low(k,1)   =
Cap_Ex_ch_DRO_SUM_low(k)* 0;

    if k==1
        Soc_DRO_SUM_low(k,1)   = SOC_0 +
cost_un_dch_DRO_SUM_low(k);
    else
        Soc_DRO_SUM_low(k,1)   = Eta_Ch
.*(Cap_PV2Bat_DRO_SUM_low(k-1)+
Cap_G2Bat_DRO_SUM_low(k-
1)+Cap_RegD_DRO_SUM_low(k-1))-
(Cap_Bat2G_DRO_SUM_low(k-
1,1)+Cap_Spin_DRO_SUM_low(k-
1)+Cap_RegU_DRO_SUM_low(k-
1)+Cap_Bat2L_DRO_SUM_low(k-1))./Eta_D;
    end
      SOC_DRO_SUM_low(k,1)   =
sum(Soc_DRO_SUM_low);
      SOCC_DRO_SUM_low(k,1)   =
SOC_DRO_SUM_low(k,1)/BAT_CAP;

   alfa = 0.001; %CVar confidence level

     a1_Risk_SUM_low = -1;
     R_w = 0.001;

     ROO_RegU_SUM_low(k,1) = 1; %
investor risk aversion
     a2_RegU_SUM_low(k,1) = -1 -
(ROO_RegU_SUM_low(k,1)/alfa);
     b1_RegU_SUM_low(k,1) =
ROO_RegU_SUM_low(k,1);
     b2_RegU_SUM_low(k,1) =
ROO_RegU_SUM_low(k,1) * (1- 1/alfa);

     ROO_Spin_SUM_low(k,1) = 1; %
investor risk aversion
```

```
     a2_Spin_SUM_low(k,1) = -1 -
(ROO_Spin_SUM_low(k,1)/alfa);
     b1_Spin_SUM_low(k,1) =
ROO_Spin_SUM_low(k,1);
     b2_Spin_SUM_low(k,1) =
ROO_Spin_SUM_low(k,1)* (1- 1/alfa);

     ROO_LMP_SUM_low(k,1) = 1; %
investor risk aversion
     a2_LMP_SUM_low(k,1) = -1 -
(ROO_LMP_SUM_low(k,1)/alfa);
     b1_LMP_SUM_low(k,1) =
ROO_LMP_SUM_low(k,1);
     b2_LMP_SUM_low(k,1) =
ROO_LMP_SUM_low(k,1) * (1- 1/alfa);

     ROO_RegD_SUM_low(k,1) = 1; %
investor risk aversion
     a2_RegD_SUM_low(k,1) = -1 -
(ROO_RegD_SUM_low(k,1)/alfa);
     b1_RegD_SUM_low(k,1) =
ROO_RegD_SUM_low(k,1);
     b2_RegD_SUM_low(k,1) =
ROO_RegD_SUM_low(k,1) * (1- 1/alfa);

     d_spin_SUM_low(k,1) =
Max_Spin_da_SUM_low(k,1);%max(Max_Spin_d
a_SUM(k,1),Max_Spin_da_SUM_test(k,1));%M
ax_Spin_da_low;%
Er_Spin_da_low_Max_Risk;%Spin_da_low_Max
;%
     d_RegU_SUM_low(k,1) =
Max_RegU_da_SUM_low(k,1);%max(Max_RegU_d
a_SUM(k,1),Max_RegU_da_SUM_test(k,1));
%Max_Reg_U_da_low;%Er_Reg_U_da_low_Max_R
isk;%
     d_LMP_SUM_low(k,1)  =
Max_LMP_da_SUM_low(k,1);%max(Max_LMP_da_
SUM(k,1),Max_LMP_da_SUM_test(k,1));
%Max_LMP_da_low;%Er_LMP_da_low_Max;%
     d_RegD_SUM_low(k,1) =
Max_RegD_da_SUM_low(k,1);%max(Max_RegD_d
a_SUM(k,1),Max_RegD_da_SUM_test(k,1));
%;

Risk_CVaR_RegU_SUM_low(k,1) =
Tr_RegU(k,1).*((1*lambda_RegU_SUM_low(k,
1).* R_w +
(sum(S_RegU_SUM_low(k,:))./N_SUM_low)));
%r_Reg_U_da_SUM_low_Risk(k,1)
Risk_CVaR_Spin_SUM_low(k,1) =
Tr_RS(k,1).*((1*lambda_Spin_SUM_low(k,1)
.* R_w +
(sum(S_Spin_SUM_low(k,:))./N_SUM_low)));
% r_Spin_da_SUM_low_Risk(k,1)
Risk_CVaR_LMP_SUM_low(k,1)  =
((1*lambda_LMP_SUM_low(k,1) .* R_w +
(sum(S_LMP_SUM_low(k,:))./N_SUM_low)));
% r_LMP_da_low(k,1)
Risk_CVaR_RegD_SUM_low(k,1) =
Tr_RegD(k,1).*((1*lambda_RegD_SUM_low(k,
1) .* R_w +
(sum(S_RegD_SUM_low(k,:))./N_SUM_low)));
%
      else

       Soc_DRO_SUM_low(k,1)  = Eta_Ch
.*(Cap_PV2Bat_DRO_SUM_low(k-1)+
Cap_G2Bat_DRO_SUM_low(k-
1)+Cap_RegD_DRO_SUM_low(k-1))-
(Cap_Bat2G_DRO_SUM_low(k-
1,1)+Cap_Spin_DRO_SUM_low(k-
1)+Cap_RegU_DRO_SUM_low(k-
1)+Cap_Bat2L_DRO_SUM_low(k-1))./Eta_D;
       SOC_DRO_SUM_low(k,1)  =
sum(Soc_DRO_SUM_low);
       SOCC_DRO_SUM_low(k,1)  =
SOC_DRO_SUM_low(k,1)/BAT_CAP;
      end
  end

  OBJ_DRO_SUM_low =
sum(cost_OP_DRO_SUM_low+cost_un_dch_DRO_
SUM_low + cost_un_ch_DRO_SUM_low +
Risk_CVaR_Spin_SUM_low +
Risk_CVaR_RegU_SUM_low +
Risk_CVaR_RegD_SUM_low +
Risk_CVaR_LMP_SUM_low);%  Cost_M1+
+sum(cost_OP_DRO_SUM_low)  +
cost_Demand_DRO_SUM_low +
cost_Charge_DRO_SUM_low

minimize(OBJ_DRO_SUM_low)

   subject to
  SOC_DRO_SUM_low(1) == SOC_0 ;% for
initial value of soc
  SOC_DRO_SUM_low(25) >=
SOC_DRO_SUM_low(1) ;
  SOC_Min <= SOC_DRO_SUM_low(25)  <=
SOC_Max ;
  for k = 1:24

    SOC_Min <= SOC_DRO_SUM_low(k)  <=
SOC_Max;
    Cap_PV2L_DRO_SUM_low(k) +
Cap_G2L_DRO_SUM_low(k)+Cap_Bat2L_DRO_SUM
_low(k) == Cap_L_sum(k);
    Cap_PV2Bat_DRO_SUM_low(k) +
Cap_PV2L_DRO_SUM_low(k) <=
Cap_PV_sum(k);
    Cap_Charge_DRO_SUM_low(k)<=
Cap_Max.*(1-M_DRO_SUM_low(k));
    Cap_Discharge_DRO_SUM_low(k)<=
Cap_Max.*(M_DRO_SUM_low(k));

   if Tr_RS(k)==0
       Cap_Spin_DRO_SUM_low(k)==0;
   end

   if Tr_RegU(k)==0
       Cap_RegU_DRO_SUM_low(k)==0;
   end

   if Tr_RegD(k)==0
       Cap_RegD_DRO_SUM_low(k)==0;
   end

for i=1:N_SUM_low

b1_Spin_SUM_low(k,1)*tou_Spin_SUM_low +
a1_Risk_SUM_low .*
a_Spin_DRO_SUM_low(k).*Spin_da_SUM_low(k
,i) + gama1_Spin_SUM_low(k,1) .*
(d_spin_SUM_low(k,1) -
Spin_da_SUM_low(k,i)) <=
S_Spin_SUM_low(k,i);

b2_Spin_SUM_low(k,1)*tou_Spin_SUM_low +
a2_Spin_SUM_low(k,1).*
a_Spin_DRO_SUM_low(k).*Spin_da_SUM_low(k
,i) + gama2_Spin_SUM_low(k,1) .*
(d_spin_SUM_low(k,1) -
Spin_da_SUM_low(k,i)) <=
S_Spin_SUM_low(k,i);
        norm((gama1_Spin_SUM_low(k,1)-
a1_Risk_SUM_low.*
```

```
a_Spin_DRO_SUM_low(k)),inf) <=
Tr_RS(k,1).*lambda_Spin_SUM_low(k,1);
        norm((gama2_Spin_SUM_low(k,1)-
a2_Spin_SUM_low(k,1).*
a_Spin_DRO_SUM_low(k)),inf)
<=Tr_RS(k,1).* lambda_Spin_SUM_low(k,1);
        0<= gama1_Spin_SUM_low(k,1);
        0<= gama2_Spin_SUM_low(k,1);


b1_RegU_SUM_low(k,1)*tou_RegU_SUM_low +
a1_Risk_SUM_low
.*a_RegU_DRO_SUM_low(k).*
RegU_da_SUM_low(k,i) +
gama1_RegU_SUM_low(k,1) .*
(d_RegU_SUM_low(k,1) -
RegU_da_SUM_low(k,i)) <=
S_RegU_SUM_low(k,i);%Er_Reg_U_da_SUM_low
%  %Er_Reg_U_da_SUM_low_Risk
%Norm_Reg_U_da_SUM_low %a_RegU_DRO

b2_RegU_SUM_low(k,1)*tou_RegU_SUM_low +
a2_RegU_SUM_low(k,1) .*
a_RegU_DRO_SUM_low(k).*RegU_da_SUM_low(k
,i) + gama2_RegU_SUM_low(k,1) .*
(d_RegU_SUM_low(k,1) -
RegU_da_SUM_low(k,i)) <=
S_RegU_SUM_low(k,i);
        norm((gama1_RegU_SUM_low(k,1)-
a1_Risk_SUM_low.*
a_RegU_DRO_SUM_low(k)),inf)
<=Tr_RegU(k,1).*
lambda_RegU_SUM_low(k,1);
        norm((gama2_RegU_SUM_low(k,1)-
a2_RegU_SUM_low(k,1).*
a_RegU_DRO_SUM_low(k)),inf)
<=Tr_RegU(k,1).*
lambda_RegU_SUM_low(k,1);
        0<= gama1_RegU_SUM_low(k,1);
        0<= gama2_RegU_SUM_low(k,1);


b1_LMP_SUM_low(k,1)*tou_LMP_SUM_low +
a1_Risk_SUM_low.*(a_LMP_DRO_SUM_low(k)+a
_RegU_DRO_SUM_low(k)+a_Spin_DRO_SUM_low(
k)-a_G2Bat_DRO_SUM_low(k,1)-
a_G2L_DRO_SUM_low(k,1))
.*LMP_da_SUM_low(k,i) +
gama1_LMP_SUM_low(k,1) .*
(d_LMP_SUM_low(k,1) -
LMP_da_SUM_low(k,i)) <=
S_LMP_SUM_low(k,i);%

b2_LMP_SUM_low(k,1)*tou_LMP_SUM_low +
a2_LMP_SUM_low(k,1).*(a_LMP_DRO_SUM_low(
k)+a_RegU_DRO_SUM_low(k)+a_Spin_DRO_SUM_
low(k)-a_G2Bat_DRO_SUM_low(k,1)-
a_G2L_DRO_SUM_low(k,1))
.*LMP_da_SUM_low(k,i) +
gama2_LMP_SUM_low(k,1) .*
(d_LMP_SUM_low(k,1) -
LMP_da_SUM_low(k,i)) <=
S_LMP_SUM_low(k,i);
        norm((gama1_LMP_SUM_low(k,1)-
a1_Risk_SUM_low.*(a_LMP_DRO_SUM_low(k)+a
_RegU_DRO_SUM_low(k)+a_Spin_DRO_SUM_low(
k)-a_G2Bat_DRO_SUM_low(k,1)-
a_G2L_DRO_SUM_low(k,1))),inf) <=
lambda_LMP_SUM_low(k,1);
        norm((gama2_LMP_SUM_low(k,1)-
a2_LMP_SUM_low(k,1).*(a_LMP_DRO_SUM_low(
k)+a_RegU_DRO_SUM_low(k)+a_Spin_DRO_SUM_
low(k)-a_G2Bat_DRO_SUM_low(k,1)-
a_G2L_DRO_SUM_low(k,1))),inf) <=
lambda_LMP_SUM_low(k,1);
        0<= gama1_LMP_SUM_low(k,1);
        0<= gama2_LMP_SUM_low(k,1);


b1_RegD_SUM_low(k,1)*tou_RegD_SUM_low +
a1_Risk_SUM_low .*
a_RegD_DRO_SUM_low(k).*RegD_da_SUM_low(k
,i) + gama1_RegD_SUM_low(k,1) .*
(d_RegD_SUM_low(k,1) -
RegD_da_SUM_low(k,i)) <=
S_RegD_SUM_low(k,i);

b2_RegD_SUM_low(k,1)*tou_RegD_SUM_low +
a2_RegD_SUM_low(k,1) .*
a_RegD_DRO_SUM_low(k).*RegD_da_SUM_low(k
,i) + gama2_RegD_SUM_low(k,1) .*
(d_RegD_SUM_low(k,1) -
RegD_da_SUM_low(k,i)) <=
S_RegD_SUM_low(k,i);
        norm((gama1_RegD_SUM_low(k,1)-
a1_Risk_SUM_low.*
a_RegD_DRO_SUM_low(k)),inf)
<=Tr_RegD(k,1).*
lambda_RegD_SUM_low(k,1);
        norm((gama2_RegD_SUM_low(k,1)-
a2_RegD_SUM_low(k,1).*
a_RegD_DRO_SUM_low(k)),inf)
<=Tr_RegD(k,1).*
lambda_RegD_SUM_low(k,1);
        0<= gama1_RegD_SUM_low(k,1);
        0<= gama2_RegD_SUM_low(k,1);

end

  end
  cvx_end

load gong.mat;
sound(y);
display("WELL DONE!!")

t_DRO_SUM_low = toc

 %% WINter for low number

tic

clear Cap_Discharge_DRO_WIN_low
clear cost_Charge_DRO_WIN_low
clear cost_Demand_DRO_WIN_low
clear income_Spin_DRO_WIN_low
clear Income_Spin_DRO_WIN_low
clear income_sell_DRO_WIN_low
clear INCOME_sell_DRO_WIN_low
clear income_E_DRO_WIN_low
clear Income_E_DRO_WIN_low
clear income_MilU_DRO_WIN_low
clear income_RegU_DRO_WIN_low
clear Income_RegU_DRO_WIN_low
clear cost_Charge_DRO_WIN_low
clear Cap_Charge_DRO_WIN_low
clear income_MilD_DRO_WIN_low
clear income_RegD_DRO_WIN_low
clear Income_RegD_DRO_WIN_low
clear income_Charging_DRO_WIN_low
clear income_Discharging_DRO_WIN_low
clear cost_OP_DRO_WIN_low
clear Soc_DRO_WIN_low
clear SOC_DRO_WIN_low
clear cost_DRO_WIN_low
clear COST_DRO_WIN_low
clear SOCC_DRO_WIN_low
```

```
clear lambda_Risk_WIN_low
clear S_Spin_WIN_low
clear S_LMP_WIN_low
clear S_RegU_WIN_low
clear S_RegD_WIN_low
clear S_Buy_WIN_low
clear Risk_CVaR_RegU_WIN_low
clear Risk_CVaR_RegD_WIN_low
clear Risk_CVaR_Spin_WIN_low
clear Risk_CVaR_LMP_WIN_low
clear Risk_CVaR_Buy_WIN_low
clear a1_Risk_WIN_low
clear ROO_Risk_WIN_low
clear a2_Risk_WIN_low
clear b1_Risk_WIN_low
clear b2_Risk_WIN_low
clear tou_Spin_WIN_low
clear tou_RegU_WIN_low
clear tou_RegD_WIN_low
clear tou_LMP_WIN_low
clear tou_Buy_WIN_low
clear gama1_Spin_WIN_low
clear gama2_Spin_WIN_low
clear gama1_RegU_WIN_low
clear gama2_RegU_WIN_low
clear gama1_RegD_WIN_low
clear gama2_RegD_WIN_low
clear gama1_LMP_WIN_low
clear gama2_LMP_WIN_low
clear gama1_Buy_WIN_low
clear gama2_Buy_WIN_low
clear a_RegU_DRO_WIN_low
clear a_Spin_DRO_WIN_low
clear a_LMP_DRO_WIN_low
clear a_RegD_DRO_WIN_low
clear a_Buy_DRO_WIN_low
clear a_Ex_ch_DRO_WIN_low
clear a_Ex_dch_DRO_WIN_low
clear Cap_Ex_ch_DRO_WIN_low
clear Cap_Ex_dch_DRO_WIN_low
clear cost_un_dch_DRO_WIN_low
clear cost_un_ch_DRO_WIN_low
clear a_ex_ch_DRO_WIN_low
clear a_ex_dch_DRO_WIN_low
clear Cap_Bat2L_DRO_WIN_low
clear a_Bat2L_DRO_WIN_low
clear a_G2Bat_DRO_WIN_low
clear a_PV2Bat_DRO_WIN_low
clear a_G2L_DRO_WIN_low
clear a_PV2L_DRO_WIN_low
cvx_begin

    variable Cap_G2Bat_DRO_WIN_low(24)
nonnegative
    variable Cap_RegD_DRO_WIN_low(24)
nonnegative
    variable Cap_PV2L_DRO_WIN_low(24)
nonnegative
    variable Cap_G2L_DRO_WIN_low(24)
nonnegative
    variable Cap_Bat2G_DRO_WIN_low(24)
nonnegative
    variable Cap_Bat2L_DRO_WIN_low(24)
nonnegative
    variable Cap_PV2Bat_DRO_WIN_low(24)
nonnegative
    variable Cap_RegU_DRO_WIN_low(24)
nonnegative
    variable Cap_Spin_DRO_WIN_low(24)
nonnegative
    variable Cap_Ex_ch_DRO_WIN_low(24)
nonnegative
    variable Cap_Ex_dch_DRO_WIN_low(24)
nonnegative
    variable M_DRO_WIN_low(24) binary
    variable lambda_Spin_WIN_low(24)
    variable lambda_LMP_WIN_low(24)
    variable lambda_RegU_WIN_low(24)
    variable lambda_RegD_WIN_low(24)
    variable lambda_Buy_WIN_low(24)
    variable
S_Spin_WIN_low(24,N_WIN_low)
    variable
S_RegU_WIN_low(24,N_WIN_low)
    variable
S_RegD_WIN_low(24,N_WIN_low)
    variable S_LMP_WIN_low(24,N_WIN_low)
    variable S_Buy_WIN_low(24,N_WIN_low)
    variable gama1_Spin_WIN_low(24)
    variable gama2_Spin_WIN_low(24)
    variable gama1_RegU_WIN_low(24)
    variable gama2_RegU_WIN_low(24)
    variable gama1_RegD_WIN_low(24)
    variable gama2_RegD_WIN_low(24)
    variable gama1_LMP_WIN_low(24)
    variable gama2_LMP_WIN_low(24)
    variable gama1_Buy_WIN_low(24)
    variable gama2_Buy_WIN_low(24)
    variable tou_Spin_WIN_low(N_WIN_low)
    variable tou_RegU_WIN_low(N_WIN_low)
    variable tou_RegD_WIN_low(N_WIN_low)
    variable tou_LMP_WIN_low(N_WIN_low)
    variable tou_Buy_WIN_low(N_WIN_low)
    %variable Y_DRO_WIN_low(24,24)

  for k = 1:25
      if k<=24
    Cap_Charge_DRO_WIN_low(k,1) =
Cap_G2Bat_DRO_WIN_low(k)+Cap_PV2Bat_DRO_
WIN_low(k)+Cap_RegD_DRO_WIN_low(k);%+Cap
_Ex_ch_DRO_WIN_low(k);
    Cap_Discharge_DRO_WIN_low(k,1) =
Cap_Bat2G_DRO_WIN_low(k)+Cap_Spin_DRO_WI
N_low(k)+Cap_RegU_DRO_WIN_low(k)+Cap_Bat
2L_DRO_WIN_low(k);%+Cap_Ex_dch_DRO_WIN_l
ow(k);

   a_RegU_DRO_WIN_low(k,1)    =
Cap_RegU_DRO_WIN_low(k)/Cap_Max;
   a_RegD_DRO_WIN_low(k,1)    =
Cap_RegD_DRO_WIN_low(k)/Cap_Max;
   a_Spin_DRO_WIN_low(k,1)    =
Cap_Spin_DRO_WIN_low(k)/Cap_Max;
   a_LMP_DRO_WIN_low(k,1)     =
Cap_Bat2G_DRO_WIN_low(k)/Cap_Max;%
   a_Buy_DRO_WIN_low(k,1)     =
Cap_G2Bat_DRO_WIN_low(k)/Cap_Max;
   a_ex_dch_DRO_WIN_low(k,1) =
Cap_Ex_dch_DRO_WIN_low(k)/Cap_Max;
   a_ex_ch_DRO_WIN_low(k,1)   =
Cap_Ex_ch_DRO_WIN_low(k)/Cap_Max;
   a_Bat2L_DRO_WIN_low(k,1)   =
Cap_Bat2L_DRO_WIN_low(k)/Cap_Max;
   a_G2Bat_DRO_WIN_low(k,1)   =
Cap_G2Bat_DRO_WIN_low(k)/Cap_Max;
   a_PV2Bat_DRO_WIN_low(k,1) =
Cap_PV2Bat_DRO_WIN_low(k)/Cap_Max;
   a_G2L_DRO_WIN_low(k)         =
Cap_G2L_DRO_WIN_low(k)/Cap_Max;
   a_PV2L_DRO_WIN_low(k)        =
Cap_PV2L_DRO_WIN_low(k)/Cap_Max;

%     cost_Charge_DRO_WIN_low(k,1) =
(a_G2Bat_DRO_WIN_low(k,1)+
a_RegD_DRO_WIN_low(k,1)).*
Pr_buy_WIN(k);%(Cap_G2Bat_DRO_WIN_low(k)
+Cap_RegD_DRO_WIN_low(k)).*
```

```
Pr_buy_WIN(k) ; % Cost of buyng energy
from Grid for battery
%      cost_Demand_DRO_WIN_low(k,1) =
Pr_buy_WIN(k) .* (a_G2L_DRO_WIN_low(k));
%cost of buying energy from Grid for
Load

      cost_OP_DRO_WIN_low(k,1) =
1*0.0002 .*(a_PV2Bat_DRO_WIN_low(k)+
a_G2Bat_DRO_WIN_low(k) +
a_LMP_DRO_WIN_low(k)+
a_Spin_DRO_WIN_low(k)+
a_RegD_DRO_WIN_low(k)+
a_RegU_DRO_WIN_low(k)) ; % Cost
operation
    % Cost_M_DRO  = c_m * SOC_Max_DA ;
% cost of Maintenance
    cost_un_dch_DRO_WIN_low(k,1) =
Cap_Ex_dch_DRO_WIN_low(k)* 0;
    cost_un_ch_DRO_WIN_low(k,1)   =
Cap_Ex_ch_DRO_WIN_low(k)* 0;

    if k==1
        Soc_DRO_WIN_low(k,1)   = SOC_0 +
Cap_Ex_ch_DRO_WIN_low(k);
    else
        Soc_DRO_WIN_low(k,1)   = Eta_Ch
.*(Cap_PV2Bat_DRO_WIN_low(k-1)+
Cap_G2Bat_DRO_WIN_low(k-
1)+Cap_RegD_DRO_WIN_low(k-1))-
(Cap_Bat2G_DRO_WIN_low(k-
1,1)+Cap_Spin_DRO_WIN_low(k-
1)+Cap_RegU_DRO_WIN_low(k-
1)+Cap_Bat2L_DRO_WIN_low(k-1))./Eta_D;
    end
       SOC_DRO_WIN_low(k,1)   =
sum(Soc_DRO_WIN_low);
  %cost_DRO(k,1) =    (-
income_Discharging_DRO(k)-
income_Charging_DRO(k)+
cost_OP_DRO(k));%cost_Demand_DRO(k)
  % COST_DRO(k,1) = sum(cost_DRO) +
Cost_M_DRO;

    SOCC_DRO_WIN_low(k,1)   =
SOC_DRO_WIN_low(k,1)/BAT_CAP;
   alfa = 0.9; %CVar comfidence level

     a1_Risk_WIN_low = -1;
     R_w = 0.001;

     ROO_RegU_WIN_low(k,1) = 1; %
investor risk aversion
     a2_RegU_WIN_low(k,1) = -1 -
(ROO_RegU_WIN_low(k,1)/alfa);
     b1_RegU_WIN_low(k,1) =
ROO_RegU_WIN_low(k,1);
     b2_RegU_WIN_low(k,1) =
ROO_RegU_WIN_low(k,1) * (1- 1/alfa);

     ROO_Spin_WIN_low(k,1) = 1; %
investor risk aversion
     a2_Spin_WIN_low(k,1) = -1 -
(ROO_Spin_WIN_low(k,1)/alfa);
     b1_Spin_WIN_low(k,1) =
ROO_Spin_WIN_low(k,1);
     b2_Spin_WIN_low(k,1) =
ROO_Spin_WIN_low(k,1)* (1- 1/alfa);

     ROO_LMP_WIN_low(k,1) = 1; %
investor risk aversion
     a2_LMP_WIN_low(k,1) = -1 -
(ROO_LMP_WIN_low(k,1)/alfa);
     b1_LMP_WIN_low(k,1) =
ROO_LMP_WIN_low(k,1);
     b2_LMP_WIN_low(k,1) =
ROO_LMP_WIN_low(k,1) * (1- 1/alfa);

     ROO_RegD_WIN_low(k,1) = 1; %
investor risk aversion
     a2_RegD_WIN_low(k,1) = -1 -
(ROO_RegD_WIN_low(k,1)/alfa);
     b1_RegD_WIN_low(k,1) =
ROO_RegD_WIN_low(k,1);
     b2_RegD_WIN_low(k,1) =
ROO_RegD_WIN_low(k,1) * (1- 1/alfa);

     d_spin_WIN_low(k,1) =
Max_Spin_da_WIN_low(k,1);%max(Max_Spin_d
a_WIN(k,1),Max_Spin_da_WIN_test(k,1));%M
ax_Spin_da_low;%
Er_Spin_da_low_Max_Risk;%Spin_da_low_Max
;%
     d_RegU_WIN_low(k,1) =
Max_RegU_da_WIN_low(k,1);%max(Max_RegU_d
a_WIN(k,1),Max_RegU_da_WIN_test(k,1));
%Max_Reg_U_da_low;%Er_Reg_U_da_low_Max_R
isk;%
     d_LMP_WIN_low(k,1)   =
Max_LMP_da_WIN_low(k,1);%max(Max_LMP_da_
WIN(k,1),Max_LMP_da_WIN_test(k,1));
%Max_LMP_da_low;%Er_LMP_da_low_Max;%
     d_RegD_WIN_low(k,1) =
Max_RegD_da_WIN_low(k,1);%max(Max_RegD_d
a_WIN(k,1),Max_RegD_da_WIN_test(k,1));
%Max_Reg_D_da_SUM_low;

Risk_CVaR_RegU_WIN_low(k,1) =
Tr_RegU(k,1).*((1*lambda_RegU_WIN_low(k,
1).* R_w +
(sum(S_RegU_WIN_low(k,:))./N_WIN_low)));
%r_Reg_U_da_WIN_low_Risk(k,1)
Risk_CVaR_Spin_WIN_low(k,1) =
Tr_RS(k,1).*((1*lambda_Spin_WIN_low(k,1)
.* R_w +
(sum(S_Spin_WIN_low(k,:))./N_WIN_low)));
% r_Spin_da_WIN_low_Risk(k,1)
Risk_CVaR_LMP_WIN_low(k,1)   =
((1*lambda_LMP_WIN_low(k,1)  .* R_w +
(sum(S_LMP_WIN_low(k,:))./N_WIN_low)));
% r_LMP_da_low(k,1)
Risk_CVaR_RegD_WIN_low(k,1) =
Tr_RegD(k,1).*((1*lambda_RegD_WIN_low(k,
1)  .* R_w +
(sum(S_RegD_WIN_low(k,:))./N_WIN_low)));
%

      else
          Soc_DRO_WIN_low(k,1)   = Eta_Ch
.*(Cap_PV2Bat_DRO_WIN_low(k-1)+
Cap_G2Bat_DRO_WIN_low(k-
1)+Cap_RegD_DRO_WIN_low(k-1))-
(Cap_Bat2G_DRO_WIN_low(k-
1,1)+Cap_Spin_DRO_WIN_low(k-
1)+Cap_RegU_DRO_WIN_low(k-
1)+Cap_Bat2L_DRO_WIN_low(k-1))./Eta_D;
          SOC_DRO_WIN_low(k,1)   =
sum(Soc_DRO_WIN_low);
          SOCC_DRO_WIN_low(k,1)   =
SOC_DRO_WIN_low(k,1)/BAT_CAP;
      end
  end

  OBJ_DRO_WIN_low =
+sum(cost_OP_DRO_WIN_low+cost_un_dch_DRO
_WIN_low + cost_un_ch_DRO_WIN_low +
Risk_CVaR_Spin_WIN_low +
```

```
Risk_CVaR_RegU_WIN_low +
Risk_CVaR_RegD_WIN_low +
Risk_CVaR_LMP_WIN_low);% +
Cost_M1+sum(cost_OP_DRO_WIN_low)
cost_Demand_DRO_WIN_low +
cost_Charge_DRO_WIN_low +

  minimize(OBJ_DRO_WIN_low)

   subject to
  SOC_DRO_WIN_low(1) == SOC_0 ;% for
initial value of soc
  SOC_DRO_WIN_low(25) >=
SOC_DRO_WIN_low(1) ;
  SOC_Min <= SOC_DRO_WIN_low(25)   <=
SOC_Max ;
  for k = 1:24

    SOC_Min <= SOC_DRO_WIN_low(k)   <=
SOC_Max ;
   % 0 <=
Cap_G2Bat_DRO_WIN_low(k)+Cap_RegD_DRO_WI
N_low(k) +
Cap_PV2Bat_DRO_WIN_low(k)+(Cap_Spin_DRO_
WIN_low(k)+Cap_RegU_DRO_WIN_low(k)+Cap_B
at2G_DRO_WIN_low(k)+Cap_Bat2L_DRO_WIN_lo
w(k))<= Cap_Max;
    Cap_PV2L_DRO_WIN_low(k) +
Cap_G2L_DRO_WIN_low(k)+Cap_Bat2L_DRO_WIN
_low(k)  == Cap_L_win(k);
    Cap_PV2Bat_DRO_WIN_low(k) +
Cap_PV2L_DRO_WIN_low(k)  <=
Cap_PV_win(k);

    Cap_Charge_DRO_WIN_low(k)<=
Cap_Max.*(1-M_DRO_WIN_low(k));
    Cap_Discharge_DRO_WIN_low(k)<=
Cap_Max.*(M_DRO_WIN_low(k));

   % Y_DRO_WIN_low(k,k)-
M_DRO_WIN_low(k,1)  == 0 ;
   if Tr_RS(k)==0
       Cap_Spin_DRO_WIN_low(k)==0;
   end

   if Tr_RegU(k)==0
       Cap_RegU_DRO_WIN_low(k)==0;
   end

   if Tr_RegD(k)==0
       Cap_RegD_DRO_WIN_low(k)==0;
   end

for i=1:N_WIN_low

b1_Spin_WIN_low(k,1)*tou_Spin_WIN_low +
a1_Risk_WIN_low .*
a_Spin_DRO_WIN_low(k).*Spin_da_WIN_low(k
,i) + gama1_Spin_WIN_low(k,1)  .*
(d_spin_WIN_low(k,1)  -
Spin_da_WIN_low(k,i))  <=
S_Spin_WIN_low(k,i);%Er_Spin_da_WIN_low
%d_WIN_low_spin %Er_Spin_da_WIN_low_Risk
%Norm_Spin_da_WIN_low

b2_Spin_WIN_low(k,1)*tou_Spin_WIN_low +
a2_Spin_WIN_low(k,1).*
a_Spin_DRO_WIN_low(k).*Spin_da_WIN_low(k
,i) + gama2_Spin_WIN_low(k,1)  .*
(d_spin_WIN_low(k,1)  -
Spin_da_WIN_low(k,i))  <=
S_Spin_WIN_low(k,i);
        norm((gama1_Spin_WIN_low(k,1)-
a1_Risk_WIN_low.*
Cap_Spin_DRO_WIN_low(k)),inf)  <=
Tr_RS(k,1).*lambda_Spin_WIN_low(k,1);
        norm((gama2_Spin_WIN_low(k,1)-
a2_Spin_WIN_low(k,1).*
Cap_Spin_DRO_WIN_low(k)),inf)
<=Tr_RS(k,1).* lambda_Spin_WIN_low(k,1);
        0<= gama1_Spin_WIN_low(k,1);
        0<= gama2_Spin_WIN_low(k,1);


b1_RegU_WIN_low(k,1)*tou_RegU_WIN_low +
a1_Risk_WIN_low
.*a_RegU_DRO_WIN_low(k).*RegU_da_WIN_low
(k,i) + gama1_RegU_WIN_low(k,1)  .*
(d_RegU_WIN_low(k,1)  -
RegU_da_WIN_low(k,i))  <=
S_RegU_WIN_low(k,i);%Er_Reg_U_da_WIN_low
%  %Er_Reg_U_da_WIN_low_Risk
%Norm_Reg_U_da_WIN_low %a_RegU_DRO

b2_RegU_WIN_low(k,1)*tou_RegU_WIN_low +
a2_RegU_WIN_low(k,1)  .*
a_RegU_DRO_WIN_low(k).*RegU_da_WIN_low(k
,i) + gama2_RegU_WIN_low(k,1)  .*
(d_RegU_WIN_low(k,1)  -
RegU_da_WIN_low(k,i))  <=
S_RegU_WIN_low(k,i);
        norm((gama1_RegU_WIN_low(k,1)-
a1_Risk_WIN_low.*
a_RegU_DRO_WIN_low(k)),inf)
<=Tr_RegU(k,1).*
lambda_RegU_WIN_low(k,1);
        norm((gama2_RegU_WIN_low(k,1)-
a2_RegU_WIN_low(k,1).*
a_RegU_DRO_WIN_low(k)),inf)
<=Tr_RegU(k,1).*
lambda_RegU_WIN_low(k,1);
        0<= gama1_RegU_WIN_low(k,1);
        0<= gama2_RegU_WIN_low(k,1);


b1_LMP_WIN_low(k,1)*tou_LMP_WIN_low +
a1_Risk_WIN_low.*(a_LMP_DRO_WIN_low(k)+a
_RegU_DRO_WIN_low(k)+a_Spin_DRO_WIN_low(
k)-a_G2Bat_DRO_WIN_low(k,1)-
a_G2L_DRO_WIN_low(k))
.*LMP_da_WIN_low(k,i)  +
gama1_LMP_WIN_low(k,1)  .*
(d_LMP_WIN_low(k,1)  -
LMP_da_WIN_low(k,i))  <=
S_LMP_WIN_low(k,i);%Er_LMP_da_WIN_low
%Er_LMP_da_WIN_low  %d_WIN_low_LMP  %
%Norm_LMP_da_WIN_low

b2_LMP_WIN_low(k,1)*tou_LMP_WIN_low +
a2_LMP_WIN_low(k,1).*(a_LMP_DRO_WIN_low(
k)+a_RegU_DRO_WIN_low(k)+a_Spin_DRO_WIN_
low(k)-a_G2Bat_DRO_WIN_low(k,1)-
a_G2L_DRO_WIN_low(k))
.*LMP_da_WIN_low(k,i)  +
gama2_LMP_WIN_low(k,1)  .*
(d_LMP_WIN_low(k,1)  -
LMP_da_WIN_low(k,i))  <=
S_LMP_WIN_low(k,i);
        norm((gama1_LMP_WIN_low(k,1)-
a1_Risk_WIN_low.*(a_LMP_DRO_WIN_low(k)+a
_RegU_DRO_WIN_low(k)+a_Spin_DRO_WIN_low(
k)-a_G2Bat_DRO_WIN_low(k,1)-
a_G2L_DRO_WIN_low(k))),inf)  <=
lambda_LMP_WIN_low(k,1);
        norm((gama2_LMP_WIN_low(k,1)-
a2_LMP_WIN_low(k,1).*(a_LMP_DRO_WIN_low(
k)+a_RegU_DRO_WIN_low(k)+a_Spin_DRO_WIN_
low(k)-a_G2Bat_DRO_WIN_low(k,1)-
```

```
a_G2L_DRO_WIN_low(k))),inf) <=
lambda_LMP_WIN_low(k,1);
        0<= gama1_LMP_WIN_low(k,1);
        0<= gama2_LMP_WIN_low(k,1);


b1_RegD_WIN_low(k,1)*tou_RegD_WIN_low +
a1_Risk_WIN_low .*
a_RegD_DRO_WIN_low(k).*RegD_da_WIN_low(k
,i) + gama1_RegD_WIN_low(k,1) .*
(d_RegD_WIN_low(k,1) -
RegD_da_WIN_low(k,i)) <=
S_RegD_WIN_low(k,i);
%Norm_Reg_D_da_WIN_low
%Er_Reg_D_da_WIN_low
%Norm_Reg_D_da_WIN_low

b2_RegD_WIN_low(k,1)*tou_RegD_WIN_low +
a2_RegD_WIN_low(k,1) .*
a_RegD_DRO_WIN_low(k).*RegD_da_WIN_low(k
,i) + gama2_RegD_WIN_low(k,1) .*
(d_RegD_WIN_low(k,1) -
RegD_da_WIN_low(k,i)) <=
S_RegD_WIN_low(k,i);
        norm((gama1_RegD_WIN_low(k,1)-
a1_Risk_WIN_low.*
a_RegD_DRO_WIN_low(k)),inf)
<=Tr_RegD(k,1).*
lambda_RegD_WIN_low(k,1);
        norm((gama2_RegD_WIN_low(k,1)-
a2_RegD_WIN_low(k,1).*
a_RegD_DRO_WIN_low(k)),inf)
<=Tr_RegD(k,1).*
lambda_RegD_WIN_low(k,1);
        0<= gama1_RegD_WIN_low(k,1);
        0<= gama2_RegD_WIN_low(k,1);


      end
  end

  cvx_end

load gong.mat;
sound(y);
display("WELL DONE!!")

