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SCUOLA DI INGEGNERIA INDUSTRIALE E DELL'INFORMAZIONE

Executive Summary of the Thesis

optimHome : a Model Predictive Control-based Home Energy Management System for Bidirectional Smart Charging

Laurea Magistrale in Energy Engineering - Ingegneria Energetica

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1. Introduction

Energy system are undergoing substantial changes to their structure due to an increasing electrified share of applications and the evolution from a centralized to a decentralized distribution paradigm. The increasing electrification in the light duty transportation sector and the simultaneous penetration of small scale non dispatchable local Renewable Energy Sources (RES) challenges the transmission and distribution network, both in terms of grid capacity and supply-demand balance. Limiting the scope to domestic applications, this complex framework may find in electric vehicles (EVs) the potential availability of a massive and decentralized energy storage. Wisely operated, they can provide flexibility to demand side decoupling the generation from the consumption profile, minimizing renewable curtailment and saving costs for the EV's owner [1, 2].

Home Energy Management Systems (HEMS) in presence of EVs has been extensively investigated in the literature and has proven as a valid solution. Fotouhi et al. [3] proposed a multi-energy scheduling model for a building energy management system in the form of a Mixed Integer Linear Programming (MILP) optimization problem. The total cost of electricity and heating was minimized in the objective function and bidirectional operation of the connected vehicles enabled the possibility to control demand according to current variable price and peak load. Heat pumps were also modeled as a controllable and shiftable load. The logic goes beyond the simple energy scheduling since optimizations are performed iteratively aiming at a close to real time control strategy. A similar approach is implemented in [4], where the objective function includes both operational cost and the fictitious degradation cost of the EV battery. In order to deal with uncertainty a real time Model Predictive Control (MPC) was proposed to make the logic resilient to changes. The method was found effective in reducing the electricity cost by 34 % with respect to a non-optimized rule-based controller. Similarly, Halvgaard et al. [5] proposed an Economic MPC for the optimal charging of a single EV. The proposed linear model, evaluated over a week, calculates the optimal charging schedule based on a statistical description of the possible driving pattern scenarios of the user. Compared to uncontrolled charging and in presence of a time of use (ToU) tariff, saving results up to 60 %.

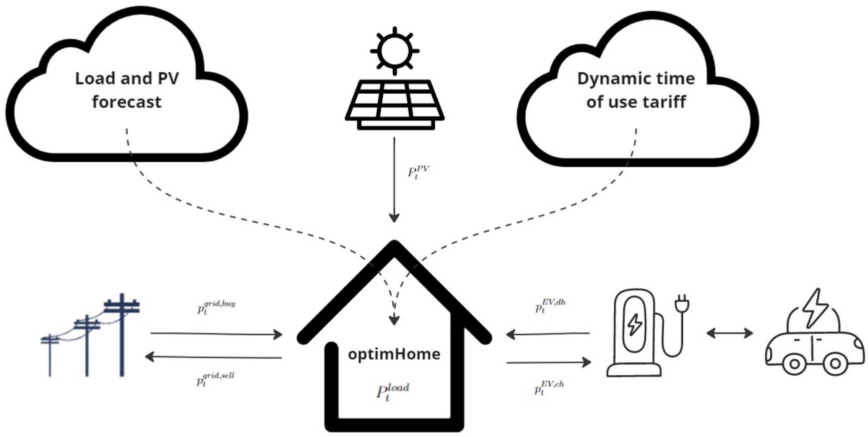

Figure 1: System architecture an entities in optimHome.

In line with the aforementioned studies, the purpose of this work is to develop an adaptable and flexible HEMS simulator to test performances under different boundary conditions. The developed tool, optimHome, is designed for a single domestic prosumer and, given in input the arrival and departure information of the EV state, is capable to calculate the optimal schedule (Figure 1). The optimization problem is formally structured as an MPC-based MILP in order to strengthen with respect to an highly uncertain framework and eventual user's changes in preferences. Main innovative contributions consist of:

- The conceptualization and identification of entities, limitations, parameters and variables necessary to constitute a tool close to a real commercial HEMS. This entire work has been enriched by a continuous and fruitful confrontation with the R&D External Charging team of Volvo Cars.
- The model is compliant with the most updated protocols' prescriptions in terms of bidirectional interaction with the EV. Moreover, the battery model is refined with a degradation coefficient and maximum power limitation at high State of Charge (SoC).
- The tool is Use Case (UC) dependent: different optimization problems are structured to offer the broadest perspective. A multi-objective function is chosen to maximize renewable self consumption by shifting EV charging.