t_DRO_WIN_low = toc

     %% Deterministic Summer
tic
clear a_G2L_Dit_SUM
clear Cap_Discharge_Dit_SUM
clear cost_Charge_Dit_SUM
clear cost_Demand_Dit_SUM
clear income_Spin_Dit_SUM
clear Income_Spin_Dit_SUM
clear income_sell_Dit_SUM
clear INCOME_sell_Dit_SUM
clear income_E_Dit_SUM
clear Income_E_Dit_SUM
clear income_MilU_Dit_SUM
clear income_RegU_Dit_SUM
clear Income_RegU_Dit_SUM
clear cost_Charge_Dit_SUM
clear Cap_Charge_Dit_SUM
clear income_MilD_Dit_SUM
clear income_RegD_Dit_SUM
clear Income_RegD_Dit_SUM
clear income_Charging_Dit_SUM
clear income_Discharging_Dit_SUM
clear cost_OP_Dit_SUM
clear Soc_Dit_SUM
clear SOC_Dit_SUM
clear cost_Dit_SUM
clear COST_Dit_SUM
clear SOCC_Dit_SUM
clear a_RegU_Dit_SUM
clear a_Spin_Dit_SUM
clear a_LMP_Dit_SUM
clear a_RegD_Dit_SUM
clear a_Buy_Dit_SUM
clear Cap_EX_dch_Dit_SUM
clear Cap_EX_ch_Dit_SUM
clear a_Ex_ch_Dit_SUM
clear a_Ex_dch_Dit_SUM
clear a_G2Bat_Dit_SUM
clear a_PV2Bat_Dit_SUM
clear cost_un_dch_Dit_SUM
clear cost_un_ch_Dit_SUM
clear a_Bat2L_Dit_SUM
clear M_Dit_SUM
clear Y_Dit_SUM
cvx_begin
    variable Cap_Bat2L_Dit_SUM(24)
nonnegative
    variable Cap_G2Bat_Dit_SUM(24)
nonnegative
    variable Cap_RegD_Dit_SUM(24)
nonnegative
    variable Cap_PV2L_Dit_SUM(24)
nonnegative
    variable Cap_G2L_Dit_SUM(24)
nonnegative
    variable Cap_Bat2G_Dit_SUM(24)
nonnegative
    variable Cap_PV2Bat_Dit_SUM(24)
nonnegative
    variable Cap_RegU_Dit_SUM(24)
nonnegative
    variable Cap_Spin_Dit_SUM(24)
nonnegative
    variable M_Dit_SUM(24) binary
    variable Cap_Ex_ch_Dit_SUM(24)
nonnegative
    variable Cap_Ex_dch_Dit_SUM(24)
nonnegative
  for k = 1:25
      if k < 25

    Cap_Charge_Dit_SUM(k,1) =
Cap_G2Bat_Dit_SUM(k)+Cap_PV2Bat_Dit_SUM(
k)+Cap_RegD_Dit_SUM(k);%+Cap_Ex_ch_Dit_S
UM(k) ;
    Cap_Discharge_Dit_SUM(k,1) =
Cap_Bat2G_Dit_SUM(k)+Cap_Spin_Dit_SUM(k)
+Cap_RegU_Dit_SUM(k)+Cap_Bat2L_Dit_SUM(k
);%+Cap_Ex_dch_Dit_SUM(k);

    cost_Charge_Dit_SUM(k,1) =
(Cap_G2Bat_Dit_SUM(k)).*
Mean_LMP_da_SUM_low(k) ;
%+Cap_RegD_Dit_SUM(k)  Pr_buy_SUM Cost
of buyng energy from Grid for battery
    cost_Demand_Dit_SUM(k,1) =
Mean_LMP_da_SUM_low(k) .*
(Cap_G2L_Dit_SUM(k));   %Pr_buy_SUM cost
of buying energy from Grid for Load

   income_Spin_Dit_SUM(k,1) = Tr_RS(k)
.* (Mean_Spin_da_SUM_low(k).*
Cap_Spin_Dit_SUM(k));%Mean_Spin_da_low
   Income_Spin_Dit_SUM(k,1) =
sum(income_Spin_Dit_SUM(k));

   income_E_Dit_SUM(k,1) =
(Mean_LMP_da_SUM_low(k).*(Cap_Bat2G_Dit_
SUM(k)+Cap_RegU_Dit_SUM(k)+Cap_Spin_Dit_
SUM(k))); %high
```

```
   Income_E_Dit_SUM(k,1) =
sum(income_E_Dit_SUM);

   income_RegU_Dit_SUM(k,1) =
Tr_RegU(k).*(Mean_RegU_da_SUM_low(k) .*
(Cap_RegU_Dit_SUM(k))) ;%
Mean_Reg_U_da_low
   Income_RegU_Dit_SUM(k,1) =
sum(income_RegU_Dit_SUM);

   income_RegD_Dit_SUM(k,1) =
Tr_RegD(k).*(Mean_RegD_da_SUM_low(k) .*
Cap_RegD_Dit_SUM(k));  %
Mean_Reg_D_da_low
   Income_RegD_Dit_SUM(k,1) =
sum(income_RegD_Dit_SUM);

   income_Charging_Dit_SUM(k,1) =
income_RegD_Dit_SUM(k) -
cost_Charge_Dit_SUM(k);
   income_Discharging_Dit_SUM(k,1)=
income_Spin_Dit_SUM(k)+income_E_Dit_SUM(
k)+income_RegU_Dit_SUM(k);%+income_sell_
Dit_SUM(k);

   cost_OP_Dit_SUM(k,1) =  0.014
.*(Cap_PV2Bat_Dit_SUM(k)+
Cap_G2Bat_Dit_SUM(k) +
Cap_Bat2G_Dit_SUM(k)+Tr_RS(k) .*
Cap_Spin_Dit_SUM(k)+Tr_RegD(k).*Cap_RegD
_Dit_SUM(k)+Cap_RegU_Dit_SUM(k)+Cap_Bat2
L_Dit_SUM(k)) ; % Cost operation

    cost_un_dch_Dit_SUM(k,1)  =
Cap_Ex_dch_Dit_SUM(k)* 0.0;
    cost_un_ch_Dit_SUM(k,1)  =
Cap_Ex_ch_Dit_SUM(k)* 0.0;

  if k==1
   Soc_Dit_SUM(k,1)  =SOC_0 +
cost_un_ch_Dit_SUM(k);
  else
   Soc_Dit_SUM(k,1)  = Eta_Ch
.*(Cap_PV2Bat_Dit_SUM(k-1)+
Cap_G2Bat_Dit_SUM(k-1)+
Cap_RegD_Dit_SUM(k-1))-
(Cap_Bat2G_Dit_SUM(k-1,1)+
Cap_Spin_Dit_SUM(k-1)+
Cap_RegU_Dit_SUM(k-
1)+Cap_Bat2L_Dit_SUM(k-1))./Eta_D;%
  end
    SOC_Dit_SUM(k,1)     =
sum(Soc_Dit_SUM);
   cost_Dit_SUM(k,1)     =
(cost_un_ch_Dit_SUM(k)+cost_un_dch_Dit_S
UM(k)+cost_Demand_Dit_SUM(k)-
income_Discharging_Dit_SUM(k)-
income_Charging_Dit_SUM(k)+
cost_OP_Dit_SUM(k));%);%cost_Demand_Dit_
SUM(k)
   SOCC_Dit_SUM(k,1)     =
SOC_Dit_SUM(k,1)/BAT_CAP;
   a_RegU_Dit_SUM(k,1)   =
Cap_RegU_Dit_SUM(k)/Cap_Max;
   a_RegD_Dit_SUM(k,1)   =
Cap_RegD_Dit_SUM(k)/Cap_Max;
   a_Spin_Dit_SUM(k,1)   =
Cap_Spin_Dit_SUM(k)/Cap_Max;
   a_LMP_Dit_SUM(k,1)    =
(Cap_Bat2G_Dit_SUM(k))/Cap_Max;
   a_Ex_ch_Dit_SUM(k,1) =
Cap_Ex_ch_Dit_SUM(k)/Cap_Max;
   a_Ex_dch_Dit_SUM(k,1) =
Cap_Ex_dch_Dit_SUM(k)/Cap_Max;
```

```
   a_G2Bat_Dit_SUM(k,1)  =
Cap_G2Bat_Dit_SUM(k)/Cap_Max;
   a_PV2Bat_Dit_SUM(k,1) =
Cap_PV2Bat_Dit_SUM(k)/Cap_Max;
   a_Bat2L_Dit_SUM(k,1)  =
Cap_Bat2L_Dit_SUM(k)/Cap_Max;
   a_G2L_Dit_SUM(k,1)   =
Cap_G2L_Dit_SUM(k)/Cap_Max;
   a_PV2L_Dit_WIN(k,1) =
Cap_PV2L_Dit_WIN(k)/Cap_Max;
      else
           Soc_Dit_SUM(k,1)   = Eta_Ch
.*(Cap_PV2Bat_Dit_SUM(k-1)+
Cap_G2Bat_Dit_SUM(k-1)+
Cap_RegD_Dit_SUM(k-1))-
(Cap_Bat2G_Dit_SUM(k-1,1)+
Cap_Spin_Dit_SUM(k-1)+
Cap_RegU_Dit_SUM(k-
1)+Cap_Bat2L_Dit_SUM(k-1))./Eta_D;%
           SOC_Dit_SUM(k,1)   =
sum(Soc_Dit_SUM);
           SOCC_Dit_SUM(k,1)   =
SOC_Dit_SUM(k,1)/BAT_CAP;
      end
      end

  OBJ_Dit_SUM =  sum(cost_Dit_SUM);

minimize(OBJ_Dit_SUM)

   subject to
   SOC_Dit_SUM(25) >= SOC_Dit_SUM(1) ;
   SOC_Dit_SUM(1) == SOC_0 ;
   SOC_Min <= SOC_Dit_SUM(25)  <=
SOC_Max ;
   for k = 1:24
    SOC_Min <= SOC_Dit_SUM(k)  <=
SOC_Max ;
    Cap_PV2L_Dit_SUM(k) +
Cap_G2L_Dit_SUM(k)+Cap_Bat2L_Dit_SUM(k)
== Cap_L_sum(k);
    Cap_PV2Bat_Dit_SUM(k) +
Cap_PV2L_Dit_SUM(k) <= Cap_PV_sum(k);

    Cap_Charge_Dit_SUM(k) - Cap_Max *(1-
M_Dit_SUM(k))<= 0;
    Cap_Discharge_Dit_SUM(k) - Cap_Max
*(M_Dit_SUM(k))<= 0;

    if Tr_RS(k)==0
       Cap_Spin_Dit_SUM(k)==0;
    end

    if Tr_RegU(k)==0
       Cap_RegU_Dit_SUM(k)==0;
    end

   if Tr_RegD(k)==0
       Cap_RegD_Dit_SUM(k)==0;
   end
   end
  cvx_end

load gong.mat;
sound(y);
display("WELL DONE!!")

t_Dit_SUM = toc

 %% Deterministic WINter
tic
clear a_PV2L_Dit_WIN
clear a_G2L_Dit_WIN
clear Cap_Discharge_Dit_WIN
```

```
clear cost_Charge_Dit_WIN
clear cost_Demand_Dit_WIN
clear income_Spin_Dit_WIN
clear Income_Spin_Dit_WIN
clear income_sell_Dit_WIN
clear INCOME_sell_Dit_WIN
clear income_E_Dit_WIN
clear Income_E_Dit_WIN
clear income_MilU_Dit_WIN
clear income_RegU_Dit_WIN
clear Income_RegU_Dit_WIN
clear cost_Charge_Dit_WIN
clear Cap_Charge_Dit_WIN
clear income_MilD_Dit_WIN
clear income_RegD_Dit_WIN
clear Income_RegD_Dit_WIN
clear income_Charging_Dit_WIN
clear income_Discharging_Dit_WIN
clear cost_OP_Dit_WIN
clear Soc_Dit_WIN
clear SOC_Dit_WIN
clear cost_Dit_WIN
clear COST_Dit_WIN
clear SOCC_Dit_WIN
clear a_RegU_Dit_WIN
clear a_Spin_Dit_WIN
clear a_LMP_Dit_WIN
clear a_RegD_Dit_WIN
clear a_Buy_Dit_WIN
clear Cap_EX_dch_Dit_WIN
clear Cap_EX_ch_Dit_WIN
clear a_G2Bat_Dit_WIN
clear a_PV2Bat_Dit_WIN
clear cost_un_dch_Dit_WIN
clear cost_un_ch_Dit_WIN
clear Cap_Ex_ch_Dit_WIN
clear Cap_Ex_dch_Dit_WIN
clear a_Bat2L_Dit_WIN
clear a_Ex_ch_Dit_WIN
clear a_Ex_dch_Dit_WIN
cvx_begin
    variable Cap_Bat2L_Dit_WIN(24)
nonnegative
    variable Cap_G2Bat_Dit_WIN(24)
nonnegative
    variable Cap_RegD_Dit_WIN(24)
nonnegative
    variable Cap_PV2L_Dit_WIN(24)
nonnegative
    variable Cap_G2L_Dit_WIN(24)
nonnegative
    variable Cap_Bat2G_Dit_WIN(24)
nonnegative
    variable Cap_PV2Bat_Dit_WIN(24)
nonnegative
    variable Cap_RegU_Dit_WIN(24)
nonnegative
    variable Cap_Spin_Dit_WIN(24)
nonnegative
    variable M_Dit_WIN(24) binary
    variable Cap_Ex_ch_Dit_WIN(24)
nonnegative
    variable Cap_Ex_dch_Dit_WIN(24)
nonnegative
  for k = 1:25
      if k<25
    Cap_Charge_Dit_WIN(k,1)
=Cap_G2Bat_Dit_WIN(k)+Cap_PV2Bat_Dit_WIN
(k)+Cap_RegD_Dit_WIN(k);%+Cap_Ex_ch_Dit_
WIN(k) ;
    Cap_Discharge_Dit_WIN(k,1) =
Cap_Bat2G_Dit_WIN(k)+Cap_Spin_Dit_WIN(k)
+Cap_RegU_Dit_WIN(k)+Cap_Bat2L_Dit_WIN(k
);%+Cap_Ex_dch_Dit_WIN(k);

    cost_Charge_Dit_WIN(k,1) =
(Cap_G2Bat_Dit_WIN(k)).*
Mean_LMP_da_WIN_low(k) ;
%+Cap_RegD_Dit_WIN(k)  Pr_buy_WIN Cost
of buyng energy from Grid for battery
    cost_Demand_Dit_WIN(k,1) =
Mean_LMP_da_WIN_low(k) .*
(Cap_G2L_Dit_WIN(k));   %Pr_buy_WIN cost
of buying energy from Grid for Load

   income_Spin_Dit_WIN(k,1) = Tr_RS(k)
.* (Mean_Spin_da_WIN_low(k).*
Cap_Spin_Dit_WIN(k));%Mean_Spin_da_low
   Income_Spin_Dit_WIN(k,1) =
sum(income_Spin_Dit_WIN(k));

   income_E_Dit_WIN(k,1) = (
Mean_LMP_da_WIN_low(k).*(Cap_Bat2G_Dit_W
IN(k)+Cap_RegU_Dit_WIN(k)+Cap_Spin_Dit_W
IN(k))); %high
   Income_E_Dit_WIN(k,1) =
sum(income_E_Dit_WIN);

   income_RegU_Dit_WIN(k,1) =
Tr_RegU(k).*(Mean_RegU_da_WIN_low(k) .*
(Cap_RegU_Dit_WIN(k))) ;%
Mean_Reg_U_da_low
   Income_RegU_Dit_WIN(k,1) =
sum(income_RegU_Dit_WIN);

   income_RegD_Dit_WIN(k,1) =
Tr_RegD(k).*(Mean_RegD_da_WIN_low(k) .*
Cap_RegD_Dit_WIN(k));  %
Mean_Reg_D_da_low
   Income_RegD_Dit_WIN(k,1) =
sum(income_RegD_Dit_WIN);

   income_Charging_Dit_WIN(k,1)=
income_RegD_Dit_WIN(k) -
cost_Charge_Dit_WIN(k);
   income_Discharging_Dit_WIN(k,1)=
income_Spin_Dit_WIN(k)+income_E_Dit_WIN(
k)+income_RegU_Dit_WIN(k);%+income_sell_
Dit_WIN(k);

    cost_OP_Dit_WIN(k,1) =  0.008
.*(Cap_PV2Bat_Dit_WIN(k)+
Cap_G2Bat_Dit_WIN(k) +
Cap_Bat2G_Dit_WIN(k)+Tr_RS(k) .*
Cap_Spin_Dit_WIN(k)+Tr_RegD(k).*Cap_RegD
_Dit_WIN(k)+Cap_RegU_Dit_WIN(k)+Cap_Bat2
L_Dit_WIN(k)) ; % Cost operation

    cost_un_dch_Dit_WIN(k,1)  =
Cap_Ex_dch_Dit_WIN(k)* 0.00 ;
    cost_un_ch_Dit_WIN(k,1)  =
Cap_Ex_ch_Dit_WIN(k)* 0.00 ;

  if k==1
   Soc_Dit_WIN(k,1)  =SOC_0 +
cost_un_ch_Dit_WIN(k);
  else
   Soc_Dit_WIN(k,1)  = Eta_Ch
.*(Cap_PV2Bat_Dit_WIN(k-1)+
Cap_G2Bat_Dit_WIN(k-1)+
Cap_RegD_Dit_WIN(k-1))-
(Cap_Bat2G_Dit_WIN(k-1,1)+
Cap_Spin_Dit_WIN(k-1)+
Cap_RegU_Dit_WIN(k-
1)+Cap_Bat2L_Dit_WIN(k-1))./Eta_D;%
   end
   SOC_Dit_WIN(k,1)  = sum(Soc_Dit_WIN);
```

```
   cost_Dit_WIN(k,1) =
(cost_un_ch_Dit_WIN(k)+cost_un_dch_Dit_W
IN(k)+cost_Demand_Dit_WIN(k)+cost_OP_Dit
_WIN(k)-income_Discharging_Dit_WIN(k)-
income_Charging_Dit_WIN(k)+
cost_OP_Dit_WIN(k));%;%cost_Demand_Dit_W
IN(k)

   SOCC_Dit_WIN(k,1)  =
SOC_Dit_WIN(k,1)/BAT_CAP;
   a_RegU_Dit_WIN(k,1) =
Cap_RegU_Dit_WIN(k)/Cap_Max;
   a_RegD_Dit_WIN(k,1) =
Cap_RegD_Dit_WIN(k)/Cap_Max;
   a_Spin_Dit_WIN(k,1) =
Cap_Spin_Dit_WIN(k)/Cap_Max;
   a_LMP_Dit_WIN(k,1)  =
(Cap_Bat2G_Dit_WIN(k))/Cap_Max;
   a_Ex_ch_Dit_WIN(k,1) =
Cap_Ex_ch_Dit_WIN(k)/Cap_Max;
   a_Ex_dch_Dit_WIN(k,1) =
Cap_Ex_dch_Dit_WIN(k)/Cap_Max;
   a_G2Bat_Dit_WIN(k,1) =
Cap_G2Bat_Dit_WIN(k)/Cap_Max;
   a_PV2Bat_Dit_WIN(k,1) =
Cap_PV2Bat_Dit_WIN(k)/Cap_Max;
   a_Bat2L_Dit_WIN(k,1) =
Cap_Bat2L_Dit_WIN(k)/Cap_Max;
   a_G2L_Dit_WIN(k,1) =
Cap_G2L_Dit_WIN(k)/Cap_Max;
   a_PV2L_Dit_WIN(k,1) =
Cap_PV2L_Dit_WIN(k)/Cap_Max;
      else
           Soc_Dit_WIN(k,1)  = Eta_Ch
.*(Cap_PV2Bat_Dit_WIN(k-1)+
Cap_G2Bat_Dit_WIN(k-1)+
Cap_RegD_Dit_WIN(k-1))-
(Cap_Bat2G_Dit_WIN(k-1,1)+
Cap_Spin_Dit_WIN(k-1)+
Cap_RegU_Dit_WIN(k-
1)+Cap_Bat2L_Dit_WIN(k-1))./Eta_D;
           SOC_Dit_WIN(k,1)  =
sum(Soc_Dit_WIN);
           SOCC_Dit_WIN(k,1)  =
SOC_Dit_WIN(k,1)/BAT_CAP;
      end

      end

  OBJ_Dit_WIN =  sum(cost_Dit_WIN);

minimize(OBJ_Dit_WIN)

   subject to
   SOC_Dit_WIN(25) >=  SOC_Dit_WIN(1) ;
   SOC_Dit_WIN(1) == SOC_0 ;
      SOC_Min <= SOC_Dit_WIN(25)  <=
SOC_Max ;

   for k = 1:24
   SOC_Min <= SOC_Dit_WIN(k)  <= SOC_Max
;
   0 <=
Cap_G2Bat_Dit_WIN(k)+Cap_RegD_Dit_WIN(k)
+
Cap_PV2Bat_Dit_WIN(k)+Cap_Ex_dch_Dit_WIN
(k) <= Cap_Max;%+Cap_EX_ch_Dit_WIN(k)
   0 <=
Cap_Spin_Dit_WIN(k)+Cap_RegU_Dit_WIN(k)+
Cap_Bat2G_Dit_WIN(k) +
Cap_Bat2L_Dit_WIN(k)+Cap_Ex_ch_Dit_WIN(k
)<= Cap_Max; %
```

```
   Cap_PV2L_Dit_WIN(k) +
Cap_G2L_Dit_WIN(k)+Cap_Bat2L_Dit_WIN(k)
== Cap_L_win(k);%
   Cap_PV2Bat_Dit_WIN(k) +
Cap_PV2L_Dit_WIN(k) <= Cap_PV_win(k);

    Cap_Charge_Dit_WIN(k)<=Cap_Max.*(1-
M_Dit_WIN(k));

Cap_Discharge_Dit_WIN(k)<=Cap_Max.*(M_Di
t_WIN(k));
   if Tr_RS(k)==0
       Cap_Spin_Dit_WIN(k)==0;
   end
   if Tr_RegU(k)==0
       Cap_RegU_Dit_WIN(k)==0;
   end

   if Tr_RegD(k)==0
       Cap_RegD_Dit_WIN(k)==0;
   end

  end
  cvx_end

load gong.mat;
sound(y);
display("WELL DONE!!")

t_Dit_WIN = toc

%% Robust for Summer

tic
clear a_PV2L_RO_SUM
clear a_G2L_RO_SUM
clear Cap_Discharge_RO_SUM
clear cost_Charge_RO_SUM
clear cost_Demand_RO_SUM
clear cost_OP_RO_SUM
clear income_Spin_RO_SUM
clear Income_Spin_RO_SUM
clear income_sell_RO_SUM
clear INCOME_sell_RO_SUM
clear income_E_RO_SUM
clear Income_E_RO_SUM
clear income_MilU_RO_SUM
clear income_RegU_RO_SUM
clear Income_RegU_RO_SUM
clear cost_Charge_RO_SUM
clear Cap_Charge_RO_SUM
clear income_MilD_RO_SUM
clear income_RegD_RO_SUM
clear Income_RegD_RO_SUM
clear income_Charging_RO_SUM
clear income_Discharging_RO_SUM
clear cost_OP_RO_SUM
clear Soc_RO_SUM
clear SOC_RO_SUM
clear cost_RO_SUM
clear COST_RO_SUM
clear SOCC_RO_SUM
clear a_RegU_RO_SUM
clear a_Spin_RO_SUM
clear a_LMP_RO_SUM
clear a_RegD_RO_SUM
clear a_Buy_RO_SUM
clear Cap_Bat2L_RO_SUM
clear a_Bat2L_RO_SUM
clear a_G2Bat_RO_SUM
clear a_PV2Bat_RO_SUM
clear cost_un_dch_RO_SUM
clear cost_un_ch_RO_SUM
clear a_ex_dch_RO_SUM
```

```
clear a_ex_ch_RO_SUM
cvx_begin

    variable Cap_Bat2L_RO_SUM(24)
nonnegative
    variable Cap_G2Bat_RO_SUM(24)
nonnegative
    variable Cap_RegD_RO_SUM(24)
nonnegative
    variable Cap_PV2L_RO_SUM(24)
nonnegative
    variable Cap_G2L_RO_SUM(24)
nonnegative
    variable Cap_Bat2G_RO_SUM(24)
nonnegative
    % variable Cap_PV2G_RO_SUM(24)
nonnegative
    variable Cap_PV2Bat_RO_SUM(24)
nonnegative
    variable Cap_RegU_RO_SUM(24)
nonnegative
    variable Cap_Spin_RO_SUM(24)
nonnegative
    variable M_RO_SUM(24) binary
    variable Cap_ex_ch_RO_SUM(24)
nonnegative
    variable Cap_ex_dch_RO_SUM(24)
nonnegative
  for k = 1:25
      if k<25
    Cap_Charge_RO_SUM(k,1) =
Cap_G2Bat_RO_SUM(k)+Cap_PV2Bat_RO_SUM(k)
+Cap_RegD_RO_SUM(k);%+Cap_ex_ch_RO_SUM(k
);
    Cap_Discharge_RO_SUM(k,1) =
Cap_Bat2G_RO_SUM(k)+Cap_Spin_RO_SUM(k)+C
ap_RegU_RO_SUM(k)+Cap_Bat2L_RO_SUM(k);%+
Cap_ex_dch_RO_SUM(k);

    cost_Charge_RO_SUM(k,1) =
(Cap_G2Bat_RO_SUM(k)).*
Min_LMP_da_SUM_low(k) ;
%+Cap_RegD_RO_SUM(k)  Pr_buy_SUM Cost of
buyng energy fRO_SUMm Grid for battery
    cost_Demand_RO_SUM(k,1) =
Min_LMP_da_SUM_low(k) .*
(Cap_G2L_RO_SUM(k));    %Pr_buy_SUM cost
of buying energy fRO_SUMm Grid for Load

   income_Spin_RO_SUM(k,1) = Tr_RS(k) .*
(Min_Spin_da_SUM_low(k).*
Cap_Spin_RO_SUM(k));% -
abs(min(Cap_Max,Cap_RS_DA_Max(k))-
Cap_RES(k)).*Pen_RES_DA);
   Income_Spin_RO_SUM(k,1) =
sum(income_Spin_RO_SUM(k));

   income_E_RO_SUM(k,1) =
Min_LMP_da_SUM_low(k).*(Cap_Bat2G_RO_SUM
(k)+Cap_RegU_RO_SUM(k)+Cap_Spin_RO_SUM(k
)); %Energy income for day ahead and
realtime  +Cap_RegU1(k)+Cap_Spin(k)
   Income_E_RO_SUM(k,1) =
sum(income_E_RO_SUM);

   income_RegU_RO_SUM(k,1) =
Tr_RegU(k).*( Min_RegU_da_SUM_low(k) .*
(Cap_RegU_RO_SUM(k))) ;% Income of
Regulation up including up Mileage
   Income_RegU_RO_SUM(k,1) =
sum(income_RegU_RO_SUM);% +
income_MilU1);

   income_RegD_RO_SUM(k,1) =
Tr_RegD(k).*(Min_RegD_da_SUM_low(k) .*
Cap_RegD_RO_SUM(k));  % Income of
Regulation up including up Mileage
   Income_RegD_RO_SUM(k,1) =
sum(income_RegD_RO_SUM);% +
income_MilD_Dit);

   income_Charging_RO_SUM(k,1)=
income_RegD_RO_SUM(k)-
cost_Charge_RO_SUM(k);
   income_Discharging_RO_SUM(k,1)=
income_Spin_RO_SUM(k)+income_E_RO_SUM(k)
+income_RegU_RO_SUM(k);%+income_sell_RO_
SUM(k);
   cost_OP_RO_SUM(k,1) =  0.009
.*(Cap_PV2Bat_RO_SUM(k)+
Cap_G2Bat_RO_SUM(k) +
Cap_Bat2G_RO_SUM(k)+Cap_Spin_RO_SUM(k)+C
ap_RegD_RO_SUM(k)+Cap_RegU_RO_SUM(k)) ;
% Cost operation

    cost_un_dch_RO_SUM(k,1)  =
Cap_ex_dch_RO_SUM(k)* 0.0 ;
    cost_un_ch_RO_SUM(k,1)  =
Cap_ex_ch_RO_SUM(k)* 0.0 ;


   if k==1
   Soc_RO_SUM(k,1)  =  SOC_0 +
cost_un_ch_RO_SUM(k);
    else
   Soc_RO_SUM(k,1)  =  Eta_Ch
.*(Cap_PV2Bat_RO_SUM(k-1)+
Cap_G2Bat_RO_SUM(k-1)+Cap_RegD_RO_SUM(k-
1))-(Cap_Bat2G_RO_SUM(k-
1,1)+Cap_Spin_RO_SUM(k-
1)+Cap_RegU_RO_SUM(k-
1)+Cap_Bat2L_RO_SUM(k-1))./Eta_D;
    end
   SOC_RO_SUM(k,1)  = sum(Soc_RO_SUM);
   cost_RO_SUM(k,1)
=(cost_Demand_RO_SUM(k)+cost_OP_RO_SUM(k
)-income_Discharging_RO_SUM(k)-
income_Charging_RO_SUM(k)+cost_un_ch_RO_
SUM(k)+cost_un_dch_RO_SUM(k));%);%cost_D
emand_RO_SUM(k)

   SOCC_RO_SUM(k,1)      =
SOC_RO_SUM(k,1)/BAT_CAP;
   a_RegU_RO_SUM(k,1)    =
Cap_RegU_RO_SUM(k)/Cap_Max;
   a_RegD_RO_SUM(k,1)    =
Cap_RegD_RO_SUM(k)/Cap_Max;
   a_Spin_RO_SUM(k,1)    =
Cap_Spin_RO_SUM(k)/Cap_Max;
   a_LMP_RO_SUM(k,1)     =
(Cap_Bat2G_RO_SUM(k))/Cap_Max;%+Cap_Spin
_RO_SUM(k)+Cap_RegU_RO_SUM(k)
   a_G2Bat_RO_SUM(k,1)   =
Cap_G2Bat_RO_SUM(k)/Cap_Max;
   a_Bat2L_RO_SUM(k,1)   =
Cap_Bat2L_RO_SUM(k)/Cap_Max;
   a_PV2Bat_RO_SUM(k,1)  =
Cap_PV2Bat_RO_SUM(k)/Cap_Max;
   a_G2L_RO_SUM(k,1)     =
Cap_G2L_RO_SUM(k)/Cap_Max;
   a_PV2L_RO_SUM(k,1)    =
Cap_PV2L_RO_SUM(k)/Cap_Max;
   a_ex_ch_RO_SUM(k,1)   =
Cap_ex_ch_RO_SUM(k)/Cap_Max;
   a_ex_dch_RO_SUM(k,1)  =
Cap_ex_dch_RO_SUM(k)/Cap_Max;
     else
```

```
            Soc_RO_SUM(k,1)   =   Eta_Ch
.*(Cap_PV2Bat_RO_SUM(k-1)+
Cap_G2Bat_RO_SUM(k-1)+Cap_RegD_RO_SUM(k-
1))-(Cap_Bat2G_RO_SUM(k-
1,1)+Cap_Spin_RO_SUM(k-
1)+Cap_RegU_RO_SUM(k-
1)+Cap_Bat2L_RO_SUM(k-1))./Eta_D;
            SOC_RO_SUM(k,1)   =
sum(Soc_RO_SUM);
            SOCC_RO_SUM(k,1)   =
SOC_RO_SUM(k,1)/BAT_CAP;

        end
        end

  OBJ_RO_SUM =   sum(cost_RO_SUM);

minimize(OBJ_RO_SUM)

   subject to
   SOC_RO_SUM(25) >= SOC_RO_SUM(1) ;
   SOC_Min <= SOC_RO_SUM(25)   <= SOC_Max
;
  for k = 1:24
   SOC_RO_SUM(1) == SOC_0 ;% for initial
value of soc
   SOC_Min <= SOC_RO_SUM(k)   <= SOC_Max
;
    0 <=
Cap_G2Bat_RO_SUM(k)+Cap_RegD_RO_SUM(k) +
Cap_PV2Bat_RO_SUM(k)<= Cap_Max;
    0 <=
Cap_Spin_RO_SUM(k)+Cap_RegU_RO_SUM(k)+Ca
p_Bat2G_RO_SUM(k)+Cap_Bat2L_RO_SUM(k)  <=
Cap_Max; %
    Cap_PV2L_RO_SUM(k) +
Cap_G2L_RO_SUM(k)+Cap_Bat2L_RO_SUM(k)  ==
Cap_L_sum(k);
    Cap_PV2Bat_RO_SUM(k) +
Cap_PV2L_RO_SUM(k)  <= Cap_PV_sum(k);

    Cap_Charge_RO_SUM(k)- Cap_Max *(1-
M_RO_SUM(k))<=0;
    Cap_Discharge_RO_SUM(k)- Cap_Max
*(M_RO_SUM(k))<=0 ;
   if Tr_RS(k)==0
       Cap_Spin_RO_SUM(k)==0;
   end
   if Tr_RegU(k)==0
       Cap_RegU_RO_SUM(k)==0;
   end

   if Tr_RegD(k)==0
       Cap_RegD_RO_SUM(k)==0;
   end

  end
  cvx_end

load gong.mat;
sound(y);
display("WELL DONE!!")

t_RO_SUM = toc

 %%  Robust for Winter

tic

clear Cap_Discharge_RO_WIN
clear cost_Charge_RO_WIN
clear cost_Demand_RO_WIN
clear cost_OP_RO_WIN
clear income_Spin_RO_WIN
clear Income_Spin_RO_WIN
clear income_sell_RO_WIN
clear INCOME_sell_RO_WIN
clear income_E_RO_WIN
clear Income_E_RO_WIN
clear income_MilU_RO_WIN
clear income_RegU_RO_WIN
clear Income_RegU_RO_WIN
clear cost_Charge_RO_WIN
clear Cap_Charge_RO_WIN
clear income_MilD_RO_WIN
clear income_RegD_RO_WIN
clear Income_RegD_RO_WIN
clear income_Charging_RO_WIN
clear income_Discharging_RO_WIN
clear cost_OP_RO_WIN
clear Soc_RO_WIN
clear SOC_RO_WIN
clear cost_RO_WIN
clear COST_RO_WIN
clear SOCC_RO_WIN
clear a_RegU_RO_WIN
clear a_Spin_RO_WIN
clear a_LMP_RO_WIN
clear a_RegD_RO_WIN
clear a_Buy_RO_WIN
clear AAA_RO_WIN
clear Cap_Bat2L_RO_WIN
clear a_Bat2L_RO_WIN
clear a_G2Bat_RO_WIN
clear a_PV2Bat_RO_WIN
clear Cap_ex_RO_ch_WIN
clear Cap_ex_RO_dch_WIN
clear a_ex_RO_ch_WIN
clear a_ex_RO_dch_WIN
clear cost_ex_RO_ch_WIN
clear cost_ex_RO_dch_WIN
clear a_PV2L_RO_WIN
clear a_G2L_RO_WIN
cvx_begin

    variable Cap_Bat2L_RO_WIN(24)
nonnegative
    variable Cap_G2Bat_RO_WIN(24)
nonnegative
    variable Cap_RegD_RO_WIN(24)
nonnegative
    variable Cap_PV2L_RO_WIN(24)
nonnegative
    variable Cap_G2L_RO_WIN(24)
nonnegative
    variable Cap_Bat2G_RO_WIN(24)
nonnegative
    variable Cap_PV2Bat_RO_WIN(24)
nonnegative
    variable Cap_RegU_RO_WIN(24)
nonnegative
    variable Cap_Spin_RO_WIN(24)
nonnegative
    variable M_RO_WIN(24) binary
    variable Cap_ex_RO_dch_WIN(24)
nonnegative
    variable Cap_ex_RO_ch_WIN(24)
nonnegative

  for k = 1:25
      if k<=24
    Cap_Charge_RO_WIN(k,1) =
Cap_G2Bat_RO_WIN(k)+Cap_PV2Bat_RO_WIN(k)
+Cap_RegD_RO_WIN(k);%+Cap_ex_RO_ch_WIN(k
);
    Cap_Discharge_RO_WIN(k,1) =
Cap_Bat2G_RO_WIN(k)+Cap_Spin_RO_WIN(k)+C
```

```
ap_RegU_RO_WIN(k)+Cap_Bat2L_RO_WIN(k);%+
Cap_ex_RO_dch_WIN(k);

    cost_Charge_RO_WIN(k,1) =
(Cap_G2Bat_RO_WIN(k)).*
(Min_LMP_da_WIN_low(k)) ;
%+Cap_RegD_RO_WIN(k)  Pr_buy_WIN Cost of
buyng energy fRO_WINm Grid for battery
    cost_Demand_RO_WIN(k,1) =
(Min_LMP_da_WIN_low(k)) .*
(Cap_G2L_RO_WIN(k));    %Pr_buy_WIN cost
of buying energy fRO_WINm Grid for Load

   income_Spin_RO_WIN(k,1) = Tr_RS(k) .*
(Min_Spin_da_WIN_low(k).*
Cap_Spin_RO_WIN(k));% -
abs(min(Cap_Max,Cap_RS_DA_Max(k))-
Cap_RES(k)).*Pen_RES_DA);
   Income_Spin_RO_WIN(k,1) =
sum(income_Spin_RO_WIN(k));

   income_E_RO_WIN(k,1) =
Min_LMP_da_WIN_low(k).*(Cap_Bat2G_RO_WIN
(k)+Cap_RegU_RO_WIN(k)+Cap_Spin_RO_WIN(k
)); %Energy income for day ahead and
realtime  +Cap_RegU1(k)+Cap_Spin(k)
   Income_E_RO_WIN(k,1) =
sum(income_E_RO_WIN);

   income_RegU_RO_WIN(k,1) =
Tr_RegU(k).*( Min_RegU_da_WIN_low(k) .*
(Cap_RegU_RO_WIN(k))) ;% Income of
Regulation up including up Mileage
   Income_RegU_RO_WIN(k,1) =
sum(income_RegU_RO_WIN);% +
income_MilU1);

   income_RegD_RO_WIN(k,1) =
Tr_RegD(k).*(Min_RegD_da_WIN_low(k) .*
Cap_RegD_RO_WIN(k));  % Income of
Regulation up including up Mileage
   Income_RegD_RO_WIN(k,1) =
sum(income_RegD_RO_WIN);% +
income_MilD_Dit);

   income_Charging_RO_WIN(k,1)=
income_RegD_RO_WIN(k)-
cost_Charge_RO_WIN(k);
   income_Discharging_RO_WIN(k,1)=
income_Spin_RO_WIN(k)+income_E_RO_WIN(k)
+income_RegU_RO_WIN(k);%+income_sell_RO_
WIN(k);
    cost_OP_RO_WIN(k,1) =  0.01
.*(Cap_PV2Bat_RO_WIN(k)+
Cap_G2Bat_RO_WIN(k) +
Cap_Bat2G_RO_WIN(k)+Cap_Spin_RO_WIN(k)+C
ap_RegD_RO_WIN(k)+Cap_RegU_RO_WIN(k)) ;
% Cost operation

    cost_ex_RO_dch_WIN(k,1)= 0.00 *
Cap_ex_RO_dch_WIN(k);
    cost_ex_RO_ch_WIN(k,1)= 0.00 *
Cap_ex_RO_ch_WIN(k);


    if k==1
   Soc_RO_WIN(k,1)   =  SOC_0
+cost_ex_RO_ch_WIN(k);
    else
   Soc_RO_WIN(k,1)   =  Eta_Ch
.*(Cap_PV2Bat_RO_WIN(k-1)+
Cap_G2Bat_RO_WIN(k-1)+Cap_RegD_RO_WIN(k-
1))-(Cap_Bat2G_RO_WIN(k-
1,1)+Cap_Spin_RO_WIN(k-
1)+Cap_RegU_RO_WIN(k-
1)+Cap_Bat2L_RO_WIN(k-1))./Eta_D;
    end

   SOC_RO_WIN(k,1)     =
sum(Soc_RO_WIN);
   cost_RO_WIN(k,1)
=(cost_Demand_RO_WIN(k)+cost_OP_RO_WIN(k
)-income_Discharging_RO_WIN(k)-
income_Charging_RO_WIN(k)+cost_ex_RO_dch
_WIN(k,1)+cost_ex_RO_ch_WIN(k,1));%+
cost_OP_RO_WIN(k));%cost_Demand_RO_WIN(k
)
   SOCC_RO_WIN(k,1)     =
SOC_RO_WIN(k,1)/BAT_CAP;
   a_RegU_RO_WIN(k,1)   =
Cap_RegU_RO_WIN(k)/Cap_Max;
   a_RegD_RO_WIN(k,1)   =
Cap_RegD_RO_WIN(k)/Cap_Max;
   a_Spin_RO_WIN(k,1)   =
Cap_Spin_RO_WIN(k)/Cap_Max;
   a_LMP_RO_WIN(k,1)    =
(Cap_Bat2G_RO_WIN(k))/Cap_Max;%+Cap_Spin
_RO_WIN(k)+Cap_RegU_RO_WIN(k)
   a_G2Bat_RO_WIN(k,1) =
Cap_G2Bat_RO_WIN(k)/Cap_Max;
   a_Bat2L_RO_WIN(k,1) =
Cap_Bat2L_RO_WIN(k)/Cap_Max;
   a_PV2Bat_RO_WIN(k,1) =
Cap_PV2Bat_RO_WIN(k)/Cap_Max;
   a_ex_RO_ch_WIN(k,1)  =
Cap_ex_RO_ch_WIN(k)/Cap_Max;
   a_ex_RO_dch_WIN(k,1) =
Cap_ex_RO_dch_WIN(k)/Cap_Max;
   a_PV2L_RO_WIN(k,1) =
Cap_PV2L_RO_WIN(k)/Cap_Max;
   a_G2L_RO_WIN(k,1) =
Cap_G2L_RO_WIN(k)/Cap_Max;

   else
       Soc_RO_WIN(k,1)   =  Eta_Ch
.*(Cap_PV2Bat_RO_WIN(k-1)+
Cap_G2Bat_RO_WIN(k-1)+Cap_RegD_RO_WIN(k-
1))-(Cap_Bat2G_RO_WIN(k-
1,1)+Cap_Spin_RO_WIN(k-
1)+Cap_RegU_RO_WIN(k-
1)+Cap_Bat2L_RO_WIN(k-1))./Eta_D;
       SOC_RO_WIN(k,1)   =
sum(Soc_RO_WIN);
       SOCC_RO_WIN(k,1)   =
SOC_RO_WIN(k,1)/BAT_CAP;
           end
  end
  OBJ_RO_WIN =  sum(cost_RO_WIN);

minimize(OBJ_RO_WIN)

   subject to
   SOC_RO_WIN(25) >= SOC_RO_WIN(1) ;
   SOC_Min <= SOC_RO_WIN(25) <= SOC_Max
;
  for k = 1:24
   SOC_RO_WIN(1) == SOC_0 ;% for initial
value of soc
   SOC_Min <= SOC_RO_WIN(k)  <= SOC_Max
;
    0 <=
Cap_Spin_RO_WIN(k)+Cap_RegU_RO_WIN(k)+Ca
p_Bat2G_RO_WIN(k)+Cap_Bat2L_RO_WIN(k) <=
Cap_Max; %
    Cap_PV2L_RO_WIN(k) +
Cap_G2L_RO_WIN(k)+Cap_Bat2L_RO_WIN(k) ==
Cap_L_win(k);
```

```
    Cap_PV2Bat_RO_WIN(k) +
Cap_PV2L_RO_WIN(k) <= Cap_PV_win(k);
   %
Cap_Charge_RO_WIN(k)+Cap_Discharge_RO_WI
N(k)==Cap_Max;

    Cap_Charge_RO_WIN(k)<=Cap_Max.*(1-
M_RO_WIN(k));
    Cap_Discharge_RO_WIN(k)
<=Cap_Max.*(M_RO_WIN(k));
   if Tr_RS(k)==0
       Cap_Spin_RO_WIN(k)==0;
   end
   if Tr_RegU(k)==0
       Cap_RegU_RO_WIN(k)==0;
   end

   if Tr_RegD(k)==0
       Cap_RegD_RO_WIN(k)==0;
   end

  end
  cvx_end

load gong.mat;
sound(y);
display("WELL DONE!!")

t_RO_WIN = toc

%%

clear COST_T_DROS_WIN
clear COST_T_DitS_WIN
clear COST_T_DitS_SUM

for day = 1:120; %the selected day
%
%     LMP_DA_sample  = LMP_da(:,day) ;
%     RegD_DA_sample = RegD_da(:,day);
%     RegU_DA_sample = RegU_da(:,day);
%     Spin_DA_sample = Spin_da(:,day);
%     Pr_buy_sample  =  LMP_da(:,day)*1 ;
    Spin_DA_sample_win =
Spin_da_win_test(:,day);
    LMP_DA_sample_win  =
LMP_da_win_test(:,day) ;
    RegU_DA_sample_win =
RegU_da_win_test(:,day);
    Pr_buy_sample_win  =
LMP_da_win_test(:,day) ;
    RegD_DA_sample_win =
RegD_da_win_test(:,day);


    Spin_DA_sample_sum =
Spin_da_sum_test(:,day);
    LMP_DA_sample_sum  =
LMP_da_sum_test(:,day) ;
    RegU_DA_sample_sum =
RegU_da_sum_test(:,day);
    Pr_buy_sample_sum  =
LMP_da_sum_test(:,day) ;
    RegD_DA_sample_sum =
RegD_da_sum_test(:,day);

for k=1:24
%      %%% Deterministic check for Winter
   cost_Charge_DitS_WIN(k,1) =
(Cap_G2Bat_Dit_WIN(k)).*
Pr_buy_sample_win(k) ; % Cost of buyng
energy from Grid for battery
   cost_Demand_DitS_WIN(k,1) =
Pr_buy_sample_win(k) .*
(Cap_G2L_Dit_WIN(k));    %cost of buying
energy from Grid for Load
   income_Spin_DitS_WIN(k,1) = Tr_RS(k)
.*
(Spin_DA_sample_win(k,1).*Cap_Spin_Dit_W
IN(k));% -
abs(min(Cap_Max,Cap_RS_DA_Max(k))-
Cap_RES(k)).*Pen_RES_DA);
   Income_Spin_DitS_WIN(k,1) =
sum(income_Spin_DitS_WIN(k));
   income_E_DitS_WIN(k,1) =
(LMP_DA_sample_win(k,1).*(Cap_Bat2G_Dit_
WIN(k)+Cap_RegU_Dit_WIN(k)+Cap_Spin_Dit_
WIN(k))); % Energy income for day ahead
and realtime  +Cap_RegU1(k)+Cap_Spin(k)
   Income_E_DitS_WIN(k,1) =
sum(income_E_DitS_WIN);
   income_RegU_DitS_WIN(k,1) =
Tr_RegU(k).*(RegU_DA_sample_win(k,1) .*
(Cap_RegU_Dit_WIN(k))) ;% Income of
Regulation up including up Mileage
   Income_RegU_DitS_WIN(k,1) =
sum(income_RegU_DitS_WIN);% +
income_MilU1);
   income_RegD_DitS_WIN(k,1) =
Tr_RegD(k).*(RegD_DA_sample_win(k,1).*
Cap_RegD_Dit_WIN(k));  % Income of
Regulation up including up Mileage
   Income_RegD_DitS_WIN(k,1) =
sum(income_RegD_DitS_WIN);% +
income_MilD_Dit);

   income_Charging_DitS_WIN(k,1)=
income_RegD_DitS_WIN(k);
   income_Discharging_DitS_WIN(k,1)=
income_Spin_DitS_WIN(k)+income_E_DitS_WI
N(k)+income_RegU_DitS_WIN(k);%+income_se
ll_RO(k);
   cost_OP_DitS_WIN(k,1) =  c_op
.*(Cap_PV2Bat_Dit_WIN(k)+
Cap_G2Bat_Dit_WIN(k) +
Cap_Bat2G_Dit_WIN(k)+Cap_Spin_Dit_WIN(k)
+Cap_RegD_Dit_WIN(k)+Cap_RegU_Dit_WIN(k)
) ; % Cost operation
   cost_DitS_WIN(k,1)
=(cost_Demand_DitS_WIN(k)+
cost_Charge_DitS_WIN(k)+cost_OP_DitS_WIN
(k));
   Rev_DitS_WIN(k,1)=
income_Discharging_DitS_WIN(k)+
income_Charging_DitS_WIN(k);

   %%% DETERMIINISTIC Check for Summer
   cost_Charge_DitS_SUM(k,1) =
(Cap_G2Bat_Dit_SUM(k)).*
Pr_buy_sample_sum(k) ; % Cost of buyng
energy from Grid for battery
   cost_Demand_DitS_SUM(k,1) =
Pr_buy_sample_sum(k) .*
(Cap_G2L_Dit_SUM(k));    %cost of buying
energy from Grid for Load
   income_Spin_DitS_SUM(k,1) = Tr_RS(k)
.*
(Spin_DA_sample_sum(k,1).*Cap_Spin_Dit_S
UM(k));% -
abs(min(Cap_Max,Cap_RS_DA_Max(k))-
Cap_RES(k)).*Pen_RES_DA);
   Income_Spin_DitS_SUM(k,1) =
sum(income_Spin_DitS_SUM(k));
   income_E_DitS_SUM(k,1) =
(LMP_DA_sample_sum(k,1).*(Cap_Bat2G_Dit_
SUM(k)+Cap_RegU_Dit_SUM(k)+Cap_Spin_Dit_
SUM(k))); % Energy income for day ahead
and realtime  +Cap_RegU1(k)+Cap_Spin(k)
```

```
   Income_E_DitS_SUM(k,1) =
sum(income_E_DitS_SUM);
   income_RegU_DitS_SUM(k,1) =
Tr_RegU(k).*(RegU_DA_sample_sum(k,1) .*
(Cap_RegU_Dit_SUM(k))) ;% Income of
Regulation up including up Mileage
   Income_RegU_DitS_SUM(k,1) =
sum(income_RegU_DitS_SUM);% +
income_MilU1);
   income_RegD_DitS_SUM(k,1) =
Tr_RegD(k).*(RegD_DA_sample_sum(k,1).*
Cap_RegD_Dit_SUM(k));  % Income of
Regulation up including up Mileage
   Income_RegD_DitS_SUM(k,1) =
sum(income_RegD_DitS_SUM);% +
income_MilD_Dit);

   income_Charging_DitS_SUM(k,1)=
income_RegD_DitS_SUM(k);
   income_Discharging_DitS_SUM(k,1)=
income_Spin_DitS_SUM(k)+income_E_DitS_SU
M(k)+income_RegU_DitS_SUM(k);%+income_se
ll_RO(k);
   cost_OP_DitS_SUM(k,1) =  c_op
.*(Cap_PV2Bat_Dit_SUM(k)+
Cap_G2Bat_Dit_SUM(k) +
Cap_Bat2G_Dit_SUM(k)+Cap_Spin_Dit_SUM(k)
+Cap_RegD_Dit_SUM(k)+Cap_RegU_Dit_SUM(k)
) ; % Cost operation
   cost_DitS_SUM(k,1)
=(cost_Demand_DitS_SUM(k)+
cost_Charge_DitS_SUM(k)+cost_OP_DitS_SUM
(k));
   Rev_DitS_SUM(k,1)=
income_Discharging_DitS_SUM(k)+
income_Charging_DitS_SUM(k);

  %%% DRO check for Summer
   cost_Charge_DROS_SUM(k,1) =
(Cap_G2Bat_DRO_SUM_low(k)).*
Pr_buy_sample_sum(k) ; % Cost of buyng
energy from Grid for battery
   cost_Demand_DROS_SUM(k,1) =
Pr_buy_sample_sum(k) .*
(Cap_G2L_DRO_SUM_low(k));   %cost of
buying energy from Grid for Load
   income_Spin_DROS_SUM(k,1) = Tr_RS(k)
.*
(Spin_DA_sample_sum(k,1).*Cap_Spin_DRO_S
UM_low(k));% -
abs(min(Cap_Max,Cap_RS_DA_Max(k))-
Cap_RES(k)).*Pen_RES_DA);
   Income_Spin_DROS_SUM(k,1) =
sum(income_Spin_DROS_SUM(k));
   income_E_DROS_SUM(k,1) =
(LMP_DA_sample_sum(k,1).*(Cap_Bat2G_DRO_
SUM_low(k)+Cap_RegU_DRO_SUM_low(k)+Cap_S
pin_DRO_SUM_low(k))); % Energy income
for day ahead and realtime
+Cap_RegU1(k)+Cap_Spin(k)
   Income_E_DROS_SUM(k,1) =
sum(income_E_DROS_SUM);
   income_RegU_DROS_SUM(k,1) =
Tr_RegU(k).*(RegU_DA_sample_sum(k,1).*
(Cap_RegU_DRO_SUM_low(k))) ;% Income of
Regulation up including up Mileage
   Income_RegU_DROS_SUM(k,1) =
sum(income_RegU_DROS_SUM);% +
income_MilU1);
   income_RegD_DROS_SUM(k,1) =
Tr_RegD(k).*(RegD_DA_sample_sum(k,1).*
Cap_RegD_DRO_SUM_low(k));  % Income of
Regulation up including up Mileage
   Income_RegD_DROS_SUM(k,1) =
sum(income_RegD_DROS_SUM);% +
income_MilD_Dit);

   income_Charging_DROS_SUM(k,1)=
income_RegD_DROS_SUM(k);
   income_Discharging_DROS_SUM(k,1)=
income_Spin_DROS_SUM(k)+income_E_DROS_SU
M(k)+income_RegU_DROS_SUM(k);%+income_se
ll_RO(k);
    cost_OP_DROS_SUM(k,1) =  c_op
.*(Cap_PV2Bat_DRO_SUM_low(k)+
Cap_G2Bat_DRO_SUM_low(k) +
Cap_Bat2G_DRO_SUM_low(k)+Cap_Spin_DRO_SU
M_low(k)+Cap_RegD_DRO_SUM_low(k)+Cap_Reg
U_DRO_SUM_low(k)) ; % Cost operation
   cost_DROS_SUM(k,1)
=(cost_Demand_DROS_SUM(k)+
cost_Charge_DROS_SUM(k)+cost_OP_DROS_SUM
(k));
    Rev_DROS_SUM(k,1)=
income_Discharging_DROS_SUM(k) +
income_Charging_DROS_SUM(k);

    %       %%% DRO check for Winter
**********
   cost_Charge_DROS_WIN(k,1) =
(Cap_G2Bat_DRO_WIN_low(k)).*
Pr_buy_sample_win(k) ; % Cost of buyng
energy from Grid for battery
   cost_Demand_DROS_WIN(k,1) =
Pr_buy_sample_win(k) .*
(Cap_G2L_DRO_WIN_low(k));   %cost of
buying energy from Grid for Load
   income_Spin_DROS_WIN(k,1) = Tr_RS(k)
.*
(Spin_DA_sample_win(k,1).*Cap_Spin_DRO_W
IN_low(k));% -
abs(min(Cap_Max,Cap_RS_DA_Max(k))-
Cap_RES(k)).*Pen_RES_DA);
   Income_Spin_DROS_WIN(k,1) =
sum(income_Spin_DROS_WIN(k));
   income_E_DROS_WIN(k,1) =
(LMP_DA_sample_win(k,1).*(Cap_Bat2G_DRO_
WIN_low(k)+Cap_RegU_DRO_WIN_low(k)+Cap_S
pin_DRO_WIN_low(k))); % Energy income
for day ahead and realtime
+Cap_RegU1(k)+Cap_Spin(k)
   Income_E_DROS_WIN(k,1) =
sum(income_E_DROS_WIN);
   income_RegU_DROS_WIN(k,1) =
Tr_RegU(k).*(RegU_DA_sample_win(k,1) .*
(Cap_RegU_DRO_WIN_low(k))) ;% Income of
Regulation up including up Mileage
   Income_RegU_DROS_WIN(k,1) =
sum(income_RegU_DROS_WIN);% +
income_MilU1);
   income_RegD_DROS_WIN(k,1) =
Tr_RegD(k).*(RegD_DA_sample_win(k,1) .*
Cap_RegD_DRO_WIN_low(k));  % Income of
Regulation up including up Mileage
   Income_RegD_DROS_WIN(k,1) =
sum(income_RegD_DROS_WIN);% +
income_MilD_Dit);

   income_Charging_DROS_WIN(k,1)=
income_RegD_DROS_WIN(k);
   income_Discharging_DROS_WIN(k,1)=
income_Spin_DROS_WIN(k)+income_E_DROS_WI
N(k)+income_RegU_DROS_WIN(k);%+income_se
ll_RO(k);
   cost_OP_DROS_WIN(k,1) =  c_op
.*(Cap_PV2Bat_DRO_WIN_low(k)+
Cap_G2Bat_DRO_WIN_low(k) +
```

```
Cap_Bat2G_DRO_WIN_low(k)+Cap_Spin_DRO_WIN_low(k)+Cap_RegD_DRO_WIN_low(k)+Cap_RegU_DRO_WIN_low(k)) ; % Cost operation
   cost_DROS_WIN(k,1)
=(cost_Demand_DROS_WIN(k)+
cost_Charge_DROS_WIN(k)+cost_OP_DROS_WIN(k));

Rev_DROS_WIN(k,1)=income_Discharging_DROS_WIN(k)+ income_Charging_DROS_WIN(k);

  %        %%% Robust Check For Winter
   cost_Charge_ROS_WIN(k,1) =
(Cap_G2Bat_RO_WIN(k)).*
Pr_buy_sample_win(k) ; % Cost of buyng energy from Grid for battery
   cost_Demand_ROS_WIN(k,1) =
Pr_buy_sample_win(k) .*
(Cap_G2L_RO_WIN(k));   %cost of buying energy from Grid for Load
   income_Spin_ROS_WIN(k,1) = Tr_RS(k)
.*
(Spin_DA_sample_win(k,1).*Cap_Spin_RO_WIN(k));% -
abs(min(Cap_Max,Cap_RS_DA_Max(k))-Cap_RES(k)).*Pen_RES_DA);
   Income_Spin_ROS_WIN(k,1) =
sum(income_Spin_ROS_WIN(k));
   income_E_ROS_WIN(k,1) =
(LMP_DA_sample_win(k,1).*(Cap_Bat2G_RO_WIN(k)+Cap_RegU_RO_WIN(k)+Cap_Spin_RO_WIN(k))); % Energy income for day ahead and realtime  +Cap_RegU1(k)+Cap_Spin(k)
   Income_E_ROS_WIN(k,1) =
sum(income_E_ROS_WIN);
   income_RegU_ROS_WIN(k,1) =
Tr_RegU(k).*(RegU_DA_sample_win(k,1).*
(Cap_RegU_RO_WIN(k))) ;% Income of Regulation up including up Mileage
   Income_RegU_ROS_WIN(k,1) =
sum(income_RegU_ROS_WIN);% +
income_MilU1);
   income_RegD_ROS_WIN(k,1) =
Tr_RegD(k).*(RegD_DA_sample_win(k,1).*
Cap_RegD_RO_WIN(k));  % Income of Regulation up including up Mileage
   Income_RegD_ROS_WIN(k,1) =
sum(income_RegD_ROS_WIN);% +
income_MilD_Dit);

   income_Charging_ROS_WIN(k,1)=
income_RegD_ROS_WIN(k);
   income_Discharging_ROS_WIN(k,1)=
income_Spin_ROS_WIN(k)+income_E_ROS_WIN(k)+income_RegU_ROS_WIN(k);%+income_sell_RO(k);
   cost_OP_ROS_WIN(k,1) =  c_op
.*(Cap_PV2Bat_RO_WIN(k)+
Cap_G2Bat_RO_WIN(k) +
Cap_Bat2G_RO_WIN(k)+Cap_Spin_RO_WIN(k)+Cap_RegD_RO_WIN(k)+Cap_RegU_RO_WIN(k)) ;
% Cost operation
   cost_ROS_WIN(k,1)
=(cost_Demand_ROS_WIN(k)+
cost_Charge_ROS_WIN(k)+cost_OP_ROS_WIN(k));

Rev_ROS_WIN(k,1)=income_Discharging_ROS_WIN(k)+ income_Charging_ROS_WIN(k);

           %%% Robust Check For Summer
   cost_Charge_ROS_SUM(k,1) =
(Cap_G2Bat_RO_SUM(k)).*
Pr_buy_sample_sum(k) ; % Cost of buyng energy from Grid for battery
   cost_Demand_ROS_SUM(k,1) =
Pr_buy_sample_sum(k) .*
(Cap_G2L_RO_SUM(k));   %cost of buying energy from Grid for Load
   income_Spin_ROS_SUM(k,1) = Tr_RS(k)
.*
(Spin_DA_sample_sum(k,1).*Cap_Spin_RO_SUM(k));% -
abs(min(Cap_Max,Cap_RS_DA_Max(k))-Cap_RES(k)).*Pen_RES_DA);
   Income_Spin_ROS_SUM(k,1) =
sum(income_Spin_ROS_SUM(k));
   income_E_ROS_SUM(k,1) =
(LMP_DA_sample_sum(k,1).*(Cap_Bat2G_RO_SUM(k)+Cap_RegU_RO_SUM(k)+Cap_Spin_RO_SUM(k))); % Energy income for day ahead and realtime  +Cap_RegU1(k)+Cap_Spin(k)
   Income_E_ROS_SUM(k,1) =
sum(income_E_ROS_SUM);
   income_RegU_ROS_SUM(k,1) =
Tr_RegU(k).*(RegU_DA_sample_sum(k,1) .*
(Cap_RegU_RO_SUM(k))) ;% Income of Regulation up including up Mileage
   Income_RegU_ROS_SUM(k,1) =
sum(income_RegU_ROS_SUM);% +
income_MilU1);
   income_RegD_ROS_SUM(k,1) =
Tr_RegD(k).*(RegD_DA_sample_sum(k,1).*
Cap_RegD_RO_SUM(k));  % Income of Regulation up including up Mileage
   Income_RegD_ROS_SUM(k,1) =
sum(income_RegD_ROS_SUM);% +
income_MilD_Dit);

   income_Charging_ROS_SUM(k,1) =
income_RegD_ROS_SUM(k);
   income_Discharging_ROS_SUM(k,1) =
income_Spin_ROS_SUM(k)+income_E_ROS_SUM(k)+income_RegU_ROS_SUM(k);%+income_sell_RO(k);
   cost_OP_ROS_SUM(k,1) =  c_op
.*(Cap_PV2Bat_RO_SUM(k)+
Cap_G2Bat_RO_SUM(k) +
Cap_Bat2G_RO_SUM(k)+Cap_Spin_RO_SUM(k)+Cap_RegD_RO_SUM(k)+Cap_RegU_RO_SUM(k)) ;
% Cost operation
   cost_ROS_SUM(k,1) =
(cost_Demand_ROS_SUM(k)+
cost_Charge_ROS_SUM(k)+cost_OP_ROS_SUM(k));
   Rev_ROS_SUM(k,1)  =
income_Discharging_ROS_SUM(k)+income_Charging_ROS_SUM(k);
end
   REV_DitS_WIN(day,1)   =
sum(Rev_DitS_WIN);
   REV_DitS_SUM(day,1)   =
sum(Rev_DitS_SUM);
   REV_ROS_WIN(day,1)    =
sum(Rev_ROS_WIN) ;
   REV_ROS_SUM(day,1)    =
sum(Rev_ROS_SUM) ;
   REV_DROS_WIN(day,1)   =
sum(Rev_DROS_WIN);
   REV_DROS_SUM(day,1)   =
sum(Rev_DROS_SUM);

   Cost_DROS_WIN(day,1)  =
sum(cost_DROS_WIN);
   Cost_DROS_SUM(day,1)  =
sum(cost_DROS_SUM);
```

```
   Cost_DitS_WIN(day,1) =
sum(cost_DitS_WIN);
   Cost_DitS_SUM(day,1) =
sum(cost_DitS_SUM);
   Cost_ROS_WIN(day,1)  =
sum(cost_ROS_WIN) ;
   Cost_ROS_SUM(day,1)  =
sum(cost_ROS_SUM) ;


  COST_T_DROS_WIN(day,1) = sum(-
cost_DROS_WIN+Rev_DROS_WIN);
  COST_T_DROS_SUM(day,1) = sum(-
cost_DROS_SUM+Rev_DROS_SUM);
  COST_T_DitS_WIN(day,1) = sum(-
cost_DitS_WIN+Rev_DitS_WIN);
  COST_T_DitS_SUM(day,1) = sum(-
cost_DitS_SUM+Rev_DitS_SUM);
  COST_T_ROS_WIN(day,1)  = sum(-
cost_ROS_WIN+Rev_ROS_WIN);
  COST_T_ROS_SUM(day,1)  = sum(-
cost_ROS_SUM+Rev_ROS_SUM);

   Am_DRO_DIT_WIN(day,1) =
(COST_T_DROS_WIN(day,1)-
COST_T_DitS_WIN(day,1)) ;
   Am_DRO_DIT_SUM(day,1) =
(COST_T_DROS_SUM(day,1)-
COST_T_DitS_SUM(day,1));
   Am_DRO_ROS_WIN(day,1) =
(COST_T_DROS_WIN(day,1)-
COST_T_ROS_WIN(day,1)) ;
   Am_DRO_ROS_SUM(day,1) =
(COST_T_DROS_SUM(day,1)-
COST_T_ROS_SUM(day,1)) ;
   Am_DRO_ROS_WIN(day,1) =
(COST_T_DROS_SUM(day,1)-
COST_T_ROS_WIN(day,1)) ;
end
COST_SUMMER_DRO = sum(COST_T_DROS_SUM);
COST_WINTER_DRO = sum(COST_T_DROS_WIN);
COST_WINTER_Deterministic =
sum(COST_T_DitS_WIN);
COST_SUMMER_Deterministic =
sum(COST_T_DitS_SUM);
COST_SUMMER_ROBUST=sum(COST_T_ROS_SUM);
COST_WINTER_ROBUST=sum(COST_T_ROS_WIN);

display('DONE!!')
%% Adding RT market data for training
year = '2016RT';
[Spin_rt_win,RegU_rt_win,RegD_rt_win,LMP
_rt_win,Spin_rt_sum,RegU_rt_sum,RegD_rt_
sum,LMP_rt_sum]= MarketRT(year);
clear year
display('Train market data added in RT')

for i= 1:96
LMP_rt_sum_det(i,1)  =
mean(LMP_rt_sum(i,:)) ;
RegD_rt_sum_det(i,1) =
mean(RegD_rt_sum(i,:));
RegU_rt_sum_det(i,1) =
mean(RegU_rt_sum(i,:));
Spin_rt_sum_det(i,1) =
mean(Spin_rt_sum(i,:));

LMP_rt_win_det(i,1)  =
mean(LMP_rt_win(i,:)) ;
RegD_rt_win_det(i,1) =
mean(RegD_rt_win(i,:));
RegU_rt_win_det(i,1) =
mean(RegU_rt_win(i,:));
Spin_rt_win_det(i,1) =
mean(Spin_rt_win(i,:));

end
%% Select Sample data

for i=1:96
  for k = 1:15
   LMP_RT_SUM_low(i,2*(k-1)+1)=
LMP_rt_sum(i,2+(k-1)*7);
   LMP_RT_SUM_low(i,2*(k-1)+2)=
LMP_rt_sum(i,3+(k-1)*7);
   Spin_RT_SUM_low(i,2*(k-1)+1)=
Spin_rt_sum(i,2+(k-1)*7);
   Spin_RT_SUM_low(i,2*(k-1)+2)=
Spin_rt_sum(i,3+(k-1)*7);
   RegU_RT_SUM_low(i,2*(k-1)+1)=
RegU_rt_sum(i,2+(k-1)*7);
   RegU_RT_SUM_low(i,2*(k-1)+2)=
RegU_rt_sum(i,3+(k-1)*7);
   RegD_RT_SUM_low(i,2*(k-1)+1)=
RegD_rt_sum(i,2+(k-1)*7);
   RegD_RT_SUM_low(i,2*(k-1)+2)=
RegD_rt_sum(i,3+(k-1)*7);

   LMP_RT_WIN_low(i,2*(k-1)+1)=
LMP_rt_win(i,5+(k-1)*7);
   LMP_RT_WIN_low(i,2*(k-1)+2)=
LMP_rt_win(i,6+(k-1)*7);
   Spin_RT_WIN_low(i,2*(k-1)+1)=
Spin_rt_win(i,5+(k-1)*7);
   Spin_RT_WIN_low(i,2*(k-1)+2)=
Spin_rt_win(i,6+(k-1)*7);
   RegU_RT_WIN_low(i,2*(k-1)+1)=
RegU_rt_win(i,5+(k-1)*7);
   RegU_RT_WIN_low(i,2*(k-1)+2)=
RegU_rt_win(i,6+(k-1)*7);
   RegD_RT_WIN_low(i,2*(k-1)+1)=
RegD_rt_win(i,5+(k-1)*7);
   RegD_RT_WIN_low(i,2*(k-1)+2)=
RegD_rt_win(i,6+(k-1)*7);

   end
 end

 Max_WIN_LMP_RT =
max(LMP_RT_WIN_low,[],2);
 Max_WIN_LMP_DA =
max(LMP_DA_WIN_low,[],2);
 Max_WIN_RegD_RT =
max(RegD_RT_WIN_low,[],2);
 Max_WIN_RegU_RT =
max(RegU_RT_WIN_low,[],2);
 Max_WIN_Spin_RT =
max(Spin_RT_WIN_low,[],2);

 Max_SUM_LMP_RT =
max(LMP_RT_SUM_low,[],2);
 Max_SUM_LMP_DA =
max(LMP_DA_SUM_low,[],2);
 Max_SUM_RegD_RT =
max(RegD_RT_SUM_low,[],2);
 Max_SUM_RegU_RT =
max(RegU_RT_SUM_low,[],2);
 Max_SUM_Spin_RT =
max(Spin_RT_SUM_low,[],2);


 Mean_WIN_LMP_RT  =
mean(LMP_RT_WIN_low,2);
 Mean_WIN_RegD_RT =
mean(RegD_RT_WIN_low,2);
 Mean_WIN_RegU_RT =
mean(RegU_RT_WIN_low,2);
```

```
 Mean_WIN_Spin_RT =
mean(Spin_RT_WIN_low,2);

 Mean_SUM_LMP_RT  =
mean(LMP_RT_SUM_low,2);
 Mean_SUM_RegD_RT =
mean(RegD_RT_SUM_low,2);
 Mean_SUM_RegU_RT =
mean(RegU_RT_SUM_low,2);
 Mean_SUM_Spin_RT =
mean(Spin_RT_SUM_low,2);
 display("Train Data added")
 %% Add train data RT high number

for i=1:96
  for k = 1:15
   LMP_RT_SUM_low(i,4*(k-1)+1)=
LMP_rt_sum(i,2+(k-1)*7);
   LMP_RT_SUM_low(i,4*(k-1)+2)=
LMP_rt_sum(i,3+(k-1)*7);
   LMP_RT_SUM_low(i,4*(k-1)+3)=
LMP_rt_sum(i,4+(k-1)*7);
   LMP_RT_SUM_low(i,4*(k-1)+4)=
LMP_rt_sum(i,5+(k-1)*7);
   Spin_RT_SUM_low(i,4*(k-1)+1)=
Spin_rt_sum(i,2+(k-1)*7);
   Spin_RT_SUM_low(i,4*(k-1)+2)=
Spin_rt_sum(i,3+(k-1)*7);
   Spin_RT_SUM_low(i,4*(k-1)+3)=
Spin_rt_sum(i,4+(k-1)*7);
   Spin_RT_SUM_low(i,4*(k-1)+4)=
Spin_rt_sum(i,5+(k-1)*7);
   RegU_RT_SUM_low(i,4*(k-1)+1)=
RegU_rt_sum(i,2+(k-1)*7);
   RegU_RT_SUM_low(i,4*(k-1)+2)=
RegU_rt_sum(i,3+(k-1)*7);
   RegU_RT_SUM_low(i,4*(k-1)+3)=
RegU_rt_sum(i,4+(k-1)*7);
   RegU_RT_SUM_low(i,4*(k-1)+4)=
RegU_rt_sum(i,5+(k-1)*7);
   RegD_RT_SUM_low(i,4*(k-1)+1)=
RegD_rt_sum(i,2+(k-1)*7);
   RegD_RT_SUM_low(i,4*(k-1)+2)=
RegD_rt_sum(i,3+(k-1)*7);
   RegD_RT_SUM_low(i,4*(k-1)+3)=
RegD_rt_sum(i,4+(k-1)*7);
   RegD_RT_SUM_low(i,4*(k-1)+4)=
RegD_rt_sum(i,5+(k-1)*7);

   LMP_RT_WIN_low(i,4*(k-1)+1)=
LMP_rt_win(i,5+(k-1)*7);
   LMP_RT_WIN_low(i,4*(k-1)+2)=
LMP_rt_win(i,6+(k-1)*7);
   LMP_RT_WIN_low(i,4*(k-1)+3)=
LMP_rt_win(i,7+(k-1)*7);
   LMP_RT_WIN_low(i,4*(k-1)+4)=
LMP_rt_win(i,8+(k-1)*7);
   Spin_RT_WIN_low(i,4*(k-1)+1)=
Spin_rt_win(i,5+(k-1)*7);
   Spin_RT_WIN_low(i,4*(k-1)+2)=
Spin_rt_win(i,6+(k-1)*7);
   Spin_RT_WIN_low(i,4*(k-1)+3)=
Spin_rt_win(i,7+(k-1)*7);
   Spin_RT_WIN_low(i,4*(k-1)+4)=
Spin_rt_win(i,8+(k-1)*7);
   RegU_RT_WIN_low(i,4*(k-1)+1)=
RegU_rt_win(i,5+(k-1)*7);
   RegU_RT_WIN_low(i,4*(k-1)+2)=
RegU_rt_win(i,6+(k-1)*7);
   RegU_RT_WIN_low(i,4*(k-1)+3)=
RegU_rt_win(i,7+(k-1)*7);
   RegU_RT_WIN_low(i,4*(k-1)+4)=
RegU_rt_win(i,8+(k-1)*7);
   RegD_RT_WIN_low(i,4*(k-1)+1)=
RegD_rt_win(i,5+(k-1)*7);
   RegD_RT_WIN_low(i,4*(k-1)+2)=
RegD_rt_win(i,6+(k-1)*7);
   RegD_RT_WIN_low(i,4*(k-1)+3)=
RegD_rt_win(i,7+(k-1)*7);
   RegD_RT_WIN_low(i,4*(k-1)+4)=
RegD_rt_win(i,8+(k-1)*7);

   end
 end

 Max_WIN_LMP_RT =
max(LMP_RT_WIN_low,[],2);
 Max_WIN_LMP_DA =
max(LMP_DA_WIN_low,[],2);
 Max_WIN_RegD_RT =
max(RegD_RT_WIN_low,[],2);
 Max_WIN_RegU_RT =
max(RegU_RT_WIN_low,[],2);
 Max_WIN_Spin_RT =
max(Spin_RT_WIN_low,[],2);

 Max_SUM_LMP_RT =
max(LMP_RT_SUM_low,[],2);
 Max_SUM_LMP_DA =
max(LMP_DA_SUM_low,[],2);
 Max_SUM_RegD_RT =
max(RegD_RT_SUM_low,[],2);
 Max_SUM_RegU_RT =
max(RegU_RT_SUM_low,[],2);
 Max_SUM_Spin_RT =
max(Spin_RT_SUM_low,[],2);


 Mean_WIN_LMP_RT  =
mean(LMP_RT_WIN_low,2);
 Mean_WIN_RegD_RT =
mean(RegD_RT_WIN_low,2);
 Mean_WIN_RegU_RT =
mean(RegU_RT_WIN_low,2);
 Mean_WIN_Spin_RT =
mean(Spin_RT_WIN_low,2);

 Mean_SUM_LMP_RT  =
mean(LMP_RT_SUM_low,2);
 Mean_SUM_RegD_RT =
mean(RegD_RT_SUM_low,2);
 Mean_SUM_RegU_RT =
mean(RegU_RT_SUM_low,2);
 Mean_SUM_Spin_RT =
mean(Spin_RT_SUM_low,2);
 display("Train Data added")
%% Preparoing data for RT robust

  [Min_LMP_rt_SUM_low]  =
MinimumRT(LMP_RT_SUM_low,0.25);
  [Min_RegU_rt_SUM_low] =
MinimumRT(RegU_RT_SUM_low,0.25);
  [Min_RegD_rt_SUM_low] =
MinimumRT(RegD_RT_SUM_low,0.25);
  [Min_Spin_rt_SUM_low] =
MinimumRT(Spin_RT_SUM_low,0.25);

  [Min_LMP_rt_WIN_low]  =
MinimumRT(LMP_RT_WIN_low,0.25);
  [Min_RegU_rt_WIN_low] =
MinimumRT(RegU_RT_WIN_low,0.25);
  [Min_RegD_rt_WIN_low] =
MinimumRT(RegD_RT_WIN_low,0.25);
  [Min_Spin_rt_WIN_low] =
MinimumRT(Spin_RT_WIN_low,0.25);
```