2. Methodology

The energy management problem is structured as an optimization of a MILP formulated problem. Different boundary conditions result in different UCs. Distinctions are deriving from different user-defined objective functions, battery discharging capacity and monetary quantification of the injected power into the grid:

Table 1: UCs' overview

UC	Mode	Objective	Price
1	V2H	Cost minimization	-
2	V2H	Self consumption	-
3	V2G	Cost minimization	Retail price
4	V2G	Cost minimization	FIT

In line with the procedure exemplified in [4, 5], the MPC based MILP optimization can be structured defining the battery model, balances and constrains. All decision variables in the model are implemented as continuous positive-defined quantities and will be referred in lower case in mathematical formulations.

2.1. Battery and degradation model

The EV battery can be formulated as a discrete time state space model in order to fit in the MPC framework:

$$\begin{aligned} x_{t+1} &= A \cdot x_t + B \cdot u_t \\ y_t &= C \cdot x_t \\ x_0 &\quad \text{given} \end{aligned} \tag{4}$$

$$P_t^{load} - P_t^{PV} + p_t^{excess} = p_t^{grid,buy} + p_t^{EV,dh} - p_t^{EV,ch} \quad (1)$$

$$P_t^{load} - P_t^{PV} = p_t^{grid,buy} + p_t^{EV,dh} - p_t^{EV,ch} - p_t^{grid,sell} \quad (2)$$

$$P^{lim,2} = P^{lim,1} - (1 - SoC^{highP})^{-1} \cdot (soc_t - SoC^{highP}) \cdot (P^{lim,1} - P^{ch,min}) \quad (3)$$

where the manipulable variable u corresponds to the charging and discharging power $[p^{ch}, p^{dh}]$ while the state variable x corresponds to the SoC. In order to account for the efficiency of the EV charging infrastructure, the state space variable of Equation 4 are defined as follow:

$$A = 1 \quad B = \left[\frac{\Delta t}{C^{EV}}\eta^{ch}, -\frac{\Delta t}{C^{EV} \cdot \eta^{dh}}\right] \quad C = 1 \quad (5)$$

At each time step t, the battery SoC is updated as a function of the optimal control sequence.
Bidirectional operations require to evaluate the induced additional degradation effect of the battery in order to maximize system effectiveness. The implemented model has been inspired by [6]. The induced percentage capacity loss q, function of the energy throughput, is multiplied for the equivalent battery pack cost resulting in D, degradation coefficient expressed in €/kWh of throughput

$$q = B1 \exp(B2 \cdot I_C)\Delta t \sum_{t=0}^{T} p_t^{EV,ch} + p_t^{EV,dh} \quad (6)$$

$$D = \frac{\hat{C^B} \cdot C^{EV}}{100 - \varphi} \cdot B1 \cdot \exp(B2 \cdot \frac{P^{avg,I_C}}{C^{EV}}) \quad (7)$$

Experimental coefficients B1 and B2 have been derived from an the experimental campaign on Li-ion degradation [7].
In order to avoid the non linearity embedded in the I_C term, following the approach implemented in [6], a beforehand defined average C-rate of the entire charging session has been included as a parameter. Seen the different battery power limitations between UC 1-2 and UC 3-4, P^{avg,I_C} depends on the selected operational mode. Specifically corresponds to the average load demand in UC 1-2 and to the average discharge capability of the EV in UC 3-4.
Calendar ageing, on the other hand, was not taken into account as it is independent of the specific charging schedule and the powers involved. This second deterioration mechanism occurs regardless of charging operations.

2.2. Conventional constrains

Enforced constrains are also UC dependent. Note that, considering the architecture in Figure 1, real power balance on the control volume corresponds to Equation 1 in UC 1-2 and as Equation