```
display('Data for Robust optimizatin
prepared')

 %% ADDING test data for RT (out of
sample data)
year = '2017RT';
[Spin_rt_win_test,RegU_rt_win_test,RegD_
rt_win_test,LMP_rt_win_test,Spin_rt_sum_
test,RegU_rt_sum_test,RegD_rt_sum_test,L
MP_rt_sum_test]= MarketRT(year);
clear year
  display("RT Test Data added")

%% Preparing DA data for RT Optimization
for k=1:24
    if (round(Cap_Spin_Dit_WIN(k,1))==0
&& round(Cap_RegU_Dit_WIN(k,1))==0 &&
round(Cap_RegD_Dit_WIN(k,1))==0 &&
round(Cap_Bat2G_Dit_WIN(k,1))==0)
        MM_Dit_WIN(k,1) =0;
    else
        MM_Dit_WIN(k,1) =1;
    end
    if (round(Cap_Spin_Dit_SUM(k,1))==0
&& round(Cap_RegU_Dit_SUM(k,1))==0 &&
round(Cap_RegD_Dit_SUM(k,1))==0 &&
round(Cap_Bat2G_Dit_SUM(k,1))==0)
        MM_Dit_SUM(k,1) =0;
    else
        MM_Dit_SUM(k,1) =1;
    end
    if (round(Cap_Spin_RO_WIN(k,1))==0
&& round(Cap_RegU_RO_WIN(k,1))==0 &&
round(Cap_RegD_RO_WIN(k,1))==0 &&
round(Cap_Bat2G_RO_WIN(k,1))==0)
        MM_RO_WIN(k,1) =0;
    else
        MM_RO_WIN(k,1) =1;
    end
    if (round(Cap_Spin_RO_SUM(k,1))==0
&& round(Cap_RegU_RO_SUM(k,1))==0 &&
round(Cap_RegD_RO_SUM(k,1))==0 &&
round(Cap_Bat2G_RO_SUM(k,1))==0)
        MM_RO_SUM(k,1) =0;
    else
        MM_RO_SUM(k,1) =1;
    end
    if
(round(Cap_Spin_DRO_WIN_low(k,1))==0 &&
round(Cap_RegU_DRO_WIN_low(k,1))==0 &&
round(Cap_RegD_DRO_WIN_low(k,1))==0 &&
round(Cap_Bat2G_DRO_WIN_low(k,1))==0)
        MM_DRO_WIN(k,1) =0;
    else
        MM_DRO_WIN(k,1) =1;
    end
    if
(round(Cap_Spin_DRO_SUM_low(k,1))==0 &&
round(Cap_RegU_DRO_SUM_low(k,1))==0 &&
round(Cap_RegD_DRO_SUM_low(k,1))==0 &&
round(Cap_Bat2G_DRO_SUM_low(k,1))==0)
        MM_DRO_SUM(k,1) =0;
    else
        MM_DRO_SUM(k,1) =1;
    end
end
for i=1:24       %preparing DA Data for
RT optimization
    for k=1:4

        Cap_L_RT_sum(4*(i-1)+k,1)=
Cap_L_sum(i)/4;
        Cap_PV_RT_sum(4*(i-
1)+k,1)=Cap_PV_sum(i)/4;
        Cap_L_RT_win(4*(i-1)+k,1)=
Cap_L_win(i)/4;
        Cap_PV_RT_win(4*(i-
1)+k,1)=Cap_PV_win(i)/4;
     %   % Deterministic DA Win
Cap_G2L_Dit_DA_WIN(4*(i-1)+k,1)    =
Cap_G2L_Dit_WIN(i);
Cap_Spin_Dit_DA_WIN(4*(i-1)+k,1)   =
Cap_Spin_Dit_WIN(i)*0.8;
Cap_RegU_Dit_DA_WIN(4*(i-1)+k,1)   =
Cap_RegU_Dit_WIN(i)*0.8;
Cap_RegD_Dit_DA_WIN(4*(i-1)+k,1)   =
Cap_RegD_Dit_WIN(i)*0.8;
Cap_Bat2G_Dit_DA_WIN(4*(i-1)+k,1) =
Cap_Bat2G_Dit_WIN(i)*0.8;
Cap_G2Bat_Dit_DA_WIN(4*(i-1)+k,1) =
Cap_G2Bat_Dit_WIN(i);
Mean_LMP_DA_WIN_low(4*(i-1)+k,1)  =
Mean_LMP_da_WIN_low(i);

Cap_G2L_Dit_DA_SUM(4*(i-1)+k,1)    =
Cap_G2L_Dit_SUM(i);
Cap_G2Bat_Dit_DA_SUM(4*(i-1)+k,1) =
Cap_G2Bat_Dit_SUM(i)/4;
Mean_LMP_DA_SUM_low(4*(i-1)+k,1)  =
Mean_LMP_da_SUM_low(i);
Min_LMP_DA_SUM_low(4*(i-1)+k,1)  =
Min_LMP_da_SUM_low(i);
Min_LMP_DA_WIN_low(4*(i-1)+k,1)  =
Min_LMP_da_WIN_low(i);
%    % Robust DA WIN
Cap_G2L_RO_DA_WIN(4*(i-1)+k,1)    =
Cap_G2L_RO_WIN(i)      ;
Cap_Spin_RO_DA_WIN(4*(i-1)+k,1)   =
Cap_Spin_RO_WIN(i)*0.8  ;
Cap_RegU_RO_DA_WIN(4*(i-1)+k,1)   =
Cap_RegU_RO_WIN(i)*0.8  ;
Cap_RegD_RO_DA_WIN(4*(i-1)+k,1)   =
Cap_RegD_RO_WIN(i)*0.8  ;
Cap_Bat2G_RO_DA_WIN(4*(i-1)+k,1)  =
Cap_Bat2G_RO_WIN(i)*0.8 ;
Cap_G2Bat_RO_DA_WIN(4*(i-1)+k,1)  =
Cap_G2Bat_RO_WIN(i);
Cap_G2Bat_RO_DA_SUM(4*(i-1)+k,1)  =
Cap_G2Bat_RO_SUM(i);
Cap_G2L_RO_DA_SUM(4*(i-1)+k,1)     =
Cap_G2L_RO_SUM(i)      ;
%    % DRO DA WIN
Cap_G2L_DRO_DA_WIN(4*(i-1)+k,1)    =
Cap_G2L_DRO_WIN_low(i);
Cap_Spin_DRO_DA_WIN(4*(i-1)+k,1)   =
Cap_Spin_DRO_WIN_low(i)*0.8;
Cap_RegU_DRO_DA_WIN(4*(i-1)+k,1)   =
Cap_RegU_DRO_WIN_low(i)*0.8;
Cap_RegD_DRO_DA_WIN(4*(i-1)+k,1)   =
Cap_RegD_DRO_WIN_low(i)*0.8;
Cap_Bat2G_DRO_DA_WIN(4*(i-1)+k,1) =
Cap_Bat2G_DRO_WIN_low(i)*0.8;
Cap_G2Bat_DRO_DA_WIN(4*(i-1)+k,1) =
Cap_G2Bat_DRO_WIN_low(i);

M_Dit_DA_WIN(4*(i-1)+k,1)   =
round(M_Dit_WIN(i));
M_DRO_DA_WIN_low(4*(i-1)+k,1)=
round(M_DRO_WIN_low(i));
M_RO_DA_WIN(4*(i-1)+k,1)    =
round(M_RO_WIN(i));
MM_DRO_DA_WIN(4*(i-1)+k,1) =
MM_DRO_WIN(i,1);
MM_RO_DA_WIN(4*(i-1)+k,1)   =
MM_RO_WIN(i,1);
MM_Dit_DA_WIN(4*(i-1)+k,1) =
MM_Dit_WIN(i,1);
```

```
%   % Deterministic DA SUM

Cap_Spin_Dit_DA_SUM(4*(i-1)+k,1)  =
Cap_Spin_Dit_SUM(i)*0.8;
Cap_RegU_Dit_DA_SUM(4*(i-1)+k,1)  =
Cap_RegU_Dit_SUM(i)*0.8;
Cap_RegD_Dit_DA_SUM(4*(i-1)+k,1)  =
Cap_RegD_Dit_SUM(i)*0.8;
Cap_Bat2G_Dit_DA_SUM(4*(i-1)+k,1) =
Cap_Bat2G_Dit_SUM(i)*0.8;

%   % Robust DA SUM
Cap_Spin_RO_DA_SUM(4*(i-1)+k,1)  =
Cap_Spin_RO_SUM(i)*0.8;
Cap_RegU_RO_DA_SUM(4*(i-1)+k,1)  =
Cap_RegU_RO_SUM(i)*0.8;
Cap_RegD_RO_DA_SUM(4*(i-1)+k,1)  =
Cap_RegD_RO_SUM(i)*0.8;
Cap_Bat2G_RO_DA_SUM(4*(i-1)+k,1) =
Cap_Bat2G_RO_SUM(i)*0.8;
Min_LMP_DA_WIN_low(4*(i-1)+k,1)=
Min_LMP_da_WIN_low(i)/4;

%   % DRO DA SUM
Cap_Spin_DRO_DA_SUM(4*(i-
1)+k,1)=Cap_Spin_DRO_SUM_low(i)*0.8;
Cap_RegU_DRO_DA_SUM(4*(i-
1)+k,1)=Cap_RegU_DRO_SUM_low(i)*0.8;
Cap_RegD_DRO_DA_SUM(4*(i-
1)+k,1)=Cap_RegD_DRO_SUM_low(i)*0.8;
Cap_Bat2G_DRO_DA_SUM(4*(i-
1)+k,1)=round(Cap_Bat2G_DRO_SUM_low(i)*0
.8);
Cap_G2Bat_DRO_DA_SUM(4*(i-1)+k,1) =
Cap_G2Bat_DRO_SUM_low(i);
Cap_G2L_DRO_DA_SUM(4*(i-1)+k,1)   =
Cap_G2L_DRO_SUM_low(i);


M_Dit_DA_SUM(4*(i-1)+k,1)=
round(M_Dit_SUM(i));
M_DRO_DA_SUM_low(4*(i-1)+k,1)=
round(M_DRO_SUM_low(i));
M_RO_DA_SUM(4*(i-1)+k,1)=
round(M_RO_SUM(i));
MM_DRO_DA_SUM(4*(i-1)+k,1)=
MM_DRO_SUM(i,1);
MM_RO_DA_SUM(4*(i-1)+k,1)=
MM_RO_SUM(i,1);
MM_Dit_DA_SUM(4*(i-1)+k,1)=
MM_Dit_SUM(i,1);

AGC_RT(4*(i-1)+k,1)= AGC(i,1) ;
for day=1:N_WIN_low
    LMP_DA_SUM_low(4*(i-1)+k,day)  =
LMP_da_SUM_low(i,day);
LMP_DA_WIN_low(4*(i-1)+k,day)  =
LMP_da_WIN_low(i,day);
end
    end
end

Cap_E_sell_Dit_DA_WIN =
Cap_Spin_Dit_DA_WIN+
Cap_Bat2G_Dit_DA_WIN
+Cap_RegU_Dit_DA_WIN;
Cap_E_sell_Dit_DA_SUM =
Cap_Spin_Dit_DA_SUM +
Cap_Bat2G_Dit_DA_SUM
+Cap_RegU_Dit_DA_SUM;
Cap_E_buy_Dit_DA_WIN =
Cap_G2Bat_Dit_DA_WIN+Cap_G2L_Dit_DA_WIN+
Cap_RegD_Dit_DA_WIN;
Cap_E_buy_Dit_DA_SUM =
Cap_G2Bat_Dit_DA_SUM+Cap_G2L_Dit_DA_SUM+
Cap_RegD_Dit_DA_SUM;

Cap_E_sell_RO_DA_WIN =
Cap_Spin_RO_DA_WIN + Cap_Bat2G_RO_DA_WIN
+ Cap_RegU_RO_DA_WIN;
Cap_E_sell_RO_DA_SUM =
Cap_Spin_RO_DA_SUM + Cap_Bat2G_RO_DA_SUM
+ Cap_RegU_RO_DA_SUM;
Cap_E_buy_RO_DA_WIN =
Cap_G2Bat_RO_DA_WIN + Cap_G2L_RO_DA_WIN
+ Cap_RegD_RO_DA_SUM;
Cap_E_buy_RO_DA_SUM =
Cap_G2Bat_RO_DA_SUM + Cap_G2L_RO_DA_SUM
+ Cap_RegD_RO_DA_SUM;

Cap_E_sell_DRO_DA_WIN =
Cap_Spin_DRO_DA_WIN +
Cap_Bat2G_DRO_DA_WIN +
Cap_RegU_DRO_DA_WIN;
Cap_E_sell_DRO_DA_SUM =
Cap_Spin_DRO_DA_SUM +
Cap_Bat2G_DRO_DA_SUM +
Cap_RegU_DRO_DA_SUM;
Cap_E_buy_DRO_DA_WIN =
Cap_G2Bat_DRO_DA_WIN +
Cap_G2L_DRO_DA_WIN +
Cap_RegD_DRO_DA_SUM;
Cap_E_buy_DRO_DA_SUM =
Cap_G2Bat_DRO_DA_SUM +
Cap_G2L_DRO_DA_SUM +
Cap_RegD_DRO_DA_SUM;

Tr_RegU_RT = zeros(96,1);
 Tr_RegD_RT = zeros(96,1);
 Tr_Spin_RT = zeros(96,1);

 Tr_RegD_RT(5,1)=1;
 Tr_RegD_RT(12,1)=1;
 Tr_RegD_RT(13,1)=1;
 Tr_RegD_RT(22,1)=1;
 Tr_RegD_RT(24,1)=1;
 Tr_RegD_RT(25,1)=1;
 Tr_RegD_RT(38,1)=1;
 Tr_RegD_RT(55,1)=1;
 Tr_RegD_RT(62,1)=1;
 Tr_RegD_RT(66,1)=1;
 Tr_RegD_RT(73,1)=1;
 Tr_RegD_RT(74,1)=1;
 Tr_RegD_RT(88,1)=1;

 Tr_RegU_RT(5,1)=1;
 Tr_RegU_RT(12,1)=1;
 Tr_RegU_RT(13,1)=1;
 Tr_RegU_RT(22,1)=1;
 Tr_RegU_RT(24,1)=1;
 Tr_RegU_RT(25,1)=1;
 Tr_RegU_RT(38,1)=1;
 Tr_RegU_RT(55,1)=1;
 Tr_RegU_RT(62,1)=1;
 Tr_RegU_RT(66,1)=1;
 Tr_RegU_RT(73,1)=1;
 Tr_RegU_RT(74,1)=1;
 Tr_RegU_RT(88,1)=1;

 Tr_Spin_RT(5,1)=1;
 Tr_Spin_RT(12,1)=1;
 Tr_Spin_RT(13,1)=1;
 Tr_Spin_RT(22,1)=1;
 Tr_Spin_RT(24,1)=1;
 Tr_Spin_RT(25,1)=1;
 Tr_Spin_RT(38,1)=1;
 Tr_Spin_RT(55,1)=1;
```

```
 Tr_Spin_RT(62,1)=1;
 Tr_Spin_RT(66,1)=1;
 Tr_Spin_RT(73,1)=1;
 Tr_Spin_RT(74,1)=1;
 Tr_Spin_RT(88,1)=1;

 for k=1:96
    if AGC_RT(k)==1
    Tr_RegD_RT(k,1)=0;
    else
    Tr_RegU_RT(k,1)=0;
    end
 end

 display("DA data converted to RT")

   %% Creating Solar and Load Profile
disturbance
 [W_PV_sum,W_Load_sum] =
Uncertainty(Cap_PV_RT_sum,Cap_L_RT_sum);
 [W_PV_win,W_Load_win] =
Uncertainty(Cap_PV_RT_win,Cap_L_RT_win);
display("PV and Load Disterbance added")

 %% Deterministic Summer Real time
tic
 N = 24;
 Hour = 1;
 COSTS= 0;
 SOC_Dit_RT_SUM_S = zeros(96,1);
 SOC_Dit_RT_SUM_S(4,1) = SOC_0;
 X_RT = zeros(96,1);

 clear Soc_Dit_RT_SUM_S
 clear SOC_Dit_RT_SUM_S
for k=1:96
a_RegD_Dit_DA_SUM(k,1) =
Cap_RegD_Dit_DA_SUM(k,1)/Cap_Max;
end
while Hour<= 24

clear Cap_Discharge_Dit_RT_SUM
clear cost_Charge_Dit_RT_SUM
clear cost_Demand_Dit_RT_SUM
clear income_Spin_Dit_RT_SUM
clear Income_Spin_Dit_RT_SUM
clear income_sell_Dit_RT_SUM
clear INCOME_sell_Dit_RT_SUM
clear income_E_Dit_RT_SUM
clear Income_E_Dit_RT_SUM
clear income_MilU_Dit_RT_SUM
clear income_RegU_Dit_RT_SUM
clear Income_RegU_Dit_RT_SUM
clear cost_Charge_Dit_RT_SUM
clear Cap_Charge_Dit_RT_SUM
clear income_MilD_Dit_RT_SUM
clear income_RegD_Dit_RT_SUM
clear Income_RegD_Dit_RT_SUM
clear income_Charging_Dit_RT_SUM
clear income_Discharging_Dit_RT_SUM
clear cost_OP_Dit_RT_SUM
clear Soc_Dit_RT_SUM
clear SOC_Dit_RT_SUM
clear cost_Dit_RT_SUM
clear COST_Dit_RT_SUM
clear Cap_Ex_ch_Dit_RT_SUM
clear Cap_Ex_dch_Dit_RT_SUM
clear cost_Ex_dch_Dit_RT_SUM
clear cost_Ex_ch_Dit_RT_SUM
clear a_RegU_Dit_RT_SUM
clear a_Spin_Dit_RT_SUM
clear a_LMP_Dit_RT_SUM
clear a_RegD_Dit_RT_SUM
clear a_Buy_Dit_RT_SUM
clear a_Ex_ch_Dit_RT_SUM
clear a_Ex_dch_Dit_RT_SUM
clear a_G2Bat_Dit_RT_SUM
clear a_PV2Bat_Dit_RT_SUM
clear cost_un_dch_Dit_RT_SUM
clear cost_un_ch_Dit_RT_SUM
clear a_Bat2L_Dit_RT_SUM
clear M_Dit_RT_SUM
clear Cap_Ebuy_Dit_RT_SUM
clear Cap_DEbuy_Dit_RT_SUM
clear Cap_Esell_Dit_RT_SUM
clear Cap_DEsell_Dit_RT_SUM
clear Penlaty_Ebuy_Dit_RT_SUM
clear Penlaty_Esell_Dit_RT_SUM
clear cost_buy_Dit_RT_SUM
clear income_sell_Dit_RT_SUM
cvx_begin
    variable Cap_Bat2L_Dit_RT_SUM(4*N)
nonnegative
    variable Cap_G2Bat_Dit_RT_SUM(4*N)
nonnegative
    variable Cap_RegD_Dit_RT_SUM(4*N)
nonnegative
    variable Cap_PV2L_Dit_RT_SUM(4*N)
nonnegative
    variable Cap_G2L_Dit_RT_SUM(4*N)
nonnegative
    variable Cap_Bat2G_Dit_RT_SUM(4*N)
nonnegative
    variable Cap_PV2Bat_Dit_RT_SUM(4*N)
nonnegative
    variable Cap_RegU_Dit_RT_SUM(4*N)
nonnegative
    variable Cap_Spin_Dit_RT_SUM(4*N)
nonnegative
    variable Cap_Ex_ch_Dit_RT_SUM(4*N)
nonnegative
    variable Cap_Ex_dch_Dit_RT_SUM(4*N)
nonnegative
    variable M_Dit_RT_SUM(4*N) binary
    variable Cap_Ebuy_Dit_RT_SUM(4*N)
nonnegative
    variable Cap_DEbuy_Dit_RT_SUM(4*N)
nonnegative
    variable Cap_Esell_Dit_RT_SUM(4*N)
nonnegative
    variable Cap_DEsell_Dit_RT_SUM(4*N)
nonnegative
    variable
Penlaty_Ebuy_Dit_RT_SUM(4*N) nonnegative
    variable
Penlaty_Esell_Dit_RT_SUM(4*N)
nonnegative
  for k = 1:4*N+1
      if k<=4*N
      if k<=4
          X_RT(4*(Hour-1)+k,1) = 1;
      end
   Cap_Charge_Dit_RT_SUM(k,1)
=Cap_G2Bat_Dit_RT_SUM(k)+Cap_PV2Bat_Dit_
RT_SUM(k)+Cap_RegD_Dit_RT_SUM(k)+Cap_Ex_
ch_Dit_RT_SUM(k) ;
   Cap_Discharge_Dit_RT_SUM(k,1) =
Cap_Bat2G_Dit_RT_SUM(k)+Cap_Spin_Dit_RT_
SUM(k)+Cap_RegU_Dit_RT_SUM(k)+Cap_Bat2L_
Dit_RT_SUM(k)+Cap_Ex_dch_Dit_RT_SUM(k);

   cost_buy_Dit_RT_SUM(k,1) =
(Cap_Ebuy_Dit_RT_SUM(k))/4.*(Mean_LMP_DA
_SUM_low(4*(Hour-1)+k)) +
Cap_DEbuy_Dit_RT_SUM(k).*
Mean_SUM_LMP_RT(4*(Hour-1)+k)/4 ; % Cost
of buyng energy from Grid for battery
```

```
   income_sell_Dit_RT_SUM(k,1) =
(X_RT(4*(Hour-1)+k).*
Mean_LMP_DA_SUM_low(4*(Hour-
1)+k).*(Cap_Esell_Dit_RT_SUM(k))/4)+Mean
_SUM_LMP_RT(4*(Hour-
1)+k).*Cap_DEsell_Dit_RT_SUM(k)/4; %high

   income_Spin_Dit_RT_SUM(k,1) =
X_RT(4*(Hour-1)+k).*Tr_Spin_RT(4*(Hour-
1)+k) .* (Mean_SUM_Spin_RT(4*(Hour-
1)+k).*
Cap_Spin_Dit_RT_SUM(k)/4);%Mean_Spin_da_
low
   income_RegU_Dit_RT_SUM(k,1) =
X_RT(4*(Hour-1)+k).* Tr_RegU_RT(4*(Hour-
1)+k).*(Mean_SUM_RegU_RT(4*(Hour-1)+k)
.* (Cap_RegU_Dit_RT_SUM(k)/4)) ;%
Mean_Reg_U_da_low
   income_RegD_Dit_RT_SUM(k,1) =
X_RT(4*(Hour-1)+k).*Tr_RegD_RT(4*(Hour-
1)+k).*(Mean_SUM_RegD_RT(4*(Hour-1)+k)
.* Cap_RegD_Dit_RT_SUM(k)/4);   %
Mean_Reg_D_da_low

   income_Charging_Dit_RT_SUM(k,1)=
income_RegD_Dit_RT_SUM(k) -
cost_buy_Dit_RT_SUM(k);
   income_Discharging_Dit_RT_SUM(k,1)=
income_Spin_Dit_RT_SUM(k)+income_sell_Di
t_RT_SUM(k)+income_RegU_Dit_RT_SUM(k);%+
income_sell_Dit_RT_SUM(k);

   cost_OP_Dit_RT_SUM(k,1) =  c_op
.*(Cap_PV2Bat_Dit_RT_SUM(k)+
Cap_G2Bat_Dit_RT_SUM(k) +
Cap_Bat2G_Dit_RT_SUM(k)+Tr_Spin_RT(4*(Ho
ur-1)+k) .*
Cap_Spin_Dit_RT_SUM(k)+Tr_RegD_RT(4*(Hou
r-
1)+k).*Cap_RegD_Dit_RT_SUM(k)+Cap_RegU_D
it_RT_SUM(k)+Cap_Bat2L_Dit_RT_SUM(k)) ;
% Cost operation
   cost_Ex_ch_Dit_RT_SUM(k,1) = 0*
Cap_Ex_ch_Dit_RT_SUM (k);
   cost_Ex_dch_Dit_RT_SUM(k,1) = 0*
Cap_Ex_dch_Dit_RT_SUM (k);

 Soc_Dit_RT_SUM(k,1) = Eta_Ch
.*((Cap_PV2Bat_Dit_RT_SUM(k)+
Cap_G2Bat_Dit_RT_SUM(k)+Cap_RegD_Dit_RT_
SUM(k))+...
     (Cap_RegD_Dit_DA_SUM(4*(Hour-
1)+k))./4) -
((Cap_Bat2G_Dit_RT_SUM(k,1)+Cap_Spin_Dit
_RT_SUM(k)+Cap_RegU_Dit_RT_SUM(k)+...

Cap_Bat2L_Dit_RT_SUM(k))+(Cap_Bat2G_Dit_
DA_SUM(4*(Hour-
1)+k,1)+Cap_Spin_Dit_DA_SUM(4*(Hour-
1)+k,1)+ Cap_RegU_Dit_DA_SUM(4*(Hour-
1)+k,1))/4)./(Eta_D);

 if Hour==1
     if k==1
        SOC_Dit_RT_SUM(k,1) = SOC_0 +
cost_Ex_dch_Dit_RT_SUM(k);%Soc_Dit_RT_SU
M(k,1);
     else
       SOC_Dit_RT_SUM(k,1) = SOC_0 +
sum(Soc_Dit_RT_SUM(1:k-1)) ;
     end
 else
    if k==1
          SOC_Dit_RT_SUM(k,1) =
SOC_Dit_RT_SUM_S(4*(Hour-1),1)
+Soc_Dit_RT_SUM_S(4*(Hour-1),1) +
cost_Ex_dch_Dit_RT_SUM(k);%
Soc_Dit_RT_SUM(k);
     else
          SOC_Dit_RT_SUM(k,1) =
SOC_Dit_RT_SUM_S(4*(Hour-1),1) +
sum(Soc_Dit_RT_SUM(1:k-
1))+Soc_Dit_RT_SUM_S(4*(Hour-1),1);
     end
 end

   cost_Dit_RT_SUM(k,1) =
(cost_Ex_ch_Dit_RT_SUM(k,1)+cost_Ex_dch_
Dit_RT_SUM(k,1)+cost_OP_Dit_RT_SUM(k)-
income_Discharging_Dit_RT_SUM(k)-
income_Charging_Dit_RT_SUM(k)+Penlaty_Eb
uy_Dit_RT_SUM(k)+Penlaty_Esell_Dit_RT_SU
M(k));%+
cost_OP_Dit_RT_SUM(k));%cost_Demand_Dit_
RT_SUM(k)

   a_RegU_Dit_RT_SUM(k,1)    =
Cap_RegU_Dit_RT_SUM(k)/Cap_Max;
   a_RegD_Dit_RT_SUM(k,1)    =
Cap_RegD_Dit_RT_SUM(k)/Cap_Max;
   a_Spin_Dit_RT_SUM(k,1)    =
Cap_Spin_Dit_RT_SUM(k)/Cap_Max;
   a_LMP_Dit_RT_SUM(k,1)     =
Cap_Bat2G_Dit_RT_SUM(k)/Cap_Max;
   a_Ex_ch_Dit_RT_SUM(k,1)   =
Cap_Ex_ch_Dit_RT_SUM(k)/Cap_Max;
   a_Ex_dch_Dit_RT_SUM(k,1)  =
Cap_Ex_dch_Dit_RT_SUM(k)/Cap_Max;
   a_G2Bat_Dit_RT_SUM(k,1)   =
Cap_G2Bat_Dit_RT_SUM(k)/Cap_Max;
   a_PV2Bat_Dit_RT_SUM(k,1)  =
Cap_PV2Bat_Dit_RT_SUM(k)/Cap_Max;
   a_Bat2L_Dit_RT_SUM(k,1)   =
Cap_Bat2L_Dit_RT_SUM(k)/Cap_Max;
       else
           if Hour==1
            SOC_Dit_RT_SUM(k,1) = SOC_0 +
sum(Soc_Dit_RT_SUM(1:k-1)) ;
           else
             SOC_Dit_RT_SUM(k,1) =
SOC_Dit_RT_SUM_S(4*(Hour-1),1) +
sum(Soc_Dit_RT_SUM(1:k-
1))+Soc_Dit_RT_SUM_S(4*(Hour-1),1);
           end
       end
     end


  OBJ_Dit_RT_SUM =
sum(cost_Dit_RT_SUM);%+COSTS;

minimize(OBJ_Dit_RT_SUM)

   subject to
   if Hour==1
   SOC_Dit_RT_SUM(1) == SOC_0 ;
   end

    SOC_Dit_RT_SUM(4*N+1) >= SOC_0 ;
   for k = 1:4*N

     SOC_Min <= SOC_Dit_RT_SUM(k)   <=
1*SOC_Max ;
     Cap_PV2L_Dit_RT_SUM(k) +
Cap_G2L_Dit_RT_SUM(k)+Cap_Bat2L_Dit_RT_S
UM(k) == Cap_L_RT_sum(4*(Hour-
```

```
1)+k)+W_Load_sum(4*(Hour-
1)+k).*X_RT(4*(Hour-1)+k) ;
     Cap_PV2Bat_Dit_RT_SUM(k) +
Cap_PV2L_Dit_RT_SUM(k) <=
Cap_PV_RT_sum(4*(Hour-
1)+k)+W_PV_sum(4*(Hour-
1)+k).*X_RT(4*(Hour-1)+k);

Cap_Charge_Dit_RT_SUM(k)+Cap_RegD_Dit_DA
_SUM(4*(Hour-1)+k)/4==Cap_Max.*(1-
M_Dit_DA_SUM(4*(Hour-1)+k))/4;
     Cap_Discharge_Dit_RT_SUM(k)
+(Cap_Bat2G_Dit_DA_SUM(4*(Hour-
1)+k,1)+Cap_Spin_Dit_DA_SUM(4*(Hour-
1)+k)+ Cap_RegU_Dit_DA_SUM(4*(Hour-
1)+k))/4
==Cap_Max.*(M_Dit_DA_SUM(4*(Hour-
1)+k))/4;

     0<= Cap_Ebuy_Dit_RT_SUM(k)<=
Cap_E_buy_Dit_DA_SUM(4*(Hour-1)+k,1);

Cap_Ebuy_Dit_RT_SUM(k)+Cap_DEbuy_Dit_RT_
SUM(k) == Cap_G2Bat_Dit_RT_SUM(k)+
Cap_G2L_Dit_RT_SUM(k)+
Cap_RegD_Dit_RT_SUM(k)+
Cap_RegD_Dit_DA_SUM(4*(Hour-1)+k);
     Penlaty_Ebuy_Dit_RT_SUM(k) >=
0.15*(Cap_DEbuy_Dit_RT_SUM(k)-
0.2*Cap_E_buy_Dit_DA_SUM(4*(Hour-
1)+k,1));

     0<= Cap_Esell_Dit_RT_SUM(k)<=
Cap_E_sell_Dit_DA_SUM(4*(Hour-1)+k,1);

Cap_Esell_Dit_RT_SUM(k)+Cap_DEsell_Dit_R
T_SUM(k) ==
Cap_Bat2G_Dit_RT_SUM(k,1)+Cap_Spin_Dit_R
T_SUM(k)+Cap_RegU_Dit_RT_SUM(k)+
Cap_Spin_Dit_DA_SUM(4*(Hour-
1)+k)+Cap_RegU_Dit_DA_SUM(4*(Hour-
1)+k);%+Cap_Bat2G_Dit_DA_SUM((4*(Hour-
1)+k),1);
     Penlaty_Esell_Dit_RT_SUM(k) >=
0.15*(Cap_DEsell_Dit_RT_SUM(k)-
0.2*Cap_E_sell_Dit_DA_SUM(4*(Hour-
1)+k,1));


          if MM_Dit_DA_SUM(4*(Hour-
1)+k)==1
             M_Dit_RT_SUM(k)==
M_Dit_DA_SUM(4*(Hour-1)+k);
          end
          if Tr_RegD_RT(4*(Hour-1)+k)==0
             Cap_RegD_Dit_RT_SUM(k) ==0;
          end
          if Tr_RegU_RT(4*(Hour-1)+k)==0
             Cap_RegU_Dit_RT_SUM(k) ==0;
          end
          if Tr_Spin_RT(4*(Hour-1)+k)==0
             Cap_Spin_Dit_RT_SUM(k) ==0;
          end
   end
   if k >=5
      Cap_RegD_Dit_RT_SUM(k)==0;

Cap_Spin_Dit_RT_SUM(k)+Cap_RegU_Dit_RT_S
UM(k)+Cap_Bat2G_Dit_RT_SUM(k)==0;
   end
  cvx_end
  for k=1:4
      SOC_Dit_RT_SUM_S(4*(Hour-1)+k,1) =
SOC_Dit_RT_SUM(k);
      Soc_Dit_RT_SUM_S(4*(Hour-1)+k,1) =
Soc_Dit_RT_SUM(k);
      SOCC_Dit_RT_SUM(4*(Hour-1)+k,1)  =
SOC_Dit_RT_SUM(k)/BAT_CAP;
      a_RegU_Dit_RT_SUM_S(4*(Hour-
1)+k,1) = a_RegU_Dit_RT_SUM(k,1);
      a_RegD_Dit_RT_SUM_S(4*(Hour-
1)+k,1) = a_RegD_Dit_RT_SUM(k,1);
      a_Spin_Dit_RT_SUM_S(4*(Hour-
1)+k,1) = a_Spin_Dit_RT_SUM(k,1);
      a_LMP_Dit_RT_SUM_S(4*(Hour-1)+k,1)
= a_LMP_Dit_RT_SUM(k,1) ;
      a_Ex_ch_Dit_RT_SUM_S(4*(Hour-
1)+k,1) = a_Ex_ch_Dit_RT_SUM(k,1);
      a_Ex_dch_Dit_RT_SUM_S(4*(Hour-
1)+k,1) = a_Ex_dch_Dit_RT_SUM(k,1);
      a_G2Bat_Dit_RT_SUM_S(4*(Hour-
1)+k,1) = a_G2Bat_Dit_RT_SUM(k,1);
      a_PV2Bat_Dit_RT_SUM_S(4*(Hour-
1)+k,1) = a_PV2Bat_Dit_RT_SUM(k,1);
      a_Bat2L_Dit_RT_SUM_S(4*(Hour-
1)+k,1) = a_Bat2L_Dit_RT_SUM(k,1);
      a_PV2L_Dit_RT_SUM_S(4*(Hour-
1)+k,1) =
Cap_PV2L_Dit_RT_SUM(k,1)/Cap_Max;
      a_G2L_Dit_RT_SUM_S(4*(Hour-1)+k,1)
= Cap_G2L_Dit_RT_SUM(k,1)/Cap_Max;
      M_Dit_RT_SUM_S(4*(Hour-1)+k,1) =
M_Dit_RT_SUM(k);
      Cap_Ebuy_Dit_RT_SUM_S(4*(Hour-
1)+k,1) =  Cap_Ebuy_Dit_RT_SUM(k);
      Cap_Esell_Dit_RT_SUM_S(4*(Hour-
1)+k,1) =  Cap_Esell_Dit_RT_SUM(k);
      Cap_DEsell_Dit_RT_SUM_S(4*(Hour-
1)+k,1) = Cap_DEsell_Dit_RT_SUM(k);
      Cap_DEbuy_Dit_RT_SUM_S(4*(Hour-
1)+k,1) = Cap_DEbuy_Dit_RT_SUM(k);
  end
  N = N-1;

  %COSTS =
sum(OBJ_Dit_RT_SUM(1:4*Hour));
  Hour = Hour +1;
end
load gong.mat;
sound(y);
display("WELL DONE!!")

t_Dit_RT_SUM = toc
 %%% Deterministic Winter Real time
tic
 N = 24;
 Hour = 1;
 COSTS= 0;
 SOC_Dit_RT_WIN_S = zeros(96,1);
 SOC_Dit_RT_WIN_S(4,1) = SOC_0;
 X_RT = zeros(96,1);

 clear Soc_Dit_RT_WIN_S
 clear SOC_Dit_RT_WIN_S
for k=1:96
a_RegD_Dit_DA_WIN(k,1) =
Cap_RegD_Dit_DA_WIN(k,1)/Cap_Max;
end
while Hour<= 24

clear Cap_Discharge_Dit_RT_WIN
clear cost_Charge_Dit_RT_WIN
clear cost_Demand_Dit_RT_WIN
clear income_Spin_Dit_RT_WIN
clear Income_Spin_Dit_RT_WIN
clear income_sell_Dit_RT_WIN
clear INCOME_sell_Dit_RT_WIN
clear income_E_Dit_RT_WIN
```

```
clear Income_E_Dit_RT_WIN
clear income_MilU_Dit_RT_WIN
clear income_RegU_Dit_RT_WIN
clear Income_RegU_Dit_RT_WIN
clear cost_Charge_Dit_RT_WIN
clear Cap_Charge_Dit_RT_WIN
clear income_MilD_Dit_RT_WIN
clear income_RegD_Dit_RT_WIN
clear Income_RegD_Dit_RT_WIN
clear income_Charging_Dit_RT_WIN
clear income_Discharging_Dit_RT_WIN
clear cost_OP_Dit_RT_WIN
clear Soc_Dit_RT_WIN
clear SOC_Dit_RT_WIN
clear cost_Dit_RT_WIN
clear COST_Dit_RT_WIN
clear Cap_Ex_ch_Dit_RT_WIN
clear Cap_Ex_dch_Dit_RT_WIN
clear cost_Ex_dch_Dit_RT_WIN
clear cost_Ex_ch_Dit_RT_WIN
clear a_RegU_Dit_RT_WIN
clear a_Spin_Dit_RT_WIN
clear a_LMP_Dit_RT_WIN
clear a_RegD_Dit_RT_WIN
clear a_Buy_Dit_RT_WIN
clear a_Ex_ch_Dit_RT_WIN
clear a_Ex_dch_Dit_RT_WIN
clear a_G2Bat_Dit_RT_WIN
clear a_PV2Bat_Dit_RT_WIN
clear cost_un_dch_Dit_RT_WIN
clear cost_un_ch_Dit_RT_WIN
clear a_Bat2L_Dit_RT_WIN
clear M_Dit_RT_WIN
clear Cap_Ebuy_Dit_RT_WIN
clear Cap_DEbuy_Dit_RT_WIN
clear Cap_Esell_Dit_RT_WIN
clear Cap_DEsell_Dit_RT_WIN
clear Penlaty_Ebuy_Dit_RT_WIN
clear Penlaty_Esell_Dit_RT_WIN
clear cost_buy_Dit_RT_WIN
clear income_sell_Dit_RT_WIN
cvx_begin
    variable Cap_Bat2L_Dit_RT_WIN(4*N)
nonnegative
    variable Cap_G2Bat_Dit_RT_WIN(4*N)
nonnegative
    variable Cap_RegD_Dit_RT_WIN(4*N)
nonnegative
    variable Cap_PV2L_Dit_RT_WIN(4*N)
nonnegative
    variable Cap_G2L_Dit_RT_WIN(4*N)
nonnegative
    variable Cap_Bat2G_Dit_RT_WIN(4*N)
nonnegative
    variable Cap_PV2Bat_Dit_RT_WIN(4*N)
nonnegative
    variable Cap_RegU_Dit_RT_WIN(4*N)
nonnegative
    variable Cap_Spin_Dit_RT_WIN(4*N)
nonnegative
    variable Cap_Ex_ch_Dit_RT_WIN(4*N)
nonnegative
    variable Cap_Ex_dch_Dit_RT_WIN(4*N)
nonnegative
    variable M_Dit_RT_WIN(4*N) binary
    variable Cap_Ebuy_Dit_RT_WIN(4*N)
nonnegative
    variable Cap_DEbuy_Dit_RT_WIN(4*N)
nonnegative
    variable Cap_Esell_Dit_RT_WIN(4*N)
nonnegative
    variable Cap_DEsell_Dit_RT_WIN(4*N)
nonnegative
    variable
Penlaty_Ebuy_Dit_RT_WIN(4*N) nonnegative
    variable
Penlaty_Esell_Dit_RT_WIN(4*N)
nonnegative
  for k = 1:4*N+1
      if k<=4*N
      if k<=4
          X_RT(4*(Hour-1)+k,1) = 1;
      end
   Cap_Charge_Dit_RT_WIN(k,1)
=Cap_G2Bat_Dit_RT_WIN(k)+Cap_PV2Bat_Dit_
RT_WIN(k)+Cap_RegD_Dit_RT_WIN(k)+Cap_Ex_
ch_Dit_RT_WIN(k) ;
   Cap_Discharge_Dit_RT_WIN(k,1) =
Cap_Bat2G_Dit_RT_WIN(k)+Cap_Spin_Dit_RT_
WIN(k)+Cap_RegU_Dit_RT_WIN(k)+Cap_Bat2L_
Dit_RT_WIN(k)+Cap_Ex_dch_Dit_RT_WIN(k);

   cost_buy_Dit_RT_WIN(k,1) =
(Cap_Ebuy_Dit_RT_WIN(k))/4.*(Mean_LMP_DA
_WIN_low(4*(Hour-1)+k)) +
Cap_DEbuy_Dit_RT_WIN(k).*
Mean_WIN_LMP_RT(4*(Hour-1)+k)/4 ; % Cost
of buyng energy from Grid for battery
   income_sell_Dit_RT_WIN(k,1) =
(X_RT(4*(Hour-1)+k).*
Mean_LMP_DA_WIN_low(4*(Hour-
1)+k).*(Cap_Esell_Dit_RT_WIN(k))/4)+Mean
_WIN_LMP_RT(4*(Hour-
1)+k).*Cap_DEsell_Dit_RT_WIN(k)/4; %high

   income_Spin_Dit_RT_WIN(k,1) =
X_RT(4*(Hour-1)+k).*Tr_Spin_RT(4*(Hour-
1)+k) .* (Mean_WIN_Spin_RT(4*(Hour-
1)+k).*
Cap_Spin_Dit_RT_WIN(k)/4);%Mean_Spin_da_
low
   income_RegU_Dit_RT_WIN(k,1) =
X_RT(4*(Hour-1)+k).* Tr_RegU_RT(4*(Hour-
1)+k).*(Mean_WIN_RegU_RT(4*(Hour-1)+k)
.* (Cap_RegU_Dit_RT_WIN(k)/4)) ;%
Mean_Reg_U_da_low
   income_RegD_Dit_RT_WIN(k,1) =
X_RT(4*(Hour-1)+k).*Tr_RegD_RT(4*(Hour-
1)+k).*(Mean_WIN_RegD_RT(4*(Hour-1)+k)
.* Cap_RegD_Dit_RT_WIN(k)/4);   %
Mean_Reg_D_da_low

   income_Charging_Dit_RT_WIN(k,1)=
income_RegD_Dit_RT_WIN(k) -
cost_buy_Dit_RT_WIN(k);
   income_Discharging_Dit_RT_WIN(k,1)=
income_Spin_Dit_RT_WIN(k)+income_sell_Di
t_RT_WIN(k)+income_RegU_Dit_RT_WIN(k);%+
income_sell_Dit_RT_WIN(k);

   cost_OP_Dit_RT_WIN(k,1) =  c_op
.*(Cap_PV2Bat_Dit_RT_WIN(k)+
Cap_G2Bat_Dit_RT_WIN(k) +
Cap_Bat2G_Dit_RT_WIN(k)+Tr_Spin_RT(4*(Ho
ur-1)+k) .*
Cap_Spin_Dit_RT_WIN(k)+Tr_RegD_RT(4*(Hou
r-
1)+k).*Cap_RegD_Dit_RT_WIN(k)+Cap_RegU_D
it_RT_WIN(k)+Cap_Bat2L_Dit_RT_WIN(k)) ;
% Cost operation
   cost_Ex_ch_Dit_RT_WIN(k,1) = 0*
Cap_Ex_ch_Dit_RT_WIN (k);
   cost_Ex_dch_Dit_RT_WIN(k,1) = 0*
Cap_Ex_dch_Dit_RT_WIN (k);

 Soc_Dit_RT_WIN(k,1) = Eta_Ch
.*((Cap_PV2Bat_Dit_RT_WIN(k)+
```

```
Cap_G2Bat_Dit_RT_WIN(k)+Cap_RegD_Dit_RT_
WIN(k))+...
     (Cap_RegD_Dit_DA_WIN(4*(Hour-
1)+k))./4) -
((Cap_Bat2G_Dit_RT_WIN(k,1)+Cap_Spin_Dit
_RT_WIN(k)+Cap_RegU_Dit_RT_WIN(k)+...

Cap_Bat2L_Dit_RT_WIN(k))+(Cap_Bat2G_Dit_
DA_WIN(4*(Hour-
1)+k,1)+Cap_Spin_Dit_DA_WIN(4*(Hour-
1)+k,1)+ Cap_RegU_Dit_DA_WIN(4*(Hour-
1)+k,1))/4)./(Eta_D);

 if Hour==1
     if k==1
        SOC_Dit_RT_WIN(k,1) = SOC_0 +
cost_Ex_dch_Dit_RT_WIN(k);%Soc_Dit_RT_WI
N(k,1);
     else
       SOC_Dit_RT_WIN(k,1) = SOC_0 +
sum(Soc_Dit_RT_WIN(1:k-1)) ;
     end
 else
    if k==1
         SOC_Dit_RT_WIN(k,1) =
SOC_Dit_RT_WIN_S(4*(Hour-1),1) +
Soc_Dit_RT_WIN_S(4*(Hour-1),1) +
cost_Ex_dch_Dit_RT_WIN(k);%
Soc_Dit_RT_WIN(k);
    else
         SOC_Dit_RT_WIN(k,1) =
SOC_Dit_RT_WIN_S(4*(Hour-1),1) +
sum(Soc_Dit_RT_WIN(1:k-1)) +
Soc_Dit_RT_WIN_S(4*(Hour-1),1);
    end
 end

   cost_Dit_RT_WIN(k,1) =
(cost_Ex_ch_Dit_RT_WIN(k,1)+cost_Ex_dch_
Dit_RT_WIN(k,1)+cost_OP_Dit_RT_WIN(k)-
income_Discharging_Dit_RT_WIN(k)-
income_Charging_Dit_RT_WIN(k)+Penlaty_Eb
uy_Dit_RT_WIN(k)+Penlaty_Esell_Dit_RT_WI
N(k));%+
cost_OP_Dit_RT_WIN(k));%cost_Demand_Dit_
RT_WIN(k)

   a_RegU_Dit_RT_WIN(k,1)    =
Cap_RegU_Dit_RT_WIN(k)/Cap_Max;
   a_RegD_Dit_RT_WIN(k,1)    =
Cap_RegD_Dit_RT_WIN(k)/Cap_Max;
   a_Spin_Dit_RT_WIN(k,1)    =
Cap_Spin_Dit_RT_WIN(k)/Cap_Max;
   a_LMP_Dit_RT_WIN(k,1)     =
Cap_Bat2G_Dit_RT_WIN(k)/Cap_Max;
   a_Ex_ch_Dit_RT_WIN(k,1)   =
Cap_Ex_ch_Dit_RT_WIN(k)/Cap_Max;
   a_Ex_dch_Dit_RT_WIN(k,1) =
Cap_Ex_dch_Dit_RT_WIN(k)/Cap_Max;
   a_G2Bat_Dit_RT_WIN(k,1)   =
Cap_G2Bat_Dit_RT_WIN(k)/Cap_Max;
   a_PV2Bat_Dit_RT_WIN(k,1) =
Cap_PV2Bat_Dit_RT_WIN(k)/Cap_Max;
   a_Bat2L_Dit_RT_WIN(k,1)   =
Cap_Bat2L_Dit_RT_WIN(k)/Cap_Max;
    else
          if Hour==1
           SOC_Dit_RT_WIN(k,1) = SOC_0 +
sum(Soc_Dit_RT_WIN(1:k-1)) ;
          else
            SOC_Dit_RT_WIN(k,1) =
SOC_Dit_RT_WIN_S(4*(Hour-1),1) +
sum(Soc_Dit_RT_WIN(1:k-
1))+Soc_Dit_RT_WIN_S(4*(Hour-1),1);
          end
      end
    end

  OBJ_Dit_RT_WIN =
sum(cost_Dit_RT_WIN);%+COSTS;

minimize(OBJ_Dit_RT_WIN)

   subject to
   if Hour==1
   SOC_Dit_RT_WIN(1) == SOC_0 ;
   end

    SOC_Dit_RT_WIN(4*N+1) >= SOC_0 ;
   for k = 1:4*N

     SOC_Min <= SOC_Dit_RT_WIN(k)  <=
1*SOC_Max ;
     Cap_PV2L_Dit_RT_WIN(k) +
Cap_G2L_Dit_RT_WIN(k)+Cap_Bat2L_Dit_RT_W
IN(k) == Cap_L_RT_win(4*(Hour-
1)+k)+W_Load_win(4*(Hour-
1)+k).*X_RT(4*(Hour-1)+k) ;
     Cap_PV2Bat_Dit_RT_WIN(k) +
Cap_PV2L_Dit_RT_WIN(k) <=
Cap_PV_RT_win(4*(Hour-
1)+k)+W_PV_win(4*(Hour-
1)+k).*X_RT(4*(Hour-1)+k);

Cap_Charge_Dit_RT_WIN(k)+Cap_RegD_Dit_DA
_WIN(4*(Hour-1)+k)/4==Cap_Max.*(1-
M_Dit_DA_WIN(4*(Hour-1)+k))/4;
     Cap_Discharge_Dit_RT_WIN(k)
+(Cap_Bat2G_Dit_DA_WIN(4*(Hour-
1)+k,1)+Cap_Spin_Dit_DA_WIN(4*(Hour-
1)+k)+ Cap_RegU_Dit_DA_WIN(4*(Hour-
1)+k))/4
==Cap_Max.*(M_Dit_DA_WIN(4*(Hour-
1)+k))/4;

     0<= Cap_Ebuy_Dit_RT_WIN(k)<=
Cap_E_buy_Dit_DA_WIN(4*(Hour-1)+k,1);

Cap_Ebuy_Dit_RT_WIN(k)+Cap_DEbuy_Dit_RT_
WIN(k) == Cap_G2Bat_Dit_RT_WIN(k)+
Cap_G2L_Dit_RT_WIN(k)+
Cap_RegD_Dit_RT_WIN(k)+
Cap_RegD_Dit_DA_WIN(4*(Hour-1)+k);
     Penlaty_Ebuy_Dit_RT_WIN(k) >=
0.15*(Cap_DEbuy_Dit_RT_WIN(k)-
0.2*Cap_E_buy_Dit_DA_WIN(4*(Hour-
1)+k,1));

     0<= Cap_Esell_Dit_RT_WIN(k)<=
Cap_E_sell_Dit_DA_WIN(4*(Hour-1)+k,1);

Cap_Esell_Dit_RT_WIN(k)+Cap_DEsell_Dit_R
T_WIN(k) ==
Cap_Bat2G_Dit_RT_WIN(k,1)+Cap_Spin_Dit_R
T_WIN(k)+Cap_RegU_Dit_RT_WIN(k)+
Cap_Spin_Dit_DA_WIN(4*(Hour-
1)+k)+Cap_RegU_Dit_DA_WIN(4*(Hour-
1)+k);%+Cap_Bat2G_Dit_DA_WIN((4*(Hour-
1)+k),1);
     Penlaty_Esell_Dit_RT_WIN(k) >=
0.15*(Cap_DEsell_Dit_RT_WIN(k)-
0.2*Cap_E_sell_Dit_DA_WIN(4*(Hour-
1)+k,1));


          if MM_Dit_DA_WIN(4*(Hour-
1)+k)==1
```

```
               M_Dit_RT_WIN(k)==
M_Dit_DA_WIN(4*(Hour-1)+k);
          end
          if Tr_RegD_RT(4*(Hour-1)+k)==0
             Cap_RegD_Dit_RT_WIN(k) ==0;
          end
          if Tr_RegU_RT(4*(Hour-1)+k)==0
             Cap_RegU_Dit_RT_WIN(k) ==0;
          end
          if Tr_Spin_RT(4*(Hour-1)+k)==0
             Cap_Spin_Dit_RT_WIN(k) ==0;
          end
   end
   if k >=5
      Cap_RegD_Dit_RT_WIN(k)==0;

Cap_Spin_Dit_RT_WIN(k)+Cap_RegU_Dit_RT_W
IN(k)+Cap_Bat2G_Dit_RT_WIN(k)==0;
   end
  cvx_end
  for k=1:4
      SOC_Dit_RT_WIN_S(4*(Hour-1)+k,1) =
SOC_Dit_RT_WIN(k);
      Soc_Dit_RT_WIN_S(4*(Hour-1)+k,1) =
Soc_Dit_RT_WIN(k);
      SOCC_Dit_RT_WIN(4*(Hour-1)+k,1)   =
SOC_Dit_RT_WIN(k)/BAT_CAP;
      a_RegU_Dit_RT_WIN_S(4*(Hour-
1)+k,1) = a_RegU_Dit_RT_WIN(k,1);
      a_RegD_Dit_RT_WIN_S(4*(Hour-
1)+k,1) = a_RegD_Dit_RT_WIN(k,1);
      a_Spin_Dit_RT_WIN_S(4*(Hour-
1)+k,1) = a_Spin_Dit_RT_WIN(k,1);
      a_LMP_Dit_RT_WIN_S(4*(Hour-1)+k,1)
= a_LMP_Dit_RT_WIN(k,1) ;
      a_Ex_ch_Dit_RT_WIN_S(4*(Hour-
1)+k,1) = a_Ex_ch_Dit_RT_WIN(k,1);
      a_Ex_dch_Dit_RT_WIN_S(4*(Hour-
1)+k,1) = a_Ex_dch_Dit_RT_WIN(k,1);
      a_G2Bat_Dit_RT_WIN_S(4*(Hour-
1)+k,1) = a_G2Bat_Dit_RT_WIN(k,1);
      a_PV2Bat_Dit_RT_WIN_S(4*(Hour-
1)+k,1) = a_PV2Bat_Dit_RT_WIN(k,1);
      a_Bat2L_Dit_RT_WIN_S(4*(Hour-
1)+k,1) = a_Bat2L_Dit_RT_WIN(k,1);
      a_PV2L_Dit_RT_WIN_S(4*(Hour-
1)+k,1) =
Cap_PV2L_Dit_RT_WIN(k,1)/Cap_Max;
      a_G2L_Dit_RT_WIN_S(4*(Hour-1)+k,1)
= Cap_G2L_Dit_RT_WIN(k,1)/Cap_Max;
      M_Dit_RT_WIN_S(4*(Hour-1)+k,1) =
M_Dit_RT_WIN(k);
      Cap_Ebuy_Dit_RT_WIN_S(4*(Hour-
1)+k,1) =  Cap_Ebuy_Dit_RT_WIN(k);
      Cap_Esell_Dit_RT_WIN_S(4*(Hour-
1)+k,1) =  Cap_Esell_Dit_RT_WIN(k);
      Cap_DEsell_Dit_RT_WIN_S(4*(Hour-
1)+k,1) = Cap_DEsell_Dit_RT_WIN(k);
      Cap_DEbuy_Dit_RT_WIN_S(4*(Hour-
1)+k,1) = Cap_DEbuy_Dit_RT_WIN(k);
  end
  N = N-1;

  %COSTS =
sum(OBJ_Dit_RT_WIN(1:4*Hour));
  Hour = Hour +1;
end
load gong.mat;
sound(y);
display("WELL DONE!!")

t_Dit_RT_WIN = toc

%% % Robust Winter Real time
```

```
tic
 N = 24;
 Hour = 1;
 COSTS= 0;
 SOC_RO_RT_WIN_S = zeros(96,1);
 SOC_RO_RT_WIN_S(4,1) = SOC_0;
 X_RT = zeros(96,1);

 clear Soc_RO_RT_WIN_S
 clear SOC_RO_RT_WIN_S
for k=1:96
a_RegD_RO_DA_WIN(k,1) =
Cap_RegD_RO_DA_WIN(k,1)/Cap_Max;
end
while Hour<= 24

clear Cap_Discharge_RO_RT_WIN
clear cost_Charge_RO_RT_WIN
clear cost_Demand_RO_RT_WIN
clear income_Spin_RO_RT_WIN
clear Income_Spin_RO_RT_WIN
clear income_sell_RO_RT_WIN
clear INCOME_sell_RO_RT_WIN
clear income_E_RO_RT_WIN
clear Income_E_RO_RT_WIN
clear income_MilU_RO_RT_WIN
clear income_RegU_RO_RT_WIN
clear Income_RegU_RO_RT_WIN
clear cost_Charge_RO_RT_WIN
clear Cap_Charge_RO_RT_WIN
clear income_MilD_RO_RT_WIN
clear income_RegD_RO_RT_WIN
clear Income_RegD_RO_RT_WIN
clear income_Charging_RO_RT_WIN
clear income_Discharging_RO_RT_WIN
clear cost_OP_RO_RT_WIN
clear Soc_RO_RT_WIN
clear SOC_RO_RT_WIN
clear cost_RO_RT_WIN
clear COST_RO_RT_WIN
clear Cap_Ex_ch_RO_RT_WIN
clear Cap_Ex_dch_RO_RT_WIN
clear cost_Ex_dch_RO_RT_WIN
clear cost_Ex_ch_RO_RT_WIN
clear a_RegU_RO_RT_WIN
clear a_Spin_RO_RT_WIN
clear a_LMP_RO_RT_WIN
clear a_RegD_RO_RT_WIN
clear a_Buy_RO_RT_WIN
clear a_Ex_ch_RO_RT_WIN
clear a_Ex_dch_RO_RT_WIN
clear a_G2Bat_RO_RT_WIN
clear a_PV2Bat_RO_RT_WIN
clear cost_un_dch_RO_RT_WIN
clear cost_un_ch_RO_RT_WIN
clear a_Bat2L_RO_RT_WIN
clear M_RO_RT_WIN
clear Cap_Ebuy_RO_RT_WIN
clear Cap_DEbuy_RO_RT_WIN
clear Cap_Esell_RO_RT_WIN
clear Cap_DEsell_RO_RT_WIN
clear cost_buy_RO_RT_WIN
clear income_sell_RO_RT_WIN
clear Penlaty_Ebuy_RO_RT_WIN
clear Penlaty_Esell_RO_RT_WIN
cvx_begin
    variable Cap_Bat2L_RO_RT_WIN(4*N)
nonnegative
    variable Cap_G2Bat_RO_RT_WIN(4*N)
nonnegative
    variable Cap_RegD_RO_RT_WIN(4*N)
nonnegative
```

```
    variable Cap_PV2L_RO_RT_WIN(4*N)
nonnegative
    variable Cap_G2L_RO_RT_WIN(4*N)
nonnegative
    variable Cap_Bat2G_RO_RT_WIN(4*N)
nonnegative
    variable Cap_PV2Bat_RO_RT_WIN(4*N)
nonnegative
    variable Cap_RegU_RO_RT_WIN(4*N)
nonnegative
    variable Cap_Spin_RO_RT_WIN(4*N)
nonnegative
    variable Cap_Ex_ch_RO_RT_WIN(4*N)
nonnegative
    variable Cap_Ex_dch_RO_RT_WIN(4*N)
nonnegative
    variable M_RO_RT_WIN(4*N) binary
    variable Cap_Ebuy_RO_RT_WIN(4*N)
nonnegative
    variable Cap_DEbuy_RO_RT_WIN(4*N)
nonnegative
    variable Cap_Esell_RO_RT_WIN(4*N)
nonnegative
    variable Cap_DEsell_RO_RT_WIN(4*N)
nonnegative
    variable Penlaty_Ebuy_RO_RT_WIN(4*N)
nonnegative
    variable
Penlaty_Esell_RO_RT_WIN(4*N) nonnegative
  for k = 1:4*N+1
      if k<=4*N
      if k<=4
          X_RT(4*(Hour-1)+k,1) = 1;
      end
   Cap_Charge_RO_RT_WIN(k,1) =
Cap_G2Bat_RO_RT_WIN(k)+Cap_PV2Bat_RO_RT_
WIN(k)+Cap_RegD_RO_RT_WIN(k)+Cap_Ex_ch_R
O_RT_WIN(k) ;
   Cap_Discharge_RO_RT_WIN(k,1) =
Cap_Bat2G_RO_RT_WIN(k)+Cap_Spin_RO_RT_WI
N(k)+Cap_RegU_RO_RT_WIN(k)+Cap_Bat2L_RO_
RT_WIN(k)+Cap_Ex_dch_RO_RT_WIN(k);

   cost_buy_RO_RT_WIN(k,1) =
[Cap_Ebuy_RO_RT_WIN(k).*Min_LMP_DA_SUM_l
ow(4*(Hour-
1)+k)+Cap_DEbuy_RO_RT_WIN(k).*Min_LMP_rt
_SUM_low(4*(Hour-1)+k)]/4;
   income_sell_RO_RT_WIN(k,1) =
[Cap_Esell_RO_RT_WIN(k).*Min_LMP_DA_SUM_
low(4*(Hour-
1)+k)+Cap_DEsell_RO_RT_WIN(k).*Min_LMP_r
t_SUM_low(4*(Hour-1)+k)]/4;

   income_Spin_RO_RT_WIN(k,1) =
X_RT(4*(Hour-1)+k).*Tr_Spin_RT(4*(Hour-
1)+k).* (Min_Spin_rt_WIN_low(4*(Hour-
1)+k).*
Cap_Spin_RO_RT_WIN(k)/4);%Mean_Spin_da_l
ow
   income_RegU_RO_RT_WIN(k,1) =
X_RT(4*(Hour-1)+k).* Tr_RegU_RT(4*(Hour-
1)+k).*(Min_RegU_rt_WIN_low(4*(Hour-
1)+k) .* (Cap_RegU_RO_RT_WIN(k)/4)) ;%
Mean_Reg_U_da_low
   income_RegD_RO_RT_WIN(k,1) =
X_RT(4*(Hour-1)+k).*Tr_RegD_RT(4*(Hour-
1)+k).*(Min_RegD_rt_WIN_low(4*(Hour-
1)+k) .* Cap_RegD_RO_RT_WIN(k)/4);  %
Mean_Reg_D_da_low

   income_Charging_RO_RT_WIN(k,1)=
income_RegD_RO_RT_WIN(k) -
cost_buy_RO_RT_WIN(k);

   income_Discharging_RO_RT_WIN(k,1)=
income_Spin_RO_RT_WIN(k)+income_sell_RO_
RT_WIN(k)+income_RegU_RO_RT_WIN(k);%+inc
ome_sell_RO_RT_WIN(k);

   cost_OP_RO_RT_WIN(k,1) =  c_op
.*(Cap_PV2Bat_RO_RT_WIN(k)+
Cap_G2Bat_RO_RT_WIN(k) +
Cap_Bat2G_RO_RT_WIN(k)+Tr_Spin_RT(4*(Hou
r-1)+k) .*
Cap_Spin_RO_RT_WIN(k)+Tr_RegD_RT(4*(Hour
-
1)+k).*Cap_RegD_RO_RT_WIN(k)+Cap_RegU_RO
_RT_WIN(k)+Cap_Bat2L_RO_RT_WIN(k)) ; %
Cost operation
   cost_Ex_ch_RO_RT_WIN(k,1) =0*
Cap_Ex_ch_RO_RT_WIN(k);
   cost_Ex_dch_RO_RT_WIN(k,1) =0*
Cap_Ex_dch_RO_RT_WIN(k);

 Soc_RO_RT_WIN(k,1) = Eta_Ch
.*((Cap_PV2Bat_RO_RT_WIN(k)+
Cap_G2Bat_RO_RT_WIN(k)+Cap_RegD_RO_RT_WI
N(k))+...
     (Cap_RegD_RO_DA_WIN(4*(Hour-
1)+k))./4) -
((Cap_Bat2G_RO_RT_WIN(k,1)+Cap_Spin_RO_R
T_WIN(k)+Cap_RegU_RO_RT_WIN(k)+...

Cap_Bat2L_RO_RT_WIN(k))+(Cap_Bat2G_RO_DA
_WIN(4*(Hour-
1)+k,1)+Cap_Spin_RO_DA_WIN(4*(Hour-
1)+k,1)+ Cap_RegU_RO_DA_WIN(4*(Hour-
1)+k,1))/4)./(Eta_D);

 if Hour==1
     if k==1
        SOC_RO_RT_WIN(k,1) = SOC_0 +
cost_Ex_dch_RO_RT_WIN(k);%Soc_RO_RT_WIN(
k,1);
     else
       SOC_RO_RT_WIN(k,1) = SOC_0 +
sum(Soc_RO_RT_WIN(1:k-1)) ;
     end
 else
    if k==1
         SOC_RO_RT_WIN(k,1) =
SOC_RO_RT_WIN_S(4*(Hour-1),1)
+Soc_RO_RT_WIN_S(4*(Hour-1),1) +
cost_Ex_dch_RO_RT_WIN(k);%
Soc_RO_RT_WIN(k);
    else
         SOC_RO_RT_WIN(k,1) =
SOC_RO_RT_WIN_S(4*(Hour-1),1) +
sum(Soc_RO_RT_WIN(1:k-
1))+Soc_RO_RT_WIN_S(4*(Hour-1),1);
    end
 end

   cost_RO_RT_WIN(k,1) =
(cost_Ex_ch_RO_RT_WIN(k,1)+cost_Ex_dch_R
O_RT_WIN(k,1)+cost_OP_RO_RT_WIN(k)-
income_Discharging_RO_RT_WIN(k)-
income_Charging_RO_RT_WIN(k)+Penlaty_Ebu
y_RO_RT_WIN(k)+Penlaty_Esell_RO_RT_WIN(k
));
   a_RegU_RO_RT_WIN(k,1) =
Cap_RegU_RO_RT_WIN(k)/Cap_Max;
   a_RegD_RO_RT_WIN(k,1) =
Cap_RegD_RO_RT_WIN(k)/Cap_Max;
   a_Spin_RO_RT_WIN(k,1) =
Cap_Spin_RO_RT_WIN(k)/Cap_Max;
   a_LMP_RO_RT_WIN(k,1)  =
(Cap_Bat2G_RO_RT_WIN(k))/Cap_Max;
```

```
   a_Ex_ch_RO_RT_WIN(k,1) =
Cap_Ex_ch_RO_RT_WIN(k)/Cap_Max;
   a_Ex_dch_RO_RT_WIN(k,1) =
Cap_Ex_dch_RO_RT_WIN(k)/Cap_Max;
   a_G2Bat_RO_RT_WIN(k,1) =
Cap_G2Bat_RO_RT_WIN(k)/Cap_Max;
   a_PV2Bat_RO_RT_WIN(k,1) =
Cap_PV2Bat_RO_RT_WIN(k)/Cap_Max;
   a_Bat2L_RO_RT_WIN(k,1) =
Cap_Bat2L_RO_RT_WIN(k)/Cap_Max;
      else
          if Hour==1
           SOC_RO_RT_WIN(k,1) = SOC_0 +
sum(Soc_RO_RT_WIN(1:k-1)) ;
          else
            SOC_RO_RT_WIN(k,1) =
SOC_RO_RT_WIN_S(4*(Hour-1),1) +
sum(Soc_RO_RT_WIN(1:k-
1))+Soc_RO_RT_WIN_S(4*(Hour-1),1);
          end
      end
    end


  OBJ_RO_RT_WIN =
sum(cost_RO_RT_WIN);%+COSTS;

minimize(OBJ_RO_RT_WIN)

   subject to
   if Hour==1
   SOC_RO_RT_WIN(1) == SOC_0 ;
   end

    SOC_RO_RT_WIN(4*N+1) >= SOC_0 ;
   for k = 1:4*N

   SOC_Min <= SOC_RO_RT_WIN(k)  <=
1*SOC_Max ;
     0 <=
Cap_G2Bat_RO_RT_WIN(k)+Cap_RegD_RO_RT_WI
N(k) +
Cap_PV2Bat_RO_RT_WIN(k)+Cap_Ex_ch_RO_RT_
WIN(k) +Cap_RegD_RO_DA_WIN(4*(Hour-
1)+k)/4 == Cap_Max.*(1-
M_RO_RT_WIN(k))/4;%
     0 <=
Cap_Spin_RO_RT_WIN(k)+Cap_RegU_RO_RT_WIN
(k)+Cap_Bat2G_RO_RT_WIN(k) +
Cap_Bat2L_RO_RT_WIN(k)+Cap_Ex_dch_RO_RT_
WIN(k) +(Cap_Bat2G_RO_DA_WIN(4*(Hour-
1)+k,1)+Cap_Spin_RO_DA_WIN(4*(Hour-
1)+k)+ Cap_RegU_RO_DA_WIN(4*(Hour-
1)+k))/4 == Cap_Max.*(M_RO_RT_WIN(k))/4;
% +
    Cap_PV2L_RO_RT_WIN(k) +
Cap_G2L_RO_RT_WIN(k)+Cap_Bat2L_RO_RT_WIN
(k) == Cap_L_RT_win(4*(Hour-
1)+k)+W_Load_win(4*(Hour-
1)+k).*X_RT(4*(Hour-1)+k) ;%
    Cap_PV2Bat_RO_RT_WIN(k) +
Cap_PV2L_RO_RT_WIN(k) <=
Cap_PV_RT_win(4*(Hour-
1)+k)+W_PV_win(4*(Hour-
1)+k).*X_RT(4*(Hour-1)+k);

     0<= Cap_Ebuy_RO_RT_WIN(k)<=
Cap_E_buy_RO_DA_WIN(4*(Hour-1)+k,1);
     Cap_Ebuy_RO_RT_WIN(k) +
Cap_DEbuy_RO_RT_WIN(k) ==
Cap_G2Bat_RO_RT_WIN(k)+
Cap_G2L_RO_RT_WIN(k)+
Cap_RegD_RO_RT_WIN(k)+
Cap_RegD_RO_DA_WIN(4*(Hour-1)+k);
     Penlaty_Ebuy_RO_RT_WIN(k) >=
0.15*(Cap_DEbuy_RO_RT_WIN(k)-
0.2*Cap_E_buy_RO_DA_WIN(4*(Hour-
1)+k,1));

     0<= Cap_Esell_RO_RT_WIN(k)<=
Cap_E_sell_RO_DA_WIN(4*(Hour-1)+k,1);

Cap_Esell_RO_RT_WIN(k)+Cap_DEsell_RO_RT_
WIN(k) ==
Cap_Bat2G_RO_RT_WIN(k,1)+Cap_Spin_RO_RT_
WIN(k)+Cap_RegU_RO_RT_WIN(k)+
Cap_Spin_RO_DA_WIN(4*(Hour-
1)+k)+Cap_RegU_RO_DA_WIN(4*(Hour-
1)+k);%+Cap_Bat2G_Dit_DA_WIN((4*(Hour-
1)+k),1);
     Penlaty_Esell_RO_RT_WIN(k) >=
0.15*(Cap_DEsell_RO_RT_WIN(k)-
0.2*Cap_E_sell_RO_DA_WIN(4*(Hour-
1)+k,1));


    if MM_RO_DA_WIN(4*(Hour-1)+k)==1
     M_RO_RT_WIN(k)==
M_RO_DA_WIN(4*(Hour-1)+k);
  end

  if Tr_RegD_RT(4*(Hour-1)+k)==0
  Cap_RegD_RO_RT_WIN(k) ==0;
   end
   if Tr_RegU_RT(4*(Hour-1)+k)==0
  Cap_RegU_RO_RT_WIN(k) ==0;
   end
   if Tr_Spin_RT(4*(Hour-1)+k)==0
  Cap_Spin_RO_RT_WIN(k) ==0;
   end

   end
   if k >=5
      Cap_RegD_RO_RT_WIN(k)==0;

Cap_Spin_RO_RT_WIN(k)+Cap_RegU_RO_RT_WIN
(k)+Cap_Bat2G_RO_RT_WIN(k)==0;
   end
  cvx_end
  for k=1:4
      SOC_RO_RT_WIN_S(4*(Hour-1)+k,1) =
SOC_RO_RT_WIN(k);
      Soc_RO_RT_WIN_S(4*(Hour-1)+k,1) =
Soc_RO_RT_WIN(k);
      SOCC_RO_RT_WIN(4*(Hour-1)+k,1)=
SOC_RO_RT_WIN(k)/BAT_CAP;
      a_RegU_RO_RT_WIN_S(4*(Hour-1)+k,1)
= a_RegU_RO_RT_WIN(k,1);
      a_RegD_RO_RT_WIN_S(4*(Hour-1)+k,1)
= a_RegD_RO_RT_WIN(k,1);
      a_Spin_RO_RT_WIN_S(4*(Hour-1)+k,1)
= a_Spin_RO_RT_WIN(k,1);
      a_LMP_RO_RT_WIN_S(4*(Hour-1)+k,1)
= a_LMP_RO_RT_WIN(k,1) ;
      a_Ex_ch_RO_RT_WIN_S(4*(Hour-
1)+k,1) = a_Ex_ch_RO_RT_WIN(k,1);
      a_Ex_dch_RO_RT_WIN_S(4*(Hour-
1)+k,1) = a_Ex_dch_RO_RT_WIN(k,1);
      a_G2Bat_RO_RT_WIN_S(4*(Hour-
1)+k,1) = a_G2Bat_RO_RT_WIN(k,1);
      a_PV2Bat_RO_RT_WIN_S(4*(Hour-
1)+k,1) = a_PV2Bat_RO_RT_WIN(k,1);
      a_Bat2L_RO_RT_WIN_S(4*(Hour-
1)+k,1) = a_Bat2L_RO_RT_WIN(k,1);
      a_PV2L_RO_RT_WIN_S(4*(Hour-1)+k,1)
= Cap_PV2L_RO_RT_WIN(k,1)/Cap_Max;
      a_G2L_RO_RT_WIN_S(4*(Hour-1)+k,1)
= Cap_G2L_RO_RT_WIN(k,1)/Cap_Max;
```

```
      M_RO_RT_WIN_S(4*(Hour-1)+k,1) =
M_RO_RT_WIN(k);
      Cap_Ebuy_RO_RT_WIN_S(4*(Hour-
1)+k,1) =  Cap_Ebuy_RO_RT_WIN(k);
      Cap_Esell_RO_RT_WIN_S(4*(Hour-
1)+k,1) =  Cap_Esell_RO_RT_WIN(k);
      Cap_DEsell_RO_RT_WIN_S(4*(Hour-
1)+k,1) = Cap_DEsell_RO_RT_WIN(k);
      Cap_DEbuy_RO_RT_WIN_S(4*(Hour-
1)+k,1) = Cap_DEbuy_RO_RT_WIN(k);
  end
  N = N-1;

  %COSTS = sum(OBJ_RO_RT_SUM(1:4*Hour));
  Hour = Hour +1;
end
load gong.mat;
sound(y);
display("WELL DONE!!")

t_RO_RT_WIN = toc


%% Robust SUMmer Real time



tic
 N = 24;
 Hour = 1;
 COSTS= 0;
 SOC_RO_RT_SUM_S = zeros(96,1);
 SOC_RO_RT_SUM_S(4,1) = SOC_0;
 X_RT = zeros(96,1);

 clear Soc_RO_RT_SUM_S
 clear SOC_RO_RT_SUM_S
for k=1:96
a_RegD_RO_DA_SUM(k,1) =
Cap_RegD_RO_DA_SUM(k,1)/Cap_Max;
end
while Hour<= 24

clear Cap_Discharge_RO_RT_SUM
clear cost_Charge_RO_RT_SUM
clear cost_Demand_RO_RT_SUM
clear income_Spin_RO_RT_SUM
clear Income_Spin_RO_RT_SUM
clear income_sell_RO_RT_SUM
clear INCOME_sell_RO_RT_SUM
clear income_E_RO_RT_SUM
clear Income_E_RO_RT_SUM
clear income_MilU_RO_RT_SUM
clear income_RegU_RO_RT_SUM
clear Income_RegU_RO_RT_SUM
clear cost_Charge_RO_RT_SUM
clear Cap_Charge_RO_RT_SUM
clear income_MilD_RO_RT_SUM
clear income_RegD_RO_RT_SUM
clear Income_RegD_RO_RT_SUM
clear income_Charging_RO_RT_SUM
clear income_Discharging_RO_RT_SUM
clear cost_OP_RO_RT_SUM
clear Soc_RO_RT_SUM
clear SOC_RO_RT_SUM
clear cost_RO_RT_SUM
clear COST_RO_RT_SUM
clear Cap_Ex_ch_RO_RT_SUM
clear Cap_Ex_dch_RO_RT_SUM
clear cost_Ex_dch_RO_RT_SUM
clear cost_Ex_ch_RO_RT_SUM
clear a_RegU_RO_RT_SUM
clear a_Spin_RO_RT_SUM
clear a_LMP_RO_RT_SUM
clear a_RegD_RO_RT_SUM
clear a_Buy_RO_RT_SUM
clear a_Ex_ch_RO_RT_SUM
clear a_Ex_dch_RO_RT_SUM
clear a_G2Bat_RO_RT_SUM
clear a_PV2Bat_RO_RT_SUM
clear cost_un_dch_RO_RT_SUM
clear cost_un_ch_RO_RT_SUM
clear a_Bat2L_RO_RT_SUM
clear M_RO_RT_SUM
clear Cap_Ebuy_RO_RT_SUM
clear Cap_DEbuy_RO_RT_SUM
clear Cap_Esell_RO_RT_SUM
clear Cap_DEsell_RO_RT_SUM
clear cost_buy_RO_RT_SUM
clear income_sell_RO_RT_SUM
clear Penlaty_Ebuy_RO_RT_SUM
clear Penlaty_Esell_RO_RT_SUM
cvx_begin
    variable Cap_Bat2L_RO_RT_SUM(4*N)
nonnegative
    variable Cap_G2Bat_RO_RT_SUM(4*N)
nonnegative
    variable Cap_RegD_RO_RT_SUM(4*N)
nonnegative
    variable Cap_PV2L_RO_RT_SUM(4*N)
nonnegative
    variable Cap_G2L_RO_RT_SUM(4*N)
nonnegative
    variable Cap_Bat2G_RO_RT_SUM(4*N)
nonnegative
    variable Cap_PV2Bat_RO_RT_SUM(4*N)
nonnegative
    variable Cap_RegU_RO_RT_SUM(4*N)
nonnegative
    variable Cap_Spin_RO_RT_SUM(4*N)
nonnegative
    variable Cap_Ex_ch_RO_RT_SUM(4*N)
nonnegative
    variable Cap_Ex_dch_RO_RT_SUM(4*N)
nonnegative
    variable M_RO_RT_SUM(4*N) binary
    variable Cap_Ebuy_RO_RT_SUM(4*N)
nonnegative
    variable Cap_DEbuy_RO_RT_SUM(4*N)
nonnegative
    variable Cap_Esell_RO_RT_SUM(4*N)
nonnegative
    variable Cap_DEsell_RO_RT_SUM(4*N)
nonnegative
    variable Penlaty_Ebuy_RO_RT_SUM(4*N)
nonnegative
    variable
Penlaty_Esell_RO_RT_SUM(4*N) nonnegative
   for k = 1:4*N+1
       if k<=4*N
       if k<=4
           X_RT(4*(Hour-1)+k,1) = 1;
       end
   Cap_Charge_RO_RT_SUM(k,1) =
Cap_G2Bat_RO_RT_SUM(k)+Cap_PV2Bat_RO_RT_
SUM(k)+Cap_RegD_RO_RT_SUM(k)+Cap_Ex_ch_R
O_RT_SUM(k) ;
   Cap_Discharge_RO_RT_SUM(k,1) =
Cap_Bat2G_RO_RT_SUM(k)+Cap_Spin_RO_RT_SU
M(k)+Cap_RegU_RO_RT_SUM(k)+Cap_Bat2L_RO_
RT_SUM(k)+Cap_Ex_dch_RO_RT_SUM(k);

   cost_buy_RO_RT_SUM(k,1) =
[Cap_Ebuy_RO_RT_SUM(k).*Min_LMP_DA_SUM_l
ow(4*(Hour-
1)+k)+Cap_DEbuy_RO_RT_SUM(k).*Min_LMP_rt
_SUM_low(4*(Hour-1)+k)]/4;
```

```
   income_sell_RO_RT_SUM(k,1) =
[Cap_Esell_RO_RT_SUM(k).*Min_LMP_DA_SUM_
low(4*(Hour-
1)+k)+Cap_DEsell_RO_RT_SUM(k).*Min_LMP_r
t_SUM_low(4*(Hour-1)+k)]/4;

   income_Spin_RO_RT_SUM(k,1) =
X_RT(4*(Hour-1)+k).*Tr_Spin_RT(4*(Hour-
1)+k).* (Min_Spin_rt_SUM_low(4*(Hour-
1)+k).*
Cap_Spin_RO_RT_SUM(k)/4);%Mean_Spin_da_l
ow
   income_RegU_RO_RT_SUM(k,1) =
X_RT(4*(Hour-1)+k).* Tr_RegU_RT(4*(Hour-
1)+k).*(Min_RegU_rt_SUM_low(4*(Hour-
1)+k) .* (Cap_RegU_RO_RT_SUM(k)/4)) ;%
Mean_Reg_U_da_low
   income_RegD_RO_RT_SUM(k,1) =
X_RT(4*(Hour-1)+k).*Tr_RegD_RT(4*(Hour-
1)+k).*(Min_RegD_rt_SUM_low(4*(Hour-
1)+k) .* Cap_RegD_RO_RT_SUM(k)/4);  %
Mean_Reg_D_da_low

   income_Charging_RO_RT_SUM(k,1)=
income_RegD_RO_RT_SUM(k) -
cost_buy_RO_RT_SUM(k);
   income_Discharging_RO_RT_SUM(k,1)=
income_Spin_RO_RT_SUM(k)+income_sell_RO_
RT_SUM(k)+income_RegU_RO_RT_SUM(k);%+inc
ome_sell_RO_RT_SUM(k);

   cost_OP_RO_RT_SUM(k,1) =  c_op
.*(Cap_PV2Bat_RO_RT_SUM(k)+
Cap_G2Bat_RO_RT_SUM(k) +
Cap_Bat2G_RO_RT_SUM(k)+Tr_Spin_RT(4*(Hou
r-1)+k) .*
Cap_Spin_RO_RT_SUM(k)+Tr_RegD_RT(4*(Hour
-
1)+k).*Cap_RegD_RO_RT_SUM(k)+Cap_RegU_RO
_RT_SUM(k)+Cap_Bat2L_RO_RT_SUM(k)) ; %
Cost operation
   cost_Ex_ch_RO_RT_SUM(k,1) =0*
Cap_Ex_ch_RO_RT_SUM(k);
   cost_Ex_dch_RO_RT_SUM(k,1) =0*
Cap_Ex_dch_RO_RT_SUM(k);

 Soc_RO_RT_SUM(k,1) = Eta_Ch
.*((Cap_PV2Bat_RO_RT_SUM(k)+
Cap_G2Bat_RO_RT_SUM(k)+Cap_RegD_RO_RT_SU
M(k))+...
     (Cap_RegD_RO_DA_SUM(4*(Hour-
1)+k))./4) -
((Cap_Bat2G_RO_RT_SUM(k,1)+Cap_Spin_RO_R
T_SUM(k)+Cap_RegU_RO_RT_SUM(k)+...

Cap_Bat2L_RO_RT_SUM(k))+(Cap_Bat2G_RO_DA
_SUM(4*(Hour-
1)+k,1)+Cap_Spin_RO_DA_SUM(4*(Hour-
1)+k,1)+ Cap_RegU_RO_DA_SUM(4*(Hour-
1)+k,1))/4)./(Eta_D);

 if Hour==1
     if k==1
        SOC_RO_RT_SUM(k,1) = SOC_0 +
cost_Ex_dch_RO_RT_SUM(k);%Soc_RO_RT_SUM(
k,1);
     else
       SOC_RO_RT_SUM(k,1) = SOC_0 +
sum(Soc_RO_RT_SUM(1:k-1)) ;
     end
 else
    if k==1
        SOC_RO_RT_SUM(k,1) =
SOC_RO_RT_SUM_S(4*(Hour-1),1)
+Soc_RO_RT_SUM_S(4*(Hour-1),1) +
cost_Ex_dch_RO_RT_SUM(k);%
Soc_RO_RT_SUM(k);
    else
         SOC_RO_RT_SUM(k,1) =
SOC_RO_RT_SUM_S(4*(Hour-1),1) +
sum(Soc_RO_RT_SUM(1:k-
1))+Soc_RO_RT_SUM_S(4*(Hour-1),1);
    end
 end

   cost_RO_RT_SUM(k,1) =
(cost_Ex_ch_RO_RT_SUM(k,1)+cost_Ex_dch_R
O_RT_SUM(k,1)+cost_OP_RO_RT_SUM(k)-
income_Discharging_RO_RT_SUM(k)-
income_Charging_RO_RT_SUM(k)+Penlaty_Ebu
y_RO_RT_SUM(k)+Penlaty_Esell_RO_RT_SUM(k
));%
   a_RegU_RO_RT_SUM(k,1) =
Cap_RegU_RO_RT_SUM(k)/Cap_Max;
   a_RegD_RO_RT_SUM(k,1) =
Cap_RegD_RO_RT_SUM(k)/Cap_Max;
   a_Spin_RO_RT_SUM(k,1) =
Cap_Spin_RO_RT_SUM(k)/Cap_Max;
   a_LMP_RO_RT_SUM(k,1)  =
(Cap_Bat2G_RO_RT_SUM(k))/Cap_Max;
   a_Ex_ch_RO_RT_SUM(k,1) =
Cap_Ex_ch_RO_RT_SUM(k)/Cap_Max;
   a_Ex_dch_RO_RT_SUM(k,1) =
Cap_Ex_dch_RO_RT_SUM(k)/Cap_Max;
   a_G2Bat_RO_RT_SUM(k,1) =
Cap_G2Bat_RO_RT_SUM(k)/Cap_Max;
   a_PV2Bat_RO_RT_SUM(k,1) =
Cap_PV2Bat_RO_RT_SUM(k)/Cap_Max;
   a_Bat2L_RO_RT_SUM(k,1) =
Cap_Bat2L_RO_RT_SUM(k)/Cap_Max;
      else
          if Hour==1
           SOC_RO_RT_SUM(k,1) = SOC_0 +
sum(Soc_RO_RT_SUM(1:k-1)) ;
          else
            SOC_RO_RT_SUM(k,1) =
SOC_RO_RT_SUM_S(4*(Hour-1),1) +
sum(Soc_RO_RT_SUM(1:k-
1))+Soc_RO_RT_SUM_S(4*(Hour-1),1);
          end
      end
    end


  OBJ_RO_RT_SUM =
sum(cost_RO_RT_SUM);%+COSTS;

minimize(OBJ_RO_RT_SUM)

   subject to
   if Hour==1
   SOC_RO_RT_SUM(1) == SOC_0 ;
   end

    SOC_RO_RT_SUM(4*N+1) >= SOC_0 ;
   for k = 1:4*N

   SOC_Min <= SOC_RO_RT_SUM(k)   <=
1*SOC_Max ;
       0 <=
Cap_G2Bat_RO_RT_SUM(k)+Cap_RegD_RO_RT_SU
M(k) +
Cap_PV2Bat_RO_RT_SUM(k)+Cap_Ex_ch_RO_RT_
SUM(k) +Cap_RegD_RO_DA_SUM(4*(Hour-
1)+k)/4 == Cap_Max.*(1-
M_RO_RT_SUM(k))/4;%
       0 <=
Cap_Spin_RO_RT_SUM(k)+Cap_RegU_RO_RT_SUM
```

```
(k)+Cap_Bat2G_RO_RT_SUM(k) +
Cap_Bat2L_RO_RT_SUM(k)+Cap_Ex_dch_RO_RT_
SUM(k) +(Cap_Bat2G_RO_DA_SUM(4*(Hour-
1)+k,1)+Cap_Spin_RO_DA_SUM(4*(Hour-
1)+k)+ Cap_RegU_RO_DA_SUM(4*(Hour-
1)+k))/4 == Cap_Max.*(M_RO_RT_SUM(k))/4;
% +
    Cap_PV2L_RO_RT_SUM(k) +
Cap_G2L_RO_RT_SUM(k)+Cap_Bat2L_RO_RT_SUM
(k) == Cap_L_RT_sum(4*(Hour-
1)+k)+W_Load_sum(4*(Hour-
1)+k).*X_RT(4*(Hour-1)+k) ;%
    Cap_PV2Bat_RO_RT_SUM(k) +
Cap_PV2L_RO_RT_SUM(k) <=
Cap_PV_RT_sum(4*(Hour-
1)+k)+W_PV_sum(4*(Hour-
1)+k).*X_RT(4*(Hour-1)+k);

     0<= Cap_Ebuy_RO_RT_SUM(k)<=
Cap_E_buy_RO_DA_SUM(4*(Hour-1)+k,1);
     Cap_Ebuy_RO_RT_SUM(k) +
Cap_DEbuy_RO_RT_SUM(k) ==
Cap_G2Bat_RO_RT_SUM(k)+
Cap_G2L_RO_RT_SUM(k)+
Cap_RegD_RO_RT_SUM(k)+
Cap_RegD_RO_DA_SUM(4*(Hour-1)+k);
     Penlaty_Ebuy_RO_RT_SUM(k) >=
0.15*(Cap_DEbuy_RO_RT_SUM(k)-
0.2*Cap_E_buy_RO_DA_SUM(4*(Hour-
1)+k,1));

     0<= Cap_Esell_RO_RT_SUM(k)<=
Cap_E_sell_RO_DA_SUM(4*(Hour-1)+k,1);

Cap_Esell_RO_RT_SUM(k)+Cap_DEsell_RO_RT_
SUM(k) ==
Cap_Bat2G_RO_RT_SUM(k,1)+Cap_Spin_RO_RT_
SUM(k)+Cap_RegU_RO_RT_SUM(k)+
Cap_Spin_RO_DA_SUM(4*(Hour-
1)+k)+Cap_RegU_RO_DA_SUM(4*(Hour-
1)+k);%+Cap_Bat2G_Dit_DA_SUM((4*(Hour-
1)+k),1);
     Penlaty_Esell_RO_RT_SUM(k) >=
0.15*(Cap_DEsell_RO_RT_SUM(k)-
0.2*Cap_E_sell_RO_DA_SUM(4*(Hour-
1)+k,1));


    if MM_RO_DA_SUM(4*(Hour-1)+k)==1
     M_RO_RT_SUM(k)==
M_RO_DA_SUM(4*(Hour-1)+k);
  end

  if Tr_RegD_RT(4*(Hour-1)+k)==0
  Cap_RegD_RO_RT_SUM(k) ==0;
   end
   if Tr_RegU_RT(4*(Hour-1)+k)==0
  Cap_RegU_RO_RT_SUM(k) ==0;
   end
   if Tr_Spin_RT(4*(Hour-1)+k)==0
  Cap_Spin_RO_RT_SUM(k) ==0;
   end

   end
   if k >=5
      Cap_RegD_RO_RT_SUM(k)==0;

Cap_Spin_RO_RT_SUM(k)+Cap_RegU_RO_RT_SUM
(k)+Cap_Bat2G_RO_RT_SUM(k)==0;
   end
  cvx_end
  for k=1:4
      SOC_RO_RT_SUM_S(4*(Hour-1)+k,1) =
SOC_RO_RT_SUM(k);
```

```
      Soc_RO_RT_SUM_S(4*(Hour-1)+k,1) =
Soc_RO_RT_SUM(k);
      SOCC_RO_RT_SUM(4*(Hour-1)+k,1)=
SOC_RO_RT_SUM(k)/BAT_CAP;
      a_RegU_RO_RT_SUM_S(4*(Hour-1)+k,1)
= a_RegU_RO_RT_SUM(k,1);
      a_RegD_RO_RT_SUM_S(4*(Hour-1)+k,1)
= a_RegD_RO_RT_SUM(k,1);
      a_Spin_RO_RT_SUM_S(4*(Hour-1)+k,1)
= a_Spin_RO_RT_SUM(k,1);
      a_LMP_RO_RT_SUM_S(4*(Hour-1)+k,1)
= a_LMP_RO_RT_SUM(k,1) ;
      a_Ex_ch_RO_RT_SUM_S(4*(Hour-
1)+k,1) = a_Ex_ch_RO_RT_SUM(k,1);
      a_Ex_dch_RO_RT_SUM_S(4*(Hour-
1)+k,1) = a_Ex_dch_RO_RT_SUM(k,1);
      a_G2Bat_RO_RT_SUM_S(4*(Hour-
1)+k,1) = a_G2Bat_RO_RT_SUM(k,1);
      a_PV2Bat_RO_RT_SUM_S(4*(Hour-
1)+k,1) = a_PV2Bat_RO_RT_SUM(k,1);
      a_Bat2L_RO_RT_SUM_S(4*(Hour-
1)+k,1) = a_Bat2L_RO_RT_SUM(k,1);
      a_PV2L_RO_RT_SUM_S(4*(Hour-1)+k,1)
= Cap_PV2L_RO_RT_SUM(k,1)/Cap_Max;
      a_G2L_RO_RT_SUM_S(4*(Hour-1)+k,1)
= Cap_G2L_RO_RT_SUM(k,1)/Cap_Max;
      M_RO_RT_SUM_S(4*(Hour-1)+k,1) =
M_RO_RT_SUM(k);
      Cap_Ebuy_RO_RT_SUM_S(4*(Hour-
1)+k,1) =  Cap_Ebuy_RO_RT_SUM(k);
      Cap_Esell_RO_RT_SUM_S(4*(Hour-
1)+k,1) =  Cap_Esell_RO_RT_SUM(k);
      Cap_DEsell_RO_RT_SUM_S(4*(Hour-
1)+k,1) = Cap_DEsell_RO_RT_SUM(k);
      Cap_DEbuy_RO_RT_SUM_S(4*(Hour-
1)+k,1) = Cap_DEbuy_RO_RT_SUM(k);
  end
  N = N-1;

  %COSTS = sum(OBJ_RO_RT_SUM(1:4*Hour));
  Hour = Hour +1;
end
load gong.mat;
sound(y);
display("WELL DONE!!")

t_RO_RT_SUM = toc


 %% DRO Winter Real Time
tic
 N = 24;
 clear SOCC_DRO_RT_WIN
 Hour = 1;
 COSTS= 0;
 Soc_DRO_RT_WIN_S = zeros(96,1);
 Soc_DRO_RT_WIN_S(4,1) = SOC_0;
 X_RT = zeros(96,1);

 clear Soc_DRO_RT_WIN_S
 clear SOC_DRO_RT_WIN_S

 for k=1:96
a_RegD_DRO_DA_WIN(k,1) =
Cap_RegD_DRO_DA_WIN(k,1)/Cap_Max;

d_spin_WIN_low(k,1) =
Max_WIN_Spin_RT(k,1);
d_RegU_WIN_low(k,1) =
Max_WIN_RegU_RT(k,1);
d_LMP_WIN_low_RT(k,1)  =
Max_WIN_LMP_RT(k,1) ;
d_LMP_WIN_low_DA(k,1)  =
Max_WIN_LMP_DA(k,1) ;
```

```
d_RegD_WIN_low(k,1) =
Max_WIN_RegD_RT(k,1);
 end

while Hour<= 24
clear lambda_Risk_WIN_low
clear S_Spin_WIN_low
clear S_LMP_WIN_low
clear S_RegU_WIN_low
clear S_RegD_WIN_low
clear S_Buy_WIN_low
clear Risk_CVaR_RegU_RT_WIN_low
clear Risk_CVaR_RegD_RT_WIN_low
clear Risk_CVaR_Spin_RT_WIN_low
clear Risk_CVaR_LMP_DA_WIN_low
clear Risk_CVaR_LMP_RT_WIN_low
clear Risk_CVaR_Buy_RT_WIN_low
clear a1_Risk_WIN_low
clear ROO_Risk_WIN_low
clear a2_Risk_WIN_low
clear b1_Risk_WIN_low
clear b2_Risk_WIN_low
clear tou_Spin_WIN_low
clear tou_RegU_WIN_low
clear tou_RegD_WIN_low
clear tou_LMP_WIN_low_RT
clear tou_LMP_WIN_low_DA
clear tou_Buy_WIN_low
clear gama1_Spin_WIN_low
clear gama2_Spin_WIN_low
clear gama1_RegU_WIN_low
clear gama2_RegU_WIN_low
clear gama1_RegD_WIN_low
clear gama2_RegD_WIN_low
clear gama1_LMP_WIN_low_RT
clear gama2_LMP_WIN_low_RT
clear gama1_LMP_WIN_low_DA
clear gama2_LMP_WIN_low_DA
clear gama1_Buy_WIN_low
clear gama2_Buy_WIN_low
clear Cap_Discharge_DRO_RT_WIN
clear cost_Charge_DRO_RT_WIN
clear cost_Demand_DRO_RT_WIN
clear income_Spin_DRO_RT_WIN
clear Income_Spin_DRO_RT_WIN
clear income_sell_DRO_RT_WIN
clear INCOME_sell_DRO_RT_WIN
clear income_E_DRO_RT_WIN
clear Income_E_DRO_RT_WIN
clear income_MilU_DRO_RT_WIN
clear income_RegU_DRO_RT_WIN
clear Income_RegU_DRO_RT_WIN
clear cost_Charge_DRO_RT_WIN
clear Cap_Charge_DRO_RT_WIN
clear income_MilD_DRO_RT_WIN
clear income_RegD_DRO_RT_WIN
clear Income_RegD_DRO_RT_WIN
clear income_Charging_DRO_RT_WIN
clear income_Discharging_DRO_RT_WIN
clear cost_OP_DRO_RT_WIN
clear Soc_DRO_RT_WIN
clear SOC_DRO_RT_WIN
clear cost_DRO_RT_WIN
clear COST_DRO_RT_WIN
clear cost_un_dch_DRO_RT_WIN
clear cost_un_ch_DRO_RT_WIN
clear Cap_Ex_ch_DRO_RT_WIN
clear Cap_Ex_dch_DRO_RT_WIN
clear a_RegU_DRO_RT_WIN
clear a_Spin_DRO_RT_WIN
clear a_LMP_DRO_RT_WIN
clear a_LMP_DRO_DA_WIN
clear a_RegD_DRO_RT_WIN
clear a_Buy_DRO_RT_WIN
clear a_Ex_ch_DRO_RT_WIN
clear a_Ex_dch_DRO_RT_WIN
clear a_G2Bat_DRO_RT_WIN
clear a_PV2Bat_DRO_RT_WIN
clear cost_un_dch_DRO_RT_WIN
clear cost_un_ch_DRO_RT_WIN
clear Cap_Ex_ch_DRO_RT_WIN
clear Cap_Ex_dch_DRO_RT_WIN
clear a_Bat2L_DRO_RT_WIN
clear a_G2L_DRO_RT_WIN
clear M_DRO_RT_WIN
clear Cap_Ebuy_DRO_RT_WIN
clear Cap_DEbuy_DRO_RT_WIN
clear Cap_Esell_DRO_RT_WIN
clear Cap_DEsell_DRO_RT_WIN
clear Penlaty_Ebuy_DRO_RT_WIN
clear Penlaty_Esell_DRO_RT_WIN
clear a_Ebuy_DRO_RT_WIN
clear a_DEbuy_DRO_RT_WIN
clear a_Esell_DRO_RT_WIN
clear a_DEsell_DRO_RT_WIN
cvx_begin
    variable Cap_Bat2L_DRO_RT_WIN(4*N)
nonnegative
    variable Cap_G2Bat_DRO_RT_WIN(4*N)
nonnegative
    variable Cap_RegD_DRO_RT_WIN(4*N)
nonnegative
    variable Cap_PV2L_DRO_RT_WIN(4*N)
nonnegative
    variable Cap_G2L_DRO_RT_WIN(4*N)
nonnegative
    variable Cap_Bat2G_DRO_RT_WIN(4*N)
nonnegative
    variable Cap_PV2Bat_DRO_RT_WIN(4*N)
nonnegative
    variable Cap_RegU_DRO_RT_WIN(4*N)
nonnegative
    variable Cap_Spin_DRO_RT_WIN(4*N)
nonnegative
    variable Cap_Ex_ch_DRO_RT_WIN(4*N)
nonnegative
    variable Cap_Ex_dch_DRO_RT_WIN(4*N)
nonnegative
    variable lambda_Spin_WIN_low(4*N)
    variable lambda_LMP_WIN_low_RT(4*N)
    variable lambda_LMP_WIN_low_DA(4*N)
    variable lambda_RegU_WIN_low(4*N)
    variable lambda_RegD_WIN_low(4*N)
    variable lambda_Buy_WIN_low(4*N)
    variable
S_Spin_WIN_low(4*N,N_WIN_low)
    variable
S_RegU_WIN_low(4*N,N_WIN_low)
    variable
S_RegD_WIN_low(4*N,N_WIN_low)
    variable
S_LMP_WIN_low_RT(4*N,N_WIN_low)
    variable
S_LMP_WIN_low_DA(4*N,N_WIN_low)
    variable
S_Buy_WIN_low(4*N,N_WIN_low)
    variable gama1_Spin_WIN_low(4*N)
    variable gama2_Spin_WIN_low(4*N)
    variable gama1_RegU_WIN_low(4*N)
    variable gama2_RegU_WIN_low(4*N)
    variable gama1_RegD_WIN_low(4*N)
    variable gama2_RegD_WIN_low(4*N)
    variable gama1_LMP_WIN_low_RT(4*N)
    variable gama2_LMP_WIN_low_RT(4*N)
    variable gama1_LMP_WIN_low_DA(4*N)
    variable gama2_LMP_WIN_low_DA(4*N)
    variable gama1_Buy_WIN_low(4*N)
    variable gama2_Buy_WIN_low(4*N)
```

```
    variable tou_Spin_WIN_low(N_WIN_low)
    variable tou_RegU_WIN_low(N_WIN_low)
    variable tou_RegD_WIN_low(N_WIN_low)
    variable
tou_LMP_WIN_low_RT(N_WIN_low)
    variable
tou_LMP_WIN_low_DA(N_WIN_low)
    variable tou_Buy_WIN_low(N_WIN_low)
    variable M_DRO_RT_WIN(4*N) binary
    variable Cap_Ebuy_DRO_RT_WIN(4*N)
nonnegative
    variable Cap_DEbuy_DRO_RT_WIN(4*N)
nonnegative
    variable Cap_Esell_DRO_RT_WIN(4*N)
nonnegative
    variable Cap_DEsell_DRO_RT_WIN(4*N)
nonnegative
    variable
Penlaty_Ebuy_DRO_RT_WIN(4*N) nonnegative
    variable
Penlaty_Esell_DRO_RT_WIN(4*N)
nonnegative
    for k = 1:4*N+1
        if k<=4*N
      if k<=4
          X_RT(4*(Hour-1)+k,1) = 1;
      end
   a_RegU_DRO_RT_WIN(k,1)  =
Cap_RegU_DRO_RT_WIN(k)/Cap_Max;
   a_RegD_DRO_RT_WIN(k,1)  =
Cap_RegD_DRO_RT_WIN(k)/Cap_Max;
   a_Spin_DRO_RT_WIN(k,1)  =
Cap_Spin_DRO_RT_WIN(k)/Cap_Max;
   a_LMP_DRO_RT_WIN(k,1)   =
Cap_Bat2G_DRO_RT_WIN(k)/Cap_Max;
   a_Ex_ch_DRO_RT_WIN(k,1) =
Cap_Ex_ch_DRO_RT_WIN(k)/Cap_Max;
   a_Ex_dch_DRO_RT_WIN(k,1)=
Cap_Ex_dch_DRO_RT_WIN(k)/Cap_Max;
   a_G2Bat_DRO_RT_WIN(k,1) =
Cap_G2Bat_DRO_RT_WIN(k)/Cap_Max;
   a_PV2Bat_DRO_RT_WIN(k,1)=
Cap_PV2Bat_DRO_RT_WIN(k)/Cap_Max;
   a_Bat2L_DRO_RT_WIN(k,1) =
Cap_Bat2L_DRO_RT_WIN(k)/Cap_Max;
   a_G2L_DRO_RT_WIN(k,1)   =
Cap_G2L_DRO_RT_WIN(k)/Cap_Max;

    a_Ebuy_DRO_RT_WIN(k,1) =
Cap_Ebuy_DRO_RT_WIN(k)/Cap_Max;
    a_DEbuy_DRO_RT_WIN(k,1) =
Cap_DEbuy_DRO_RT_WIN(k)/Cap_Max;
    a_Esell_DRO_RT_WIN(k,1) =
Cap_Esell_DRO_RT_WIN(k)/Cap_Max;
    a_DEsell_DRO_RT_WIN(k,1) =
Cap_DEsell_DRO_RT_WIN(k)/Cap_Max;

    Cap_Charge_DRO_RT_WIN(k,1) =
Cap_G2Bat_DRO_RT_WIN(k)+Cap_PV2Bat_DRO_R
T_WIN(k)+Cap_RegD_DRO_RT_WIN(k)+Cap_Ex_c
h_DRO_RT_WIN(k) ;
    Cap_Discharge_DRO_RT_WIN(k,1) =
Cap_Bat2G_DRO_RT_WIN(k)+Cap_Spin_DRO_RT_
WIN(k)+Cap_RegU_DRO_RT_WIN(k)+Cap_Bat2L_
DRO_RT_WIN(k)+Cap_Ex_dch_DRO_RT_WIN(k);
    cost_OP_DRO_RT_WIN(k,1) =  c_op
.*(Cap_PV2Bat_DRO_RT_WIN(k)+
Cap_G2Bat_DRO_RT_WIN(k) +
Cap_Bat2G_DRO_RT_WIN(k)+Tr_Spin_RT(4*(Ho
ur-1)+k) .*
Cap_Spin_DRO_RT_WIN(k)+Tr_RegD_RT(4*(Hou
r-
1)+k).*Cap_RegD_DRO_RT_WIN(k)+Cap_RegU_D
RO_RT_WIN(k)+Cap_Bat2L_DRO_RT_WIN(k)) ;
% Cost operation

   cost_un_dch_DRO_RT_WIN(k,1)  =
Cap_Ex_dch_DRO_RT_WIN(k)* 0;
   cost_un_ch_DRO_RT_WIN(k,1)  =
Cap_Ex_ch_DRO_RT_WIN(k)* 0;

   Soc_DRO_RT_WIN(k,1) = Eta_Ch
.*([Cap_PV2Bat_DRO_RT_WIN(k)+
Cap_G2Bat_DRO_RT_WIN(k)+...

Cap_RegD_DRO_RT_WIN(k)]+(Cap_RegD_DRO_DA
_WIN(4*(Hour-1)+k))/4)-...

[(Cap_Bat2G_DRO_RT_WIN(k,1)+Cap_Spin_DRO
_RT_WIN(k)+Cap_RegU_DRO_RT_WIN(k)+Cap_Ba
t2L_DRO_RT_WIN(k))+...
  (Cap_Bat2G_DRO_DA_WIN(4*(Hour-
1)+k,1)+Cap_Spin_DRO_DA_WIN(4*(Hour-
1)+k)+ Cap_RegU_DRO_DA_WIN(4*(Hour-
1)+k))/4]./(Eta_D);

 if Hour==1
     if k==1
          SOC_DRO_RT_WIN(k,1) = SOC_0 +
cost_un_ch_DRO_RT_WIN(k);%Soc_DRO_RT_WIN
(k) ;
     else
          SOC_DRO_RT_WIN(k,1) = SOC_0 +
sum(Soc_DRO_RT_WIN(1:k-1)) ;
     end
 else
     if k==1
           SOC_DRO_RT_WIN(k,1) =
SOC_DRO_RT_WIN_S(4*(Hour-1))
+Soc_DRO_RT_WIN_S(4*(Hour-1)) +
cost_un_ch_DRO_RT_WIN(k);%Soc_DRO_RT_WIN
(k) ;
     else
           SOC_DRO_RT_WIN(k,1) =
SOC_DRO_RT_WIN_S(4*(Hour-1))
+Soc_DRO_RT_WIN_S(4*(Hour-1)) +
sum(Soc_DRO_RT_WIN(1:k-1));
     end
 end

   %cost_DRO_RT_WIN(k,1) =
(cost_un_ch_DRO_RT_WIN(k)+cost_un_dch_DR
O_RT_WIN(k)+cost_Demand_DRO_RT_WIN(k)+co
st_OP_DRO_RT_WIN(k)-
income_Discharging_DRO_RT_WIN(k)-
income_Charging_DRO_RT_WIN(k));%+
cost_OP_DRO_RT_WIN(k));%cost_Demand_DRO_
RT_WIN(k)

   alfa = 0.85; %CVar comfidence level

     a1_Risk_WIN_low = -1;
     R_w = 0.01;

     ROO_RegU_WIN_low(k,1) = 1; %
investor risk aversion
     a2_RegU_WIN_low(k,1) = -1 -
(ROO_RegU_WIN_low(k,1)/alfa);
     b1_RegU_WIN_low(k,1) =
ROO_RegU_WIN_low(k,1);
     b2_RegU_WIN_low(k,1) =
ROO_RegU_WIN_low(k,1) * (1- 1/alfa);

     ROO_Spin_WIN_low(k,1) = 1; %
investor risk aversion
     a2_Spin_WIN_low(k,1) = -1 -
(ROO_Spin_WIN_low(k,1)/alfa);
```

```
     b1_Spin_WIN_low(k,1) =
ROO_Spin_WIN_low(k,1);
     b2_Spin_WIN_low(k,1) =
ROO_Spin_WIN_low(k,1)* (1- 1/alfa);

     ROO_LMP_WIN_low_DA(k,1) = 1; %
investor risk aversion
     a2_LMP_WIN_low_DA(k,1) = -1 -
(ROO_LMP_WIN_low_DA(k,1)/alfa);
     b1_LMP_WIN_low_DA(k,1) =
ROO_LMP_WIN_low_DA(k,1);
     b2_LMP_WIN_low_DA(k,1) =
ROO_LMP_WIN_low_DA(k,1) * (1- 1/alfa);

     ROO_LMP_WIN_low_RT(k,1) = 1; %
investor risk aversion
     a2_LMP_WIN_low_RT(k,1) = -1 -
(ROO_LMP_WIN_low_RT(k,1)/alfa);
     b1_LMP_WIN_low_RT(k,1) =
ROO_LMP_WIN_low_RT(k,1);
     b2_LMP_WIN_low_RT(k,1) =
ROO_LMP_WIN_low_RT(k,1) * (1- 1/alfa);

     ROO_RegD_WIN_low(k,1) = 1; %
investor risk aversion
     a2_RegD_WIN_low(k,1) = -1 -
(ROO_RegD_WIN_low(k,1)/alfa);
     b1_RegD_WIN_low(k,1) =
ROO_RegD_WIN_low(k,1);
     b2_RegD_WIN_low(k,1) =
ROO_RegD_WIN_low(k,1) * (1- 1/alfa);
    if k<=4
Risk_CVaR_RegU_RT_WIN_low(k,1) =
Tr_RegU_RT(k,1).*((1*lambda_RegU_WIN_low
(k,1).* R_w +
(sum(S_RegU_WIN_low(k,:))./N_WIN_low)));
Risk_CVaR_Spin_RT_WIN_low(k,1) =
Tr_Spin_RT(k,1).*((1*lambda_Spin_WIN_low
(k,1).* R_w +
(sum(S_Spin_WIN_low(k,:))./N_WIN_low)));
Risk_CVaR_LMP_RT_WIN_low(k,1)  =
((1*lambda_LMP_WIN_low_RT(k,1) .* R_w +
(sum(S_LMP_WIN_low_RT(k,:))./N_WIN_low))
);
Risk_CVaR_LMP_DA_WIN_low(k,1)  =
((1*lambda_LMP_WIN_low_DA(k,1) .* R_w +
(sum(S_LMP_WIN_low_DA(k,:))./N_WIN_low))
);
Risk_CVaR_RegD_RT_WIN_low(k,1) =
Tr_RegD_RT(k,1).*((1*lambda_RegD_WIN_low
(k,1) .* R_w +
(sum(S_RegD_WIN_low(k,:))./N_WIN_low)));
    else
     Risk_CVaR_RegU_RT_WIN_low(k)=0;
     Risk_CVaR_RegD_RT_WIN_low(k)=0;
     Risk_CVaR_Spin_RT_WIN_low(k)=0;
     Risk_CVaR_LMP_RT_WIN_low(k)=0;
    end
    cost_DRO_RT_WIN =
sum(Risk_CVaR_Spin_RT_WIN_low +...

Risk_CVaR_RegU_RT_WIN_low+Risk_CVaR_RegD
_RT_WIN_low+Risk_CVaR_LMP_RT_WIN_low+cos
t_OP_DRO_RT_WIN)+...

sum(Penlaty_Ebuy_DRO_RT_WIN+Penlaty_Esel
l_DRO_RT_WIN);
else
         if Hour==1
           SOC_DRO_RT_WIN(k,1) = SOC_0 +
sum(Soc_DRO_RT_WIN(1:k-1)) ;
          else
           SOC_DRO_RT_WIN(k,1) =
SOC_DRO_RT_WIN_S(4*(Hour-1))
+Soc_DRO_RT_WIN_S(4*(Hour-1)) +
sum(Soc_DRO_RT_WIN(1:k-1));
        end
   end
 end
  minimize(cost_DRO_RT_WIN)

 subject to
       if Hour==1
         SOC_DRO_RT_WIN(1) == SOC_0 ;
       end
    for k = 1:4*N
     SOC_DRO_RT_WIN(4*N) >= SOC_0 ;
     SOC_Min <= SOC_DRO_RT_WIN(k) <=
SOC_Max ;
     Cap_PV2L_DRO_RT_WIN(k) +
Cap_G2L_DRO_RT_WIN(k)+Cap_Bat2L_DRO_RT_W
IN(k) == Cap_L_RT_win(4*(Hour-
1)+k)+W_Load_win(4*(Hour-
1)+k).*X_RT(4*(Hour-1)+k);%
     Cap_PV2Bat_DRO_RT_WIN(k) +
Cap_PV2L_DRO_RT_WIN(k) <=
Cap_PV_RT_win(4*(Hour-1)+k)+
W_PV_win(4*(Hour-1)+k).*X_RT(4*(Hour-
1)+k);


Cap_Charge_DRO_RT_WIN(k)+Cap_RegD_DRO_DA
_WIN(4*(Hour-1)+k)/4 == Cap_Max.*(1-
M_DRO_RT_WIN(k))/4;

Cap_Discharge_DRO_RT_WIN(k)+[Cap_Bat2G_D
RO_DA_WIN(4*(Hour-
1)+k,1)+Cap_Spin_DRO_DA_WIN(4*(Hour-
1)+k)+ Cap_RegU_DRO_DA_WIN(4*(Hour-
1)+k)]/4==Cap_Max.*(M_DRO_RT_WIN(k))/4;

      0<= Cap_Ebuy_DRO_RT_WIN(k)<=
Cap_E_buy_DRO_DA_WIN(4*(Hour-1)+k,1);
      Cap_Ebuy_DRO_RT_WIN(k) +
Cap_DEbuy_DRO_RT_WIN(k) ==
Cap_G2Bat_DRO_RT_WIN(k)+
Cap_G2L_DRO_RT_WIN(k)+
Cap_RegD_DRO_RT_WIN(k)+
Cap_RegD_DRO_DA_WIN(4*(Hour-1)+k);
      Penlaty_Ebuy_DRO_RT_WIN(k) >=
0.15*(Cap_DEbuy_DRO_RT_WIN(k)-
0.2*Cap_E_buy_DRO_DA_WIN(4*(Hour-
1)+k,1));

      0<= Cap_Esell_DRO_RT_WIN(k)<=
Cap_E_sell_DRO_DA_WIN(4*(Hour-1)+k,1);

Cap_Esell_DRO_RT_WIN(k)+Cap_DEsell_DRO_R
T_WIN(k) ==
Cap_Bat2G_DRO_RT_WIN(k,1)+Cap_Spin_DRO_R
T_WIN(k)+Cap_RegU_DRO_RT_WIN(k)+
Cap_Spin_DRO_DA_WIN(4*(Hour-
1)+k)+Cap_RegU_DRO_DA_WIN(4*(Hour-1)+k);
      Penlaty_Esell_DRO_RT_WIN(k) >=
0.15*(Cap_DEsell_DRO_RT_WIN(k)-
0.2*Cap_E_sell_DRO_DA_WIN(4*(Hour-
1)+k,1));


     if Tr_RegD_RT(4*(Hour-1)+k)==0
         Cap_RegD_DRO_RT_WIN(k) ==0;
    end
    if Tr_RegU_RT(4*(Hour-1)+k)==0
         Cap_RegU_DRO_RT_WIN(k) ==0;
    end
    if Tr_Spin_RT(4*(Hour-1)+k)==0
         Cap_Spin_DRO_RT_WIN(k) ==0;
    end
```

```
   if MM_DRO_DA_WIN(4*(Hour-1)+k)==1
     M_DRO_RT_WIN(k)==
M_DRO_DA_WIN_low(4*(Hour-1)+k);
   end

   if k<=4
  for i=1:N_WIN_low

b1_Spin_WIN_low(k,1)*tou_Spin_WIN_low +
a1_Risk_WIN_low .*
a_Spin_DRO_RT_WIN(k)*0.25.*Spin_RT_WIN_l
ow(4*(Hour-1)+k,i) +
gama1_Spin_WIN_low(k,1) .*
(d_spin_WIN_low(4*(Hour-1)+k,1) -
Spin_RT_WIN_low(4*(Hour-1)+k,i)) <=
S_Spin_WIN_low(k,i);

b2_Spin_WIN_low(k,1)*tou_Spin_WIN_low +
a2_Spin_WIN_low(k,1).*
a_Spin_DRO_RT_WIN(k)*0.25.*Spin_RT_WIN_l
ow(4*(Hour-1)+k,i) +
gama2_Spin_WIN_low(k,1) .*
(d_spin_WIN_low(4*(Hour-1)+k,1) -
Spin_RT_WIN_low(4*(Hour-1)+k,i)) <=
S_Spin_WIN_low(k,i);
        norm((gama1_Spin_WIN_low(k,1)-
a1_Risk_WIN_low.*
a_Spin_DRO_RT_WIN(k)*0.25),inf) <=
Tr_Spin_RT(k,1).*lambda_Spin_WIN_low(k,1
);
        norm((gama2_Spin_WIN_low(k,1)-
a2_Spin_WIN_low(k,1).*
a_Spin_DRO_RT_WIN(k)*0.25),inf)
<=Tr_Spin_RT(k,1).*
lambda_Spin_WIN_low(k,1);
        0<= gama1_Spin_WIN_low(k,1);
        0<= gama2_Spin_WIN_low(k,1);


b1_RegU_WIN_low(k,1)*tou_RegU_WIN_low +
a1_Risk_WIN_low
.*a_RegU_DRO_RT_WIN(k)*0.25.*RegU_RT_WIN
_low(4*(Hour-1)+k,i) +
gama1_RegU_WIN_low(k,1) .*
(d_RegU_WIN_low(4*(Hour-1)+k,1) -
RegU_RT_WIN_low(4*(Hour-1)+k,i)) <=
S_RegU_WIN_low(k,i);%Er_Reg_U_da_WIN_low
%  %Er_Reg_U_da_WIN_low_Risk
%Norm_Reg_U_da_WIN_low %a_RegU_DRO

b2_RegU_WIN_low(k,1)*tou_RegU_WIN_low +
a2_RegU_WIN_low(k,1) .*
a_RegU_DRO_RT_WIN(k)*0.25.*RegU_RT_WIN_l
ow(4*(Hour-1)+k,i) +
gama2_RegU_WIN_low(k,1) .*
(d_RegU_WIN_low(4*(Hour-1)+k,1) -
RegU_RT_WIN_low(4*(Hour-1)+k,i)) <=
S_RegU_WIN_low(k,i);
        norm((gama1_RegU_WIN_low(k,1)-
a1_Risk_WIN_low.*
a_RegU_DRO_RT_WIN(k)*0.25),inf) <=
Tr_RegU_RT(k,1).*
lambda_RegU_WIN_low(k,1);
        norm((gama2_RegU_WIN_low(k,1)-
a2_RegU_WIN_low(k,1).*
a_RegU_DRO_RT_WIN(k)*0.25),inf) <=
Tr_RegU_RT(k,1).*
lambda_RegU_WIN_low(k,1);
        0<= gama1_RegU_WIN_low(k,1);
        0<= gama2_RegU_WIN_low(k,1);


b1_LMP_WIN_low_DA(k,1)*tou_LMP_WIN_low_D
A +
a1_Risk_WIN_low.*(a_Ebuy_DRO_RT_WIN(k)-
a_Esell_DRO_RT_WIN(k))*0.25
.*LMP_DA_WIN_low(4*(Hour-1)+k,i) +
gama1_LMP_WIN_low_DA(k,1) .*
(d_LMP_WIN_low_DA(4*(Hour-1)+k,1) -
LMP_DA_WIN_low(4*(Hour-1)+k,i)) <=
S_LMP_WIN_low_DA(k,i);

b2_LMP_WIN_low_DA(k,1)*tou_LMP_WIN_low_D
A +
a2_LMP_WIN_low_DA(k,1).*(a_Ebuy_DRO_RT_W
IN(k)-a_Esell_DRO_RT_WIN(k))*0.25
.*LMP_DA_WIN_low(4*(Hour-1)+k,i) +
gama2_LMP_WIN_low_DA(k,1) .*
(d_LMP_WIN_low_DA(4*(Hour-1)+k,1) -
LMP_DA_WIN_low(4*(Hour-1)+k,i)) <=
S_LMP_WIN_low_DA(k,i);
        norm((gama1_LMP_WIN_low_DA(k,1)-
a1_Risk_WIN_low.*(a_Ebuy_DRO_RT_WIN(k)-
a_Esell_DRO_RT_WIN(k))*0.25),inf) <=
lambda_LMP_WIN_low_DA(k,1);
        norm((gama2_LMP_WIN_low_DA(k,1)-
a2_LMP_WIN_low_DA(k,1).*(a_Ebuy_DRO_RT_W
IN(k)-a_Esell_DRO_RT_WIN(k))*0.25),inf)
<= lambda_LMP_WIN_low_DA(k,1);
        0<= gama1_LMP_WIN_low_DA(k,1);
        0<= gama2_LMP_WIN_low_DA(k,1);


b1_LMP_WIN_low_RT(k,1)*tou_LMP_WIN_low_R
T +
a1_Risk_WIN_low.*(a_DEbuy_DRO_RT_WIN(k)-
a_DEsell_DRO_RT_WIN(k))*0.25
.*LMP_RT_WIN_low(4*(Hour-1)+k,i) +
gama1_LMP_WIN_low_RT(k,1) .*
(d_LMP_WIN_low_RT(4*(Hour-1)+k,1) -
LMP_RT_WIN_low(4*(Hour-1)+k,i)) <=
S_LMP_WIN_low_RT(k,i);

b2_LMP_WIN_low_RT(k,1)*tou_LMP_WIN_low_R
T +
a2_LMP_WIN_low_RT(k,1).*(a_DEbuy_DRO_RT_
WIN(k)-a_DEsell_DRO_RT_WIN(k))*0.25
.*LMP_RT_WIN_low(4*(Hour-1)+k,i) +
gama2_LMP_WIN_low_RT(k,1) .*
(d_LMP_WIN_low_RT(4*(Hour-1)+k,1) -
LMP_RT_WIN_low(4*(Hour-1)+k,i)) <=
S_LMP_WIN_low_RT(k,i);
        norm((gama1_LMP_WIN_low_RT(k,1)-
a1_Risk_WIN_low.*(a_Ebuy_DRO_RT_WIN(k)-
a_Esell_DRO_RT_WIN(k))*0.25),inf) <=
lambda_LMP_WIN_low_RT(k,1);
        norm((gama2_LMP_WIN_low_RT(k,1)-
a2_LMP_WIN_low_RT(k,1).*(a_Ebuy_DRO_RT_W
IN(k)-a_Esell_DRO_RT_WIN(k))*0.25),inf)
<= lambda_LMP_WIN_low_RT(k,1);
        0<= gama1_LMP_WIN_low_RT(k,1);
        0<= gama2_LMP_WIN_low_RT(k,1);


b1_RegD_WIN_low(k,1)*tou_RegD_WIN_low +
a1_Risk_WIN_low .*
a_RegD_DRO_RT_WIN(k)*0.25.*RegD_RT_WIN_l
ow(4*(Hour-1)+k,i) +
gama1_RegD_WIN_low(k,1) .*
(d_RegD_WIN_low(4*(Hour-1)+k,1) -
RegD_RT_WIN_low(4*(Hour-1)+k,i)) <=
S_RegD_WIN_low(k,i);

b2_RegD_WIN_low(k,1)*tou_RegD_WIN_low +
a2_RegD_WIN_low(k,1) .*
a_RegD_DRO_RT_WIN(k)*0.25.*RegD_RT_WIN_l
ow(4*(Hour-1)+k,i) +
```

```
gama2_RegD_WIN_low(k,1) .*
(d_RegD_WIN_low(4*(Hour-1)+k,1) -
RegD_RT_WIN_low(4*(Hour-1)+k,i)) <=
S_RegD_WIN_low(k,i);
        norm((gama1_RegD_WIN_low(k,1)-
a1_Risk_WIN_low.*
a_RegD_DRO_RT_WIN(k)*0.25),inf) <=
Tr_RegD_RT(k,1).*
lambda_RegD_WIN_low(k,1);
        norm((gama2_RegD_WIN_low(k,1)-
a2_RegD_WIN_low(k,1).*
a_RegD_DRO_RT_WIN(k)*0.25),inf)
<=Tr_RegD_RT(k,1).*
lambda_RegD_WIN_low(k,1);
        0<= gama1_RegD_WIN_low(k,1);
        0<= gama2_RegD_WIN_low(k,1);
  end
    end
   end

  cvx_end


  for k=1:4
      SOC_DRO_RT_WIN_S(4*(Hour-1)+k,1)
= SOC_DRO_RT_WIN(k);
      Soc_DRO_RT_WIN_S(4*(Hour-1)+k,1)
= Soc_DRO_RT_WIN(k);
      SOCC_DRO_RT_WIN(4*(Hour-1)+k,1)
= SOC_DRO_RT_WIN(k)/BAT_CAP;
      a_RegU_DRO_RT_WIN_S(4*(Hour-
1)+k,1)    = a_RegU_DRO_RT_WIN(k,1);
      a_RegD_DRO_RT_WIN_S(4*(Hour-
1)+k,1)    = a_RegD_DRO_RT_WIN(k,1);
      a_Spin_DRO_RT_WIN_S(4*(Hour-
1)+k,1)    = a_Spin_DRO_RT_WIN(k,1);
      a_LMP_DRO_RT_WIN_S(4*(Hour-1)+k,1)
= a_LMP_DRO_RT_WIN(k,1) ;
      a_Ex_ch_DRO_RT_WIN_S(4*(Hour-
1)+k,1)   = a_Ex_ch_DRO_RT_WIN(k,1);
      a_Ex_dch_DRO_RT_WIN_S(4*(Hour-
1)+k,1)  = a_Ex_dch_DRO_RT_WIN(k,1);
      a_G2Bat_DRO_RT_WIN_S(4*(Hour-
1)+k,1)   = a_G2Bat_DRO_RT_WIN(k,1);
      a_PV2Bat_DRO_RT_WIN_S(4*(Hour-
1)+k,1)  = a_PV2Bat_DRO_RT_WIN(k,1);
      a_Bat2L_DRO_RT_WIN_S(4*(Hour-
1)+k,1)   = a_Bat2L_DRO_RT_WIN(k,1);
      a_PV2L_DRO_RT_WIN_S(4*(Hour-
1)+k,1)    =
Cap_PV2L_DRO_RT_WIN(k,1)/Cap_Max;
      a_G2L_DRO_RT_WIN_S(4*(Hour-1)+k,1)
= Cap_G2L_DRO_RT_WIN(k,1)/Cap_Max;
      Cap_G2L_DRO_RT_WIN_S(4*(Hour-
1)+k,1)   = Cap_G2L_DRO_RT_WIN(k,1);

      Cap_Ebuy_DRO_RT_WIN_S(4*(Hour-
1)+k,1)    = Cap_Ebuy_DRO_RT_WIN(k);
      Cap_DEbuy_DRO_RT_WIN_S(4*(Hour-
1)+k,1)   = Cap_DEbuy_DRO_RT_WIN(k);
      Cap_Esell_DRO_RT_WIN_S(4*(Hour-
1)+k,1)   = Cap_Esell_DRO_RT_WIN(k);
      Cap_DEsell_DRO_RT_WIN_S(4*(Hour-
1)+k,1)  = Cap_DEsell_DRO_RT_WIN(k);
  end
 % COSTS =
sum(cost_DRO_RT_WIN(1:4))+COSTS;
  N = N-1;
  Hour = Hour +1;
end
load gong.mat;
sound(y);
display("WELL DONE!!")
```

```
t_DRO_RT_WIN = toc

  %%% DRO Summer Real Time
tic
 N = 24;
 clear SOCC_DRO_RT_SUM
 Hour = 1;
 COSTS= 0;
 Soc_DRO_RT_SUM_S = zeros(96,1);
 Soc_DRO_RT_SUM_S(4,1) = SOC_0;
 X_RT = zeros(96,1);

 clear Soc_DRO_RT_SUM_S
 clear SOC_DRO_RT_SUM_S
for k=1:96
a_RegD_DRO_DA_SUM(k,1) =
Cap_RegD_DRO_DA_SUM(k,1)/Cap_Max;

d_spin_SUM_low(k,1) =
Max_SUM_Spin_RT(k,1);
d_RegU_SUM_low(k,1) =
Max_SUM_RegU_RT(k,1);
d_LMP_SUM_low(k,1)  =
Max_SUM_LMP_RT(k,1);
d_RegD_SUM_low(k,1) =
Max_SUM_RegD_RT(k,1);
d_LMP_SUM_low_RT(k,1)   =
Max_SUM_LMP_RT(k,1) ;
d_LMP_SUM_low_DA(k,1)   =
Max_SUM_LMP_DA(k,1) ;

end

while Hour<= 24
clear lambda_Risk_SUM_low
clear S_Spin_SUM_low
clear S_LMP_SUM_low
clear S_RegU_SUM_low
clear S_RegD_SUM_low
clear S_Buy_SUM_low
clear Risk_CVaR_RegU_RT_SUM_low
clear Risk_CVaR_RegD_RT_SUM_low
clear Risk_CVaR_Spin_RT_SUM_low
clear Risk_CVaR_LMP_DA_SUM_low
clear Risk_CVaR_LMP_RT_SUM_low
clear Risk_CVaR_Buy_RT_SUM_low
clear a1_Risk_SUM_low
clear ROO_Risk_SUM_low
clear a2_Risk_SUM_low
clear b1_Risk_SUM_low
clear b2_Risk_SUM_low
clear tou_Spin_SUM_low
clear tou_RegU_SUM_low
clear tou_RegD_SUM_low
clear tou_LMP_SUM_low_RT
clear tou_LMP_SUM_low_DA
clear tou_Buy_SUM_low
clear gama1_Spin_SUM_low
clear gama2_Spin_SUM_low
clear gama1_RegU_SUM_low
clear gama2_RegU_SUM_low
clear gama1_RegD_SUM_low
clear gama2_RegD_SUM_low
clear gama1_LMP_SUM_low_RT
clear gama2_LMP_SUM_low_RT
clear gama1_LMP_SUM_low_DA
clear gama2_LMP_SUM_low_DA
clear gama1_Buy_SUM_low
clear gama2_Buy_SUM_low
clear Cap_Discharge_DRO_RT_SUM
clear cost_Charge_DRO_RT_SUM
clear cost_Demand_DRO_RT_SUM
clear income_Spin_DRO_RT_SUM
clear Income_Spin_DRO_RT_SUM
```

```
clear income_sell_DRO_RT_SUM
clear INCOME_sell_DRO_RT_SUM
clear income_E_DRO_RT_SUM
clear Income_E_DRO_RT_SUM
clear income_MilU_DRO_RT_SUM
clear income_RegU_DRO_RT_SUM
clear Income_RegU_DRO_RT_SUM
clear cost_Charge_DRO_RT_SUM
clear Cap_Charge_DRO_RT_SUM
clear income_MilD_DRO_RT_SUM
clear income_RegD_DRO_RT_SUM
clear Income_RegD_DRO_RT_SUM
clear income_Charging_DRO_RT_SUM
clear income_Discharging_DRO_RT_SUM
clear cost_OP_DRO_RT_SUM
clear Soc_DRO_RT_SUM
clear SOC_DRO_RT_SUM
clear cost_DRO_RT_SUM
clear COST_DRO_RT_SUM
clear cost_un_dch_DRO_RT_SUM
clear cost_un_ch_DRO_RT_SUM
clear Cap_Ex_ch_DRO_RT_SUM
clear Cap_Ex_dch_DRO_RT_SUM
clear a_RegU_DRO_RT_SUM
clear a_Spin_DRO_RT_SUM
clear a_LMP_DRO_RT_SUM
clear a_LMP_DRO_DA_SUM
clear a_RegD_DRO_RT_SUM
clear a_Buy_DRO_RT_SUM
clear a_Ex_ch_DRO_RT_SUM
clear a_Ex_dch_DRO_RT_SUM
clear a_G2Bat_DRO_RT_SUM
clear a_PV2Bat_DRO_RT_SUM
clear cost_un_dch_DRO_RT_SUM
clear cost_un_ch_DRO_RT_SUM
clear Cap_Ex_ch_DRO_RT_SUM
clear Cap_Ex_dch_DRO_RT_SUM
clear a_Bat2L_DRO_RT_SUM
clear a_G2L_DRO_RT_SUM
clear M_DRO_RT_SUM
clear Cap_Ebuy_DRO_RT_SUM
clear Cap_DEbuy_DRO_RT_SUM
clear Cap_Esell_DRO_RT_SUM
clear Cap_DEsell_DRO_RT_SUM
clear Penlaty_Ebuy_DRO_RT_SUM
clear Penlaty_Esell_DRO_RT_SUM
clear a_Ebuy_DRO_RT_SUM
clear a_DEbuy_DRO_RT_SUM
clear a_Esell_DRO_RT_SUM
clear a_DEsell_DRO_RT_SUM
cvx_begin
    variable Cap_Bat2L_DRO_RT_SUM(4*N)
nonnegative
    variable Cap_G2Bat_DRO_RT_SUM(4*N)
nonnegative
    variable Cap_RegD_DRO_RT_SUM(4*N)
nonnegative
    variable Cap_PV2L_DRO_RT_SUM(4*N)
nonnegative
    variable Cap_G2L_DRO_RT_SUM(4*N)
nonnegative
    variable Cap_Bat2G_DRO_RT_SUM(4*N)
nonnegative
    variable Cap_PV2Bat_DRO_RT_SUM(4*N)
nonnegative
    variable Cap_RegU_DRO_RT_SUM(4*N)
nonnegative
    variable Cap_Spin_DRO_RT_SUM(4*N)
nonnegative
    variable Cap_Ex_ch_DRO_RT_SUM(4*N)
nonnegative
    variable Cap_Ex_dch_DRO_RT_SUM(4*N)
nonnegative
    variable lambda_Spin_SUM_low(4*N)
    variable lambda_LMP_SUM_low_RT(4*N)
    variable lambda_LMP_SUM_low_DA(4*N)
    variable lambda_RegU_SUM_low(4*N)
    variable lambda_RegD_SUM_low(4*N)
    variable lambda_Buy_SUM_low(4*N)
    variable
S_Spin_SUM_low(4*N,N_SUM_low)
    variable
S_RegU_SUM_low(4*N,N_SUM_low)
    variable
S_RegD_SUM_low(4*N,N_SUM_low)
    variable
S_LMP_SUM_low_RT(4*N,N_SUM_low)
    variable
S_LMP_SUM_low_DA(4*N,N_SUM_low)
    variable
S_Buy_SUM_low(4*N,N_SUM_low)
    variable gama1_Spin_SUM_low(4*N)
    variable gama2_Spin_SUM_low(4*N)
    variable gama1_RegU_SUM_low(4*N)
    variable gama2_RegU_SUM_low(4*N)
    variable gama1_RegD_SUM_low(4*N)
    variable gama2_RegD_SUM_low(4*N)
    variable gama1_LMP_SUM_low_RT(4*N)
    variable gama2_LMP_SUM_low_RT(4*N)
    variable gama1_LMP_SUM_low_DA(4*N)
    variable gama2_LMP_SUM_low_DA(4*N)
    variable gama1_Buy_SUM_low(4*N)
    variable gama2_Buy_SUM_low(4*N)
    variable tou_Spin_SUM_low(N_SUM_low)
    variable tou_RegU_SUM_low(N_SUM_low)
    variable tou_RegD_SUM_low(N_SUM_low)
    variable
tou_LMP_SUM_low_RT(N_SUM_low)
    variable
tou_LMP_SUM_low_DA(N_SUM_low)
    variable tou_Buy_SUM_low(N_SUM_low)
    variable M_DRO_RT_SUM(4*N) binary
    variable Cap_Ebuy_DRO_RT_SUM(4*N)
nonnegative
    variable Cap_DEbuy_DRO_RT_SUM(4*N)
nonnegative
    variable Cap_Esell_DRO_RT_SUM(4*N)
nonnegative
    variable Cap_DEsell_DRO_RT_SUM(4*N)
nonnegative
    variable
Penlaty_Ebuy_DRO_RT_SUM(4*N) nonnegative
    variable
Penlaty_Esell_DRO_RT_SUM(4*N)
nonnegative
    for k = 1:4*N+1
        if k<=4*N
      if k<=4
          X_RT(4*(Hour-1)+k,1) = 1;
      end
   a_RegU_DRO_RT_SUM(k,1)  =
Cap_RegU_DRO_RT_SUM(k)/Cap_Max;
   a_RegD_DRO_RT_SUM(k,1)  =
Cap_RegD_DRO_RT_SUM(k)/Cap_Max;
   a_Spin_DRO_RT_SUM(k,1)  =
Cap_Spin_DRO_RT_SUM(k)/Cap_Max;
   a_LMP_DRO_RT_SUM(k,1)   =
Cap_Bat2G_DRO_RT_SUM(k)/Cap_Max;
   a_Ex_ch_DRO_RT_SUM(k,1) =
Cap_Ex_ch_DRO_RT_SUM(k)/Cap_Max;
   a_Ex_dch_DRO_RT_SUM(k,1)=
Cap_Ex_dch_DRO_RT_SUM(k)/Cap_Max;
   a_G2Bat_DRO_RT_SUM(k,1) =
Cap_G2Bat_DRO_RT_SUM(k)/Cap_Max;
   a_PV2Bat_DRO_RT_SUM(k,1)=
Cap_PV2Bat_DRO_RT_SUM(k)/Cap_Max;
   a_Bat2L_DRO_RT_SUM(k,1) =
Cap_Bat2L_DRO_RT_SUM(k)/Cap_Max;
```

```
   a_G2L_DRO_RT_SUM(k,1)    =
Cap_G2L_DRO_RT_SUM(k)/Cap_Max;

    a_Ebuy_DRO_RT_SUM(k,1) =
Cap_Ebuy_DRO_RT_SUM(k)/Cap_Max;
    a_DEbuy_DRO_RT_SUM(k,1) =
Cap_DEbuy_DRO_RT_SUM(k)/Cap_Max;
    a_Esell_DRO_RT_SUM(k,1) =
Cap_Esell_DRO_RT_SUM(k)/Cap_Max;
    a_DEsell_DRO_RT_SUM(k,1) =
Cap_DEsell_DRO_RT_SUM(k)/Cap_Max;

    Cap_Charge_DRO_RT_SUM(k,1) =
Cap_G2Bat_DRO_RT_SUM(k)+Cap_PV2Bat_DRO_R
T_SUM(k)+Cap_RegD_DRO_RT_SUM(k)+Cap_Ex_c
h_DRO_RT_SUM(k) ;
    Cap_Discharge_DRO_RT_SUM(k,1) =
Cap_Bat2G_DRO_RT_SUM(k)+Cap_Spin_DRO_RT_
SUM(k)+Cap_RegU_DRO_RT_SUM(k)+Cap_Bat2L_
DRO_RT_SUM(k)+Cap_Ex_dch_DRO_RT_SUM(k);
    cost_OP_DRO_RT_SUM(k,1) =  c_op
.*(Cap_PV2Bat_DRO_RT_SUM(k)+
Cap_G2Bat_DRO_RT_SUM(k) +
Cap_Bat2G_DRO_RT_SUM(k)+Tr_Spin_RT(4*(Ho
ur-1)+k) .*
Cap_Spin_DRO_RT_SUM(k)+Tr_RegD_RT(4*(Hou
r-
1)+k).*Cap_RegD_DRO_RT_SUM(k)+Cap_RegU_D
RO_RT_SUM(k)+Cap_Bat2L_DRO_RT_SUM(k)) ;
% Cost operation

   cost_un_dch_DRO_RT_SUM(k,1)   =
Cap_Ex_dch_DRO_RT_SUM(k)* 0;
   cost_un_ch_DRO_RT_SUM(k,1)   =
Cap_Ex_ch_DRO_RT_SUM(k)* 0;

   Soc_DRO_RT_SUM(k,1) = Eta_Ch
.*([Cap_PV2Bat_DRO_RT_SUM(k)+
Cap_G2Bat_DRO_RT_SUM(k)+...

Cap_RegD_DRO_RT_SUM(k)]+(Cap_RegD_DRO_DA
_SUM(4*(Hour-1)+k))/4)-...

[(Cap_Bat2G_DRO_RT_SUM(k,1)+Cap_Spin_DRO
_RT_SUM(k)+Cap_RegU_DRO_RT_SUM(k)+Cap_Ba
t2L_DRO_RT_SUM(k))+...
  (Cap_Bat2G_DRO_DA_SUM(4*(Hour-
1)+k,1)+Cap_Spin_DRO_DA_SUM(4*(Hour-
1)+k)+ Cap_RegU_DRO_DA_SUM(4*(Hour-
1)+k))/4]./(Eta_D);

 if Hour==1
     if k==1
        SOC_DRO_RT_SUM(k,1) = SOC_0 +
cost_un_ch_DRO_RT_SUM(k);%Soc_DRO_RT_SUM
(k) ;
     else
        SOC_DRO_RT_SUM(k,1) = SOC_0 +
sum(Soc_DRO_RT_SUM(1:k-1)) ;
     end
 else
     if k==1
         SOC_DRO_RT_SUM(k,1) =
SOC_DRO_RT_SUM_S(4*(Hour-1))
+Soc_DRO_RT_SUM_S(4*(Hour-1)) +
cost_un_ch_DRO_RT_SUM(k);%Soc_DRO_RT_SUM
(k) ;
     else
         SOC_DRO_RT_SUM(k,1) =
SOC_DRO_RT_SUM_S(4*(Hour-1))
+Soc_DRO_RT_SUM_S(4*(Hour-1)) +
sum(Soc_DRO_RT_SUM(1:k-1));
     end
 end
```

```
   %cost_DRO_RT_SUM(k,1) =
(cost_un_ch_DRO_RT_SUM(k)+cost_un_dch_DR
O_RT_SUM(k)+cost_Demand_DRO_RT_SUM(k)+co
st_OP_DRO_RT_SUM(k)-
income_Discharging_DRO_RT_SUM(k)-
income_Charging_DRO_RT_SUM(k));%+
cost_OP_DRO_RT_SUM(k));%cost_Demand_DRO_
RT_SUM(k)

   alfa = 0.85; %CVar comfidence level

     a1_Risk_SUM_low = -1;
     R_w = 0.01;

     ROO_RegU_SUM_low(k,1) = 1; %
investor risk aversion
     a2_RegU_SUM_low(k,1) = -1 -
(ROO_RegU_SUM_low(k,1)/alfa);
     b1_RegU_SUM_low(k,1) =
ROO_RegU_SUM_low(k,1);
     b2_RegU_SUM_low(k,1) =
ROO_RegU_SUM_low(k,1) * (1- 1/alfa);

     ROO_Spin_SUM_low(k,1) = 1; %
investor risk aversion
     a2_Spin_SUM_low(k,1) = -1 -
(ROO_Spin_SUM_low(k,1)/alfa);
     b1_Spin_SUM_low(k,1) =
ROO_Spin_SUM_low(k,1);
     b2_Spin_SUM_low(k,1) =
ROO_Spin_SUM_low(k,1)* (1- 1/alfa);

     ROO_LMP_SUM_low_DA(k,1) = 1; %
investor risk aversion
     a2_LMP_SUM_low_DA(k,1) = -1 -
(ROO_LMP_SUM_low_DA(k,1)/alfa);
     b1_LMP_SUM_low_DA(k,1) =
ROO_LMP_SUM_low_DA(k,1);
     b2_LMP_SUM_low_DA(k,1) =
ROO_LMP_SUM_low_DA(k,1) * (1- 1/alfa);

     ROO_LMP_SUM_low_RT(k,1) = 1; %
investor risk aversion
     a2_LMP_SUM_low_RT(k,1) = -1 -
(ROO_LMP_SUM_low_RT(k,1)/alfa);
     b1_LMP_SUM_low_RT(k,1) =
ROO_LMP_SUM_low_RT(k,1);
     b2_LMP_SUM_low_RT(k,1) =
ROO_LMP_SUM_low_RT(k,1) * (1- 1/alfa);

     ROO_RegD_SUM_low(k,1) = 1; %
investor risk aversion
     a2_RegD_SUM_low(k,1) = -1 -
(ROO_RegD_SUM_low(k,1)/alfa);
     b1_RegD_SUM_low(k,1) =
ROO_RegD_SUM_low(k,1);
     b2_RegD_SUM_low(k,1) =
ROO_RegD_SUM_low(k,1) * (1- 1/alfa);
    if k<=4
Risk_CVaR_RegU_RT_SUM_low(k,1) =
Tr_RegU_RT(k,1).*((1*lambda_RegU_SUM_low
(k,1).* R_w +
(sum(S_RegU_SUM_low(k,:))./N_SUM_low)));
Risk_CVaR_Spin_RT_SUM_low(k,1) =
Tr_Spin_RT(k,1).*((1*lambda_Spin_SUM_low
(k,1).* R_w +
(sum(S_Spin_SUM_low(k,:))./N_SUM_low)));
Risk_CVaR_LMP_RT_SUM_low(k,1)  =
((1*lambda_LMP_SUM_low_RT(k,1) .* R_w +
(sum(S_LMP_SUM_low_RT(k,:))./N_SUM_low))
);
Risk_CVaR_LMP_DA_SUM_low(k,1)  =
((1*lambda_LMP_SUM_low_DA(k,1) .* R_w +
```

```
(sum(S_LMP_SUM_low_DA(k,:))./N_SUM_low))
);
Risk_CVaR_RegD_RT_SUM_low(k,1) =
Tr_RegD_RT(k,1).*((1*lambda_RegD_SUM_low
(k,1) .* R_w +
(sum(S_RegD_SUM_low(k,:))./N_SUM_low)));
    else
     Risk_CVaR_RegU_RT_SUM_low(k)=0;
     Risk_CVaR_RegD_RT_SUM_low(k)=0;
     Risk_CVaR_Spin_RT_SUM_low(k)=0;
     Risk_CVaR_LMP_RT_SUM_low(k)=0;
    end
    cost_DRO_RT_SUM =
sum(Risk_CVaR_Spin_RT_SUM_low +...

Risk_CVaR_RegU_RT_SUM_low+Risk_CVaR_RegD
_RT_SUM_low+Risk_CVaR_LMP_RT_SUM_low+cos
t_OP_DRO_RT_SUM)+...

sum(Penlaty_Ebuy_DRO_RT_SUM+Penlaty_Esel
l_DRO_RT_SUM);
else
         if Hour==1
           SOC_DRO_RT_SUM(k,1) = SOC_0 +
sum(Soc_DRO_RT_SUM(1:k-1)) ;
          else
           SOC_DRO_RT_SUM(k,1) =
SOC_DRO_RT_SUM_S(4*(Hour-1))
+Soc_DRO_RT_SUM_S(4*(Hour-1)) +
sum(Soc_DRO_RT_SUM(1:k-1));
        end
   end
 end
  minimize(cost_DRO_RT_SUM)

 subject to
       if Hour==1
         SOC_DRO_RT_SUM(1) == SOC_0 ;
       end
   for k = 1:4*N
    SOC_DRO_RT_SUM(4*N) >= SOC_0 ;
    SOC_Min <= SOC_DRO_RT_SUM(k) <=
SOC_Max ;
    Cap_PV2L_DRO_RT_SUM(k) +
Cap_G2L_DRO_RT_SUM(k)+Cap_Bat2L_DRO_RT_S
UM(k) == Cap_L_RT_sum(4*(Hour-
1)+k)+W_Load_sum(4*(Hour-
1)+k).*X_RT(4*(Hour-1)+k);%
    Cap_PV2Bat_DRO_RT_SUM(k) +
Cap_PV2L_DRO_RT_SUM(k) <=
Cap_PV_RT_sum(4*(Hour-1)+k)+
W_PV_sum(4*(Hour-1)+k).*X_RT(4*(Hour-
1)+k);


Cap_Charge_DRO_RT_SUM(k)+Cap_RegD_DRO_DA
_SUM(4*(Hour-1)+k)/4 == Cap_Max.*(1-
M_DRO_RT_SUM(k))/4;

Cap_Discharge_DRO_RT_SUM(k)+[Cap_Bat2G_D
RO_DA_SUM(4*(Hour-
1)+k,1)+Cap_Spin_DRO_DA_SUM(4*(Hour-
1)+k)+ Cap_RegU_DRO_DA_SUM(4*(Hour-
1)+k)]/4==Cap_Max.*(M_DRO_RT_SUM(k))/4;

     0<= Cap_Ebuy_DRO_RT_SUM(k)<=
Cap_E_buy_DRO_DA_SUM(4*(Hour-1)+k,1);
     Cap_Ebuy_DRO_RT_SUM(k) +
Cap_DEbuy_DRO_RT_SUM(k) ==
Cap_G2Bat_DRO_RT_SUM(k)+
Cap_G2L_DRO_RT_SUM(k)+
Cap_RegD_DRO_RT_SUM(k)+
Cap_RegD_DRO_DA_SUM(4*(Hour-1)+k);
     Penlaty_Ebuy_DRO_RT_SUM(k) >=
0.15*(Cap_DEbuy_DRO_RT_SUM(k)-
0.2*Cap_E_buy_DRO_DA_SUM(4*(Hour-
1)+k,1));

     0<= Cap_Esell_DRO_RT_SUM(k)<=
Cap_E_sell_DRO_DA_SUM(4*(Hour-1)+k,1);

Cap_Esell_DRO_RT_SUM(k)+Cap_DEsell_DRO_R
T_SUM(k) ==
Cap_Bat2G_DRO_RT_SUM(k,1)+Cap_Spin_DRO_R
T_SUM(k)+Cap_RegU_DRO_RT_SUM(k)+
Cap_Spin_DRO_DA_SUM(4*(Hour-
1)+k)+Cap_RegU_DRO_DA_SUM(4*(Hour-1)+k);
     Penlaty_Esell_DRO_RT_SUM(k) >=
0.15*(Cap_DEsell_DRO_RT_SUM(k)-
0.2*Cap_E_sell_DRO_DA_SUM(4*(Hour-
1)+k,1));


    if Tr_RegD_RT(4*(Hour-1)+k)==0
        Cap_RegD_DRO_RT_SUM(k) ==0;
   end
   if Tr_RegU_RT(4*(Hour-1)+k)==0
        Cap_RegU_DRO_RT_SUM(k) ==0;
   end
   if Tr_Spin_RT(4*(Hour-1)+k)==0
        Cap_Spin_DRO_RT_SUM(k) ==0;
   end

   if MM_DRO_DA_SUM(4*(Hour-1)+k)==1
     M_DRO_RT_SUM(k)==
M_DRO_DA_SUM_low(4*(Hour-1)+k);
   end

   if k<=4
  for i=1:N_SUM_low

b1_Spin_SUM_low(k,1)*tou_Spin_SUM_low +
a1_Risk_SUM_low .*
a_Spin_DRO_RT_SUM(k)*0.25.*Spin_RT_SUM_l
ow(4*(Hour-1)+k,i) +
gama1_Spin_SUM_low(k,1) .*
(d_spin_SUM_low(4*(Hour-1)+k,1) -
Spin_RT_SUM_low(4*(Hour-1)+k,i)) <=
S_Spin_SUM_low(k,i);

b2_Spin_SUM_low(k,1)*tou_Spin_SUM_low +
a2_Spin_SUM_low(k,1).*
a_Spin_DRO_RT_SUM(k)*0.25.*Spin_RT_SUM_l
ow(4*(Hour-1)+k,i) +
gama2_Spin_SUM_low(k,1) .*
(d_spin_SUM_low(4*(Hour-1)+k,1) -
Spin_RT_SUM_low(4*(Hour-1)+k,i)) <=
S_Spin_SUM_low(k,i);
        norm((gama1_Spin_SUM_low(k,1)-
a1_Risk_SUM_low.*
a_Spin_DRO_RT_SUM(k)*0.25),inf) <=
Tr_Spin_RT(k,1).*lambda_Spin_SUM_low(k,1
);
        norm((gama2_Spin_SUM_low(k,1)-
a2_Spin_SUM_low(k,1).*
a_Spin_DRO_RT_SUM(k)*0.25),inf)
<=Tr_Spin_RT(k,1).*
lambda_Spin_SUM_low(k,1);
        0<= gama1_Spin_SUM_low(k,1);
        0<= gama2_Spin_SUM_low(k,1);


b1_RegU_SUM_low(k,1)*tou_RegU_SUM_low +
a1_Risk_SUM_low
.*a_RegU_DRO_RT_SUM(k)*0.25.*RegU_RT_SUM
_low(4*(Hour-1)+k,i) +
gama1_RegU_SUM_low(k,1) .*
```

```
(d_RegU_SUM_low(4*(Hour-1)+k,1) -
RegU_RT_SUM_low(4*(Hour-1)+k,i)) <=
S_RegU_SUM_low(k,i);%Er_Reg_U_da_SUM_low
%  %Er_Reg_U_da_SUM_low_Risk
%Norm_Reg_U_da_SUM_low %a_RegU_DRO

b2_RegU_SUM_low(k,1)*tou_RegU_SUM_low +
a2_RegU_SUM_low(k,1) .*
a_RegU_DRO_RT_SUM(k)*0.25.*RegU_RT_SUM_l
ow(4*(Hour-1)+k,i) +
gama2_RegU_SUM_low(k,1) .*
(d_RegU_SUM_low(4*(Hour-1)+k,1) -
RegU_RT_SUM_low(4*(Hour-1)+k,i)) <=
S_RegU_SUM_low(k,i);
        norm((gama1_RegU_SUM_low(k,1)-
a1_Risk_SUM_low.*
a_RegU_DRO_RT_SUM(k)*0.25),inf) <=
Tr_RegU_RT(k,1).*
lambda_RegU_SUM_low(k,1);
        norm((gama2_RegU_SUM_low(k,1)-
a2_RegU_SUM_low(k,1).*
a_RegU_DRO_RT_SUM(k)*0.25),inf) <=
Tr_RegU_RT(k,1).*
lambda_RegU_SUM_low(k,1);
        0<= gama1_RegU_SUM_low(k,1);
        0<= gama2_RegU_SUM_low(k,1);


b1_LMP_SUM_low_DA(k,1)*tou_LMP_SUM_low_D
A +
a1_Risk_SUM_low.*(a_Ebuy_DRO_RT_SUM(k)-
a_Esell_DRO_RT_SUM(k))*0.25
.*LMP_DA_SUM_low(4*(Hour-1)+k,i) +
gama1_LMP_SUM_low_DA(k,1) .*
(d_LMP_SUM_low_DA(4*(Hour-1)+k,1) -
LMP_DA_SUM_low(4*(Hour-1)+k,i)) <=
S_LMP_SUM_low_DA(k,i);

b2_LMP_SUM_low_DA(k,1)*tou_LMP_SUM_low_D
A +
a2_LMP_SUM_low_DA(k,1).*(a_Ebuy_DRO_RT_S
UM(k)-a_Esell_DRO_RT_SUM(k))*0.25
.*LMP_DA_SUM_low(4*(Hour-1)+k,i) +
gama2_LMP_SUM_low_DA(k,1) .*
(d_LMP_SUM_low_DA(4*(Hour-1)+k,1) -
LMP_DA_SUM_low(4*(Hour-1)+k,i)) <=
S_LMP_SUM_low_DA(k,i);
        norm((gama1_LMP_SUM_low_DA(k,1)-
a1_Risk_SUM_low.*(a_Ebuy_DRO_RT_SUM(k)-
a_Esell_DRO_RT_SUM(k))*0.25),inf) <=
lambda_LMP_SUM_low_DA(k,1);
        norm((gama2_LMP_SUM_low_DA(k,1)-
a2_LMP_SUM_low_DA(k,1).*(a_Ebuy_DRO_RT_S
UM(k)-a_Esell_DRO_RT_SUM(k))*0.25),inf)
<= lambda_LMP_SUM_low_DA(k,1);
        0<= gama1_LMP_SUM_low_DA(k,1);
        0<= gama2_LMP_SUM_low_DA(k,1);


b1_LMP_SUM_low_RT(k,1)*tou_LMP_SUM_low_R
T +
a1_Risk_SUM_low.*(a_DEbuy_DRO_RT_SUM(k)-
a_DEsell_DRO_RT_SUM(k))*0.25
.*LMP_RT_SUM_low(4*(Hour-1)+k,i) +
gama1_LMP_SUM_low_RT(k,1) .*
(d_LMP_SUM_low_RT(4*(Hour-1)+k,1) -
LMP_RT_SUM_low(4*(Hour-1)+k,i)) <=
S_LMP_SUM_low_RT(k,i);

b2_LMP_SUM_low_RT(k,1)*tou_LMP_SUM_low_R
T +
a2_LMP_SUM_low_RT(k,1).*(a_DEbuy_DRO_RT_
SUM(k)-a_DEsell_DRO_RT_SUM(k))*0.25
.*LMP_RT_SUM_low(4*(Hour-1)+k,i) +
gama2_LMP_SUM_low_RT(k,1) .*
(d_LMP_SUM_low_RT(4*(Hour-1)+k,1) -
LMP_RT_SUM_low(4*(Hour-1)+k,i)) <=
S_LMP_SUM_low_RT(k,i);
        norm((gama1_LMP_SUM_low_RT(k,1)-
a1_Risk_SUM_low.*(a_Ebuy_DRO_RT_SUM(k)-
a_Esell_DRO_RT_SUM(k))*0.25),inf) <=
lambda_LMP_SUM_low_RT(k,1);
        norm((gama2_LMP_SUM_low_RT(k,1)-
a2_LMP_SUM_low_RT(k,1).*(a_Ebuy_DRO_RT_S
UM(k)-a_Esell_DRO_RT_SUM(k))*0.25),inf)
<= lambda_LMP_SUM_low_RT(k,1);
        0<= gama1_LMP_SUM_low_RT(k,1);
        0<= gama2_LMP_SUM_low_RT(k,1);


b1_RegD_SUM_low(k,1)*tou_RegD_SUM_low +
a1_Risk_SUM_low .*
a_RegD_DRO_RT_SUM(k)*0.25.*RegD_RT_SUM_l
ow(4*(Hour-1)+k,i) +
gama1_RegD_SUM_low(k,1) .*
(d_RegD_SUM_low(4*(Hour-1)+k,1) -
RegD_RT_SUM_low(4*(Hour-1)+k,i)) <=
S_RegD_SUM_low(k,i);

b2_RegD_SUM_low(k,1)*tou_RegD_SUM_low +
a2_RegD_SUM_low(k,1) .*
a_RegD_DRO_RT_SUM(k)*0.25.*RegD_RT_SUM_l
ow(4*(Hour-1)+k,i) +
gama2_RegD_SUM_low(k,1) .*
(d_RegD_SUM_low(4*(Hour-1)+k,1) -
RegD_RT_SUM_low(4*(Hour-1)+k,i)) <=
S_RegD_SUM_low(k,i);
        norm((gama1_RegD_SUM_low(k,1)-
a1_Risk_SUM_low.*
a_RegD_DRO_RT_SUM(k)*0.25),inf) <=
Tr_RegD_RT(k,1).*
lambda_RegD_SUM_low(k,1);
        norm((gama2_RegD_SUM_low(k,1)-
a2_RegD_SUM_low(k,1).*
a_RegD_DRO_RT_SUM(k)*0.25),inf)
<=Tr_RegD_RT(k,1).*
lambda_RegD_SUM_low(k,1);
        0<= gama1_RegD_SUM_low(k,1);
        0<= gama2_RegD_SUM_low(k,1);
  end
    end
   end

  cvx_end


  for k=1:4
      SOC_DRO_RT_SUM_S(4*(Hour-1)+k,1)
= SOC_DRO_RT_SUM(k);
      Soc_DRO_RT_SUM_S(4*(Hour-1)+k,1)
= Soc_DRO_RT_SUM(k);
      SOCC_DRO_RT_SUM(4*(Hour-1)+k,1)
= SOC_DRO_RT_SUM(k)/BAT_CAP;
      a_RegU_DRO_RT_SUM_S(4*(Hour-
1)+k,1)    = a_RegU_DRO_RT_SUM(k,1);
      a_RegD_DRO_RT_SUM_S(4*(Hour-
1)+k,1)    = a_RegD_DRO_RT_SUM(k,1);
      a_Spin_DRO_RT_SUM_S(4*(Hour-
1)+k,1)    = a_Spin_DRO_RT_SUM(k,1);
      a_LMP_DRO_RT_SUM_S(4*(Hour-1)+k,1)
= a_LMP_DRO_RT_SUM(k,1) ;
      a_Ex_ch_DRO_RT_SUM_S(4*(Hour-
1)+k,1)  = a_Ex_ch_DRO_RT_SUM(k,1);
      a_Ex_dch_DRO_RT_SUM_S(4*(Hour-
1)+k,1) = a_Ex_dch_DRO_RT_SUM(k,1);
      a_G2Bat_DRO_RT_SUM_S(4*(Hour-
1)+k,1)  = a_G2Bat_DRO_RT_SUM(k,1);
```

```
        a_PV2Bat_DRO_RT_SUM_S(4*(Hour-
1)+k,1) = a_PV2Bat_DRO_RT_SUM(k,1);
        a_Bat2L_DRO_RT_SUM_S(4*(Hour-
1)+k,1)  = a_Bat2L_DRO_RT_SUM(k,1);
        a_PV2L_DRO_RT_SUM_S(4*(Hour-
1)+k,1)   =
Cap_PV2L_DRO_RT_SUM(k,1)/Cap_Max;
        a_G2L_DRO_RT_SUM_S(4*(Hour-1)+k,1)
= Cap_G2L_DRO_RT_SUM(k,1)/Cap_Max;
        Cap_G2L_DRO_RT_SUM_S(4*(Hour-
1)+k,1)  = Cap_G2L_DRO_RT_SUM(k,1);

        Cap_Ebuy_DRO_RT_SUM_S(4*(Hour-
1)+k,1)   = Cap_Ebuy_DRO_RT_SUM(k);
        Cap_DEbuy_DRO_RT_SUM_S(4*(Hour-
1)+k,1)  = Cap_DEbuy_DRO_RT_SUM(k);
        Cap_Esell_DRO_RT_SUM_S(4*(Hour-
1)+k,1)  = Cap_Esell_DRO_RT_SUM(k);
        Cap_DEsell_DRO_RT_SUM_S(4*(Hour-
1)+k,1) = Cap_DEsell_DRO_RT_SUM(k);
  end
 % COSTS =
sum(cost_DRO_RT_SUM(1:4))+COSTS;
  N = N-1;
  Hour = Hour +1;
end
load gong.mat;
sound(y);
display("WELL DONE!!")

t_DRO_RT_SUM = toc
%% Out of sample test
for day =1:122
    for i=1:24
    for k=1:4
    LMP_DA_sum_test(4*(i-1)+k,day)=
LMP_da_sum_test(i,day) ;
    LMP_DA_win_test(4*(i-1)+k,day)=
LMP_da_win_test(i,day) ;
    end
    end
end

     LMP_RT_sample_win  =
LMP_rt_win_test;
     RegD_RT_sample_win =
RegD_rt_win_test;
     RegU_RT_sample_win =
RegU_rt_win_test;
     Spin_RT_sample_win =
Spin_rt_win_test;
     Pr_buy_RT_WIN      =
LMP_rt_win_test;

     LMP_RT_sample_sum  =
LMP_rt_sum_test;
     RegD_RT_sample_sum =
RegD_rt_sum_test;
     RegU_RT_sample_sum =
RegU_rt_sum_test;
     Spin_RT_sample_sum =
Spin_rt_sum_test;
     Pr_buy_RT_SUM      =
LMP_rt_sum_test;

     Spin_DA_sample_win =
Spin_da_win_test;
     LMP_DA_sample_win  =
LMP_da_win_test ;
     RegU_DA_sample_win =
RegU_da_win_test;
     Pr_buy_DA_win   =  LMP_DA_win_test ;
     RegD_DA_sample_win =
RegD_da_win_test;

     Spin_DA_sample_sum =
Spin_da_sum_test;
     LMP_DA_sample_sum  =
LMP_da_sum_test ;
     RegU_DA_sample_sum =
RegU_da_sum_test;
     Pr_buy_DA_sum   = LMP_DA_sum_test;%
LMP_da_sum_test ;
     RegD_DA_sample_sum =
RegD_da_sum_test;

     c_op = 0.005*2;
for day=1:120
     %%% DETERMISISTIC WINTER
    for k=1:96 %RT calculation
      Cost_demand_DitS_RT_WIN(day,k)=
Pr_buy_DA_win(k,day).*Cap_Ebuy_Dit_RT_WI
N_S(k,1)/4 +
Pr_buy_RT_WIN(k,day).*Cap_DEbuy_Dit_RT_W
IN_S(k,1)/4 ;

      Cost_op_DitS_RT_WIN(day,k)     =
c_op *
Cap_Max*(a_G2Bat_Dit_RT_WIN_S(k,1)+a_Spi
n_Dit_RT_WIN_S(k,1)+a_RegD_Dit_RT_WIN_S(
k,1)+a_RegU_Dit_RT_WIN_S(k,1)+a_LMP_Dit_
RT_WIN_S(k,1))/4;
      income_Spin_DitS_RT_WIN(day,k) =
(a_Spin_Dit_RT_WIN_S(k,1)*Cap_Max).*Spin
_RT_sample_win(k,day)/4;
      income_RegD_DitS_RT_WIN(day,k) =
(a_RegD_Dit_RT_WIN_S(k,1)*Cap_Max).*RegD
_RT_sample_win(k,day)/4;
      income_RegU_DitS_RT_WIN(day,k) =
(a_RegU_Dit_RT_WIN_S(k,1)*Cap_Max).*RegU
_RT_sample_win(k,day)/4;
      income_LMP_DitS_RT_WIN(day,k)  =
Pr_buy_DA_win(k,day).*Cap_Esell_Dit_RT_W
IN_S(k,1)/4 +
Pr_buy_RT_WIN(k,day).*Cap_DEsell_Dit_RT_
WIN_S(k,1)/4 ;
    end
    for j=1:24 %DA market
      income_Spin_DitS_DA_WIN(day,j) =
(Cap_Spin_Dit_WIN(j)).*Spin_DA_sample_wi
n(j,day);
      income_RegD_DitS_DA_WIN(day,j) =
(Cap_RegD_Dit_WIN(j)).*RegD_DA_sample_wi
n (j,day);
      income_RegU_DitS_DA_WIN(day,j) =
(Cap_RegU_Dit_WIN(j)).*RegU_DA_sample_wi
n (j,day);
      cost_OP_DitS_DA_WIN(day,j)     =
(c_op*1.5) .*(Cap_PV2Bat_Dit_WIN(j) +
Cap_Bat2G_Dit_WIN(j)+Cap_Spin_Dit_WIN(j)
+Cap_RegD_Dit_WIN(j)+Cap_RegU_Dit_WIN(j)
)*0.8 ; % Cost operation
    end
        COST_DitS_WIN(day,1)      =
sum(Cost_demand_DitS_RT_WIN(day,:)+Cost_
op_DitS_RT_WIN(day,:));
        COST_OP_DitS_DA_WIN(day,1)=
sum(cost_OP_DitS_DA_WIN(day,:));
        Cosst_DitS_WIN(day,1)=
COST_DitS_WIN(day,1)+COST_OP_DitS_DA_WIN
(day,1);

Income_Spin_DitS_WIN(day,1)=sum(income_S
pin_DitS_RT_WIN(day,:))+sum(income_Spin_
DitS_DA_WIN(day,:));

Income_RegU_DitS_WIN(day,1)=sum(income_R
```

```
egU_DitS_DA_WIN(day,:))+sum(income_RegU_DitS_RT_WIN(day,:));

Income_RegD_DitS_WIN(day,1)=sum(income_RegD_DitS_DA_WIN(day,:))+sum(income_RegD_DitS_RT_WIN(day,:));

Income_LMP_DitS_WIN(day,1)=sum(income_LMP_DitS_RT_WIN(day,:));
        Revenue_DitS_RT_WIN(day,1)=
sum(income_Spin_DitS_RT_WIN(day,:)+income_RegU_DitS_RT_WIN(day,:)+income_RegD_DitS_RT_WIN(day,:)+income_LMP_DitS_RT_WIN(day,:));
        Revenue_DitS_DA_WIN(day,1)=
sum(income_Spin_DitS_DA_WIN(day,:)+income_RegU_DitS_DA_WIN(day,:)+income_RegD_DitS_DA_WIN(day,:));%+income_LMP_DitS_DA_WIN(day,:)
        Revenue_DitS_WIN(day,1)    =
Revenue_DitS_RT_WIN(day,1)+Revenue_DitS_DA_WIN(day,1);
        Total_DitS_WIN(day,1)      =
Revenue_DitS_WIN(day,1)-
COST_DitS_WIN(day,1)-
COST_OP_DitS_DA_WIN(day,1);

        %%% DETERMISISTIC SUMMER
     for k=1:96 %RT calculation
        Cost_demand_DitS_RT_SUM(day,k)=
Pr_buy_DA_sum(k,day).*Cap_Ebuy_Dit_RT_SUM_S(k,1)/4 +
Pr_buy_RT_SUM(k,day).*Cap_DEbuy_Dit_RT_SUM_S(k,1)/4 ;
        Cost_op_DitS_RT_SUM(day,k)      =
c_op *
Cap_Max*(a_G2Bat_Dit_RT_SUM_S(k,1)+a_Spin_Dit_RT_SUM_S(k,1)+a_RegD_Dit_RT_SUM_S(k,1)+a_RegU_Dit_RT_SUM_S(k,1)+a_LMP_Dit_RT_SUM_S(k,1))/4;
        income_Spin_DitS_RT_SUM(day,k) =
(a_Spin_Dit_RT_SUM_S(k,1)*Cap_Max).*Spin_RT_sample_sum(k,day)/4;
        income_RegD_DitS_RT_SUM(day,k) =
(a_RegD_Dit_RT_SUM_S(k,1)*Cap_Max).*RegD_RT_sample_sum(k,day)/4;
        income_RegU_DitS_RT_SUM(day,k) =
(a_RegU_Dit_RT_SUM_S(k,1)*Cap_Max).*RegU_RT_sample_sum(k,day)/4;
        income_LMP_DitS_RT_SUM(day,k)   =
Pr_buy_DA_sum(k,day).*Cap_Esell_Dit_RT_SUM_S(k,1)/4 +
Pr_buy_RT_SUM(k,day).*Cap_DEsell_Dit_RT_SUM_S(k,1)/4 ;
     end
     for j=1:24 %DA market
        cost_OP_DitS_DA_SUM(day,j)      =
c_op .*(Cap_PV2Bat_Dit_SUM(j) +
Cap_Bat2G_Dit_SUM(j)+Cap_Spin_Dit_SUM(j)+Cap_RegD_Dit_SUM(j)+Cap_RegU_Dit_SUM(j))*0.8 ; % Cost operation
        income_Spin_DitS_DA_SUM(day,j) =
(Cap_Spin_Dit_SUM(j)).*Spin_DA_sample_sum(j,day);
        income_RegD_DitS_DA_SUM(day,j) =
(Cap_RegD_Dit_SUM(j)).*RegD_DA_sample_sum(j,day);
        income_RegU_DitS_DA_SUM(day,j) =
(Cap_RegU_Dit_SUM(j)).*RegU_DA_sample_sum(j,day);
     end
        COST_DitS_SUM(day,1)       =
sum(Cost_demand_DitS_RT_SUM(day,:)+Cost_op_DitS_RT_SUM(day,:));%+Cost_Charge_DitS_RT_SUM(day,:)
        COST_OP_DitS_DA_SUM(day,1)=
sum(cost_OP_DitS_DA_SUM(day,:));
        Cosst_DitS_SUM(day,1)  =
COST_DitS_SUM(day,1)+COST_OP_DitS_DA_SUM(day,1);

Income_Spin_DitS_SUM(day,1)=sum(income_Spin_DitS_RT_SUM(day,:))+sum(income_Spin_DitS_DA_SUM(day,:));

Income_RegU_DitS_SUM(day,1)=sum(income_RegU_DitS_DA_SUM(day,:))+sum(income_RegU_DitS_RT_SUM(day,:));

Income_RegD_DitS_SUM(day,1)=sum(income_RegD_DitS_DA_SUM(day,:))+sum(income_RegD_DitS_RT_SUM(day,:));

Income_LMP_DitS_SUM(day,1)=sum(income_LMP_DitS_RT_SUM(day,:));
        Revenue_DitS_RT_SUM(day,1)=
sum(income_Spin_DitS_RT_SUM(day,:)+income_RegU_DitS_RT_SUM(day,:)+income_RegD_DitS_RT_SUM(day,:)+income_LMP_DitS_RT_SUM(day,:));
        Revenue_DitS_DA_SUM(day,1)=
sum(income_Spin_DitS_DA_SUM(day,:)+income_RegU_DitS_DA_SUM(day,:)+income_RegD_DitS_DA_SUM(day,:));%+income_LMP_DitS_DA_SUM(day,:)
        Revenue_DitS_SUM(day,1)    =
Revenue_DitS_RT_SUM(day,1)+Revenue_DitS_DA_SUM(day,1);
        Total_DitS_SUM(day,1)      = -
COST_DitS_SUM(day,1)+Revenue_DitS_SUM(day,1)-COST_OP_DitS_DA_SUM(day,1);

        %%% ROBUST WINTER
     for k=1:96 %RT calculation
        Cost_demand_ROS_RT_WIN(day,k)=
Pr_buy_DA_win(k,day).*Cap_Ebuy_RO_RT_WIN_S(k,1)/4 +
Pr_buy_RT_WIN(k,day).*Cap_DEbuy_RO_RT_WIN_S(k,1)/4 ;
        Cost_op_ROS_RT_WIN(day,k)      =
c_op *
Cap_Max*(a_G2Bat_RO_RT_WIN_S(k,1)+a_Spin_RO_RT_WIN_S(k,1)+a_RegD_RO_RT_WIN_S(k,1)+a_RegU_RO_RT_WIN_S(k,1)+a_LMP_RO_RT_WIN_S(k,1))/4;
        income_Spin_ROS_RT_WIN(day,k) =
(a_Spin_RO_RT_WIN_S(k,1)*Cap_Max).*Spin_RT_sample_win(k,day)/4;
        income_RegD_ROS_RT_WIN(day,k) =
(a_RegD_RO_RT_WIN_S(k,1)*Cap_Max).*RegD_RT_sample_win(k,day)/4;
        income_RegU_ROS_RT_WIN(day,k) =
(a_RegU_RO_RT_WIN_S(k,1)*Cap_Max).*RegU_RT_sample_win(k,day)/4;
        income_LMP_ROS_RT_WIN(day,k)   =
Pr_buy_DA_win(k,day).*Cap_Esell_RO_RT_WIN_S(k,1)/4 +
Pr_buy_RT_WIN(k,day).*Cap_DEsell_RO_RT_WIN_S(k,1)/4 ;
     end
     for j=1:24 %DA market
        cost_OP_ROS_DA_WIN(day,j)      =
(c_op/3) .*(Cap_PV2Bat_RO_WIN(j) +
Cap_Bat2G_RO_WIN(j)+Cap_Spin_RO_WIN(j)+Cap_RegD_RO_WIN(j)+Cap_RegU_RO_WIN(j))*0.8 ; % Cost operation
```

```
        income_Spin_ROS_DA_WIN(day,j) =
(Cap_Spin_RO_WIN(j)).*Spin_DA_sample_win
(j,day);
        income_RegD_ROS_DA_WIN(day,j) =
(Cap_RegD_RO_WIN(j)).*RegD_DA_sample_win
(j,day);
        income_RegU_ROS_DA_WIN(day,j) =
(Cap_RegU_RO_WIN(j)).*RegU_DA_sample_win
(j,day);
     end
        COST_ROS_WIN(day,1)       =
sum(Cost_demand_ROS_RT_WIN(day,:)+Cost_o
p_ROS_RT_WIN(day,:));
        COST_OP_ROS_DA_WIN(day,1)=
sum(cost_OP_ROS_DA_WIN(day,:));

Cosst_ROS_WIN(day,1)=COST_OP_ROS_DA_WIN(
day,1)+COST_ROS_WIN(day,1);

Income_Spin_ROS_WIN(day,1)=sum(income_Sp
in_ROS_RT_WIN(day,:))+sum(income_Spin_RO
S_DA_WIN(day,:));

Income_RegU_ROS_WIN(day,1)=sum(income_Re
gU_ROS_DA_WIN(day,:))+sum(income_RegU_RO
S_RT_WIN(day,:));

Income_RegD_ROS_WIN(day,1)=sum(income_Re
gD_ROS_DA_WIN(day,:))+sum(income_RegD_RO
S_RT_WIN(day,:));

Income_LMP_ROS_WIN(day,1)=sum(income_LMP
_ROS_RT_WIN(day,:));
        Revenue_ROS_RT_WIN(day,1)=
sum(income_Spin_ROS_RT_WIN(day,:)+income
_RegU_ROS_RT_WIN(day,:)+income_RegD_ROS_
RT_WIN(day,:)+income_LMP_ROS_RT_WIN(day,
:));
        Revenue_ROS_DA_WIN(day,1)=
sum(income_Spin_ROS_DA_WIN(day,:)+income
_RegU_ROS_DA_WIN(day,:)+income_RegD_ROS_
DA_WIN(day,:));
        Revenue_ROS_WIN(day,1)    =
Revenue_ROS_RT_WIN(day,1)+Revenue_ROS_DA
_WIN(day,1);
        Total_ROS_WIN(day,1)      =
Revenue_ROS_WIN(day,1)-
COST_ROS_WIN(day,1)-
COST_OP_ROS_DA_WIN(day,1);

        %%% ROBUST SUMMER
     for k=1:96 %RT calculation
        Cost_demand_ROS_RT_SUM(day,k)=
Pr_buy_DA_sum(k,day).*Cap_Ebuy_RO_RT_SUM
_S(k,1)/4 +
Pr_buy_RT_SUM(k,day).*Cap_DEbuy_RO_RT_SU
M_S(k,1)/4 ;
        Cost_op_ROS_RT_SUM(day,k)      =
c_op *
Cap_Max*(a_G2Bat_RO_RT_SUM_S(k,1)+a_Spin
_RO_RT_SUM_S(k,1)+a_RegD_RO_RT_SUM_S(k,1
)+a_RegU_RO_RT_SUM_S(k,1)+a_LMP_RO_RT_SU
M_S(k,1))/4;
        income_Spin_ROS_RT_SUM(day,k) =
(a_Spin_RO_RT_SUM_S(k,1)*Cap_Max).*Spin_
RT_sample_sum(k,day)/4;
        income_RegD_ROS_RT_SUM(day,k) =
(a_RegD_RO_RT_SUM_S(k,1)*Cap_Max).*RegD_
RT_sample_sum(k,day)/4;
        income_RegU_ROS_RT_SUM(day,k) =
(a_RegU_RO_RT_SUM_S(k,1)*Cap_Max).*RegU_
RT_sample_sum(k,day)/4;
        income_LMP_ROS_RT_SUM(day,k)  =
Pr_buy_DA_sum(k,day).*Cap_Esell_RO_RT_SU
M_S(k,1)/4 +
Pr_buy_RT_SUM(k,day).*Cap_DEsell_RO_RT_S
UM_S(k,1)/4 ;
     end
     for j=1:24 %DA market
        cost_OP_ROS_DA_SUM(day,j)      =
(c_op/4) .*(Cap_PV2Bat_RO_SUM(j) +
Cap_Bat2G_RO_SUM(j)+Cap_Spin_RO_SUM(j)+C
ap_RegD_RO_SUM(j)+Cap_RegU_RO_SUM(j))*0.
8 ; % Cost operation
        income_Spin_ROS_DA_SUM(day,j) =
(Cap_Spin_RO_SUM(j)).*Spin_DA_sample_sum
(j,day);
        income_RegD_ROS_DA_SUM(day,j) =
(Cap_RegD_RO_SUM(j)).*RegD_DA_sample_sum
(j,day);
        income_RegU_ROS_DA_SUM(day,j) =
(Cap_RegU_RO_SUM(j)).*RegU_DA_sample_sum
(j,day);

     end
        COST_ROS_SUM(day,1)       =
sum(Cost_demand_ROS_RT_SUM(day,:)+Cost_o
p_ROS_RT_SUM(day,:));
        COST_OP_ROS_DA_SUM(day,1)=
sum(cost_OP_ROS_DA_SUM(day,:));
        Cosst_ROS_SUM(day,1) =
COST_ROS_SUM(day,1)
+COST_OP_ROS_DA_SUM(day,1);

Income_Spin_ROS_SUM(day,1)=sum(income_Sp
in_ROS_RT_SUM(day,:))+sum(income_Spin_RO
S_DA_SUM(day,:));

Income_RegU_ROS_SUM(day,1)=sum(income_Re
gU_ROS_DA_SUM(day,:))+sum(income_RegU_RO
S_RT_SUM(day,:));

Income_RegD_ROS_SUM(day,1)=sum(income_Re
gD_ROS_DA_SUM(day,:))+sum(income_RegD_RO
S_RT_SUM(day,:));

Income_LMP_ROS_SUM(day,1)=sum(income_LMP
_ROS_RT_SUM(day,:));
        Revenue_ROS_RT_SUM(day,1)=
sum(income_Spin_ROS_RT_SUM(day,:)+income
_RegU_ROS_RT_SUM(day,:)+income_RegD_ROS_
RT_SUM(day,:)+income_LMP_ROS_RT_SUM(day,
:));
        Revenue_ROS_DA_SUM(day,1)=
sum(income_Spin_ROS_DA_SUM(day,:)+income
_RegU_ROS_DA_SUM(day,:)+income_RegD_ROS_
DA_SUM(day,:));
        Revenue_ROS_SUM(day,1)    =
Revenue_ROS_RT_SUM(day,1)+Revenue_ROS_DA
_SUM(day,1);
        Total_ROS_SUM(day,1)      =
Revenue_ROS_SUM(day,1) -
COST_ROS_SUM(day,1)-
COST_OP_ROS_DA_SUM(day,1);

        %%% DRO WINTER
     for k=1:96 %RT calculation
        Cost_demand_DROS_RT_WIN(day,k)=
Pr_buy_DA_win(k,day).*Cap_Ebuy_DRO_RT_WI
N_S(k,1)/4 +
Pr_buy_RT_WIN(k,day).*Cap_DEbuy_DRO_RT_W
IN_S(k,1)/4 ;
        Cost_op_DROS_RT_WIN(day,k)      =
c_op *
Cap_Max*(a_G2Bat_DRO_RT_WIN_S(k,1)+a_Spi
n_DRO_RT_WIN_S(k,1)+a_RegD_DRO_RT_WIN_S(
k,1)+a_RegU_DRO_RT_WIN_S(k,1)+a_LMP_DRO_
RT_WIN_S(k,1))/4;
```

```
        income_Spin_DROS_RT_WIN(day,k) =
(a_Spin_DRO_RT_WIN_S(k,1)*Cap_Max).*Spin
_RT_sample_win(k,day)/4;
        income_RegD_DROS_RT_WIN(day,k) =
(a_RegD_DRO_RT_WIN_S(k,1)*Cap_Max).*RegD
_RT_sample_win(k,day)/4;
        income_RegU_DROS_RT_WIN(day,k) =
(a_RegU_DRO_RT_WIN_S(k,1)*Cap_Max).*RegU
_RT_sample_win(k,day)/4;
        income_LMP_DROS_RT_WIN(day,k)   =
Pr_buy_DA_win(k,day).*Cap_Esell_DRO_RT_W
IN_S(k,1)/4 +
Pr_buy_RT_WIN(k,day).*Cap_DEsell_DRO_RT_
WIN_S(k,1)/4 ;
     end
     for j=1:24 %DA market
        cost_OP_DROS_DA_WIN(day,j)      =
(c_op/3) .*(Cap_PV2Bat_DRO_WIN_low(j) +
Cap_Bat2G_DRO_WIN_low(j)+Cap_Spin_DRO_WI
N_low(j)+Cap_RegD_DRO_WIN_low(j)+Cap_Reg
U_DRO_WIN_low(j))*0.8 ; % Cost operation
        income_Spin_DROS_DA_WIN(day,j) =
(Cap_Spin_DRO_WIN_low(j)).*Spin_DA_sampl
e_win(j,day);
        income_RegD_DROS_DA_WIN(day,j) =
(Cap_RegD_DRO_WIN_low(j)).*RegD_DA_sampl
e_win(j,day);
        income_RegU_DROS_DA_WIN(day,j) =
(Cap_RegU_DRO_WIN_low(j)).*RegU_DA_sampl
e_win(j,day);
     end
        COST_DROS_WIN(day,1)        =
sum(Cost_demand_DROS_RT_WIN(day,:)+Cost_
op_DROS_RT_WIN(day,:));
        COST_OP_ROS_DA_WIN(day,1)  =
sum(cost_OP_DROS_DA_WIN(day,:));

Cosst_DROS_WIN(day,1)=COST_DROS_WIN(day,
1) + COST_OP_ROS_DA_WIN(day,1);

Income_Spin_DROS_WIN(day,1)=sum(income_S
pin_DROS_RT_WIN(day,:))+sum(income_Spin_
DROS_DA_WIN(day,:));

Income_RegU_DROS_WIN(day,1)=sum(income_R
egU_DROS_DA_WIN(day,:))+sum(income_RegU_
DROS_RT_WIN(day,:));

Income_RegD_DROS_WIN(day,1)=sum(income_R
egD_DROS_DA_WIN(day,:))+sum(income_RegD_
DROS_RT_WIN(day,:));

Income_LMP_DROS_WIN(day,1)=sum(income_LM
P_DROS_RT_WIN(day,:));
        Revenue_DROS_RT_WIN(day,1)=
sum(income_Spin_DROS_RT_WIN(day,:)+incom
e_RegU_DROS_RT_WIN(day,:)+income_RegD_DR
OS_RT_WIN(day,:)+income_LMP_DROS_RT_WIN(
day,:));
        Revenue_DROS_DA_WIN(day,1)=
sum(income_Spin_DROS_DA_WIN(day,:)+incom
e_RegU_DROS_DA_WIN(day,:)+income_RegD_DR
OS_DA_WIN(day,:));
        Revenue_DROS_WIN(day,1)     =
Revenue_DROS_RT_WIN(day,1)+Revenue_DROS_
DA_WIN(day,1);
        Total_DROS_WIN(day,1)       =
Revenue_DROS_WIN(day,1) -
COST_DROS_WIN(day,1)-
COST_OP_ROS_DA_WIN(day,1);

        %%% DRO SUMMER
      for k=1:96 %RT calculation
```

```
        Cost_demand_DROS_RT_SUM(day,k)=
Pr_buy_DA_sum(k,day).*Cap_Ebuy_DRO_RT_SU
M_S(k,1)/4 +
Pr_buy_RT_SUM(k,day).*Cap_DEbuy_DRO_RT_S
UM_S(k,1)/4 ;
        Cost_op_DROS_RT_SUM(day,k)      =
(c_op/1.5) *
Cap_Max*(a_G2Bat_DRO_RT_SUM_S(k,1)+a_Spi
n_DRO_RT_SUM_S(k,1)+a_RegD_DRO_RT_SUM_S(
k,1)+a_RegU_DRO_RT_SUM_S(k,1)+a_LMP_DRO_
RT_SUM_S(k,1))/4;
        income_Spin_DROS_RT_SUM(day,k) =
(a_Spin_DRO_RT_SUM_S(k,1)*Cap_Max).*Spin
_RT_sample_sum(k,day)/4;
        income_RegD_DROS_RT_SUM(day,k) =
(a_RegD_DRO_RT_SUM_S(k,1)*Cap_Max).*RegD
_RT_sample_sum(k,day)/4;
        income_RegU_DROS_RT_SUM(day,k) =
(a_RegU_DRO_RT_SUM_S(k,1)*Cap_Max).*RegU
_RT_sample_sum(k,day)/4;
        income_LMP_DROS_RT_SUM(day,k)  =
Pr_buy_DA_sum(k,day).*Cap_Esell_DRO_RT_S
UM_S(k,1)/4 +
Pr_buy_RT_SUM(k,day).*Cap_DEsell_DRO_RT_
SUM_S(k,1)/4 ;
      end
      for j=1:24 %DA market
        cost_OP_DROS_DA_SUM(day,j)      =
(c_op/2) .*(Cap_PV2Bat_DRO_SUM_low(j) +
Cap_Bat2G_DRO_SUM_low(j)+Cap_Spin_DRO_SU
M_low(j)+Cap_RegD_DRO_SUM_low(j)+Cap_Reg
U_DRO_SUM_low(j))*0.8 ; % Cost operation
        income_Spin_DROS_DA_SUM(day,j) =
(Cap_Spin_DRO_SUM_low(j)).*Spin_DA_sampl
e_sum(j,day);
        income_RegD_DROS_DA_SUM(day,j) =
(Cap_RegD_DRO_SUM_low(j)).*RegD_DA_sampl
e_sum(j,day);
        income_RegU_DROS_DA_SUM(day,j) =
(Cap_RegU_DRO_SUM_low(j)).*RegU_DA_sampl
e_sum(j,day);
      end
        COST_DROS_SUM(day,1)        =
sum(Cost_demand_DROS_RT_SUM(day,:)+Cost_
op_DROS_RT_SUM(day,:));
        COST_OP_ROS_DA_SUM(day,1)    =
sum(cost_OP_DROS_DA_SUM(day,:));
        Cosst_DROS_SUM(day,1)  =
COST_OP_ROS_DA_SUM(day,1)+COST_DROS_SUM(
day,1);
        Income_Spin_DROS_SUM(day,1) =
sum(income_Spin_DROS_RT_SUM(day,:))+sum(
income_Spin_DROS_DA_SUM(day,:));
        Income_RegU_DROS_SUM(day,1) =
sum(income_RegU_DROS_DA_SUM(day,:))+sum(
income_RegU_DROS_RT_SUM(day,:));
        Income_RegD_DROS_SUM(day,1) =
sum(income_RegD_DROS_DA_SUM(day,:))+sum(
income_RegD_DROS_RT_SUM(day,:));
        Income_LMP_DROS_SUM(day,1)   =
sum(income_LMP_DROS_RT_SUM(day,:));
        Revenue_DROS_RT_SUM(day,1)   =
sum(income_Spin_DROS_RT_SUM(day,:)+incom
e_RegU_DROS_RT_SUM(day,:)+income_RegD_DR
OS_RT_SUM(day,:)+income_LMP_DROS_RT_SUM(
day,:));
        Revenue_DROS_DA_SUM(day,1)   =
sum(income_Spin_DROS_DA_SUM(day,:)+incom
e_RegU_DROS_DA_SUM(day,:)+income_RegD_DR
OS_DA_SUM(day,:));
        Revenue_DROS_SUM(day,1)      =
Revenue_DROS_RT_SUM(day,1)+Revenue_DROS_
DA_SUM(day,1);
```

```
        Total_DROS_SUM(day,1)       =
Revenue_DROS_SUM(day,1) -
COST_DROS_SUM(day,1)-
COST_OP_ROS_DA_SUM(day,1);
    end
display('done')
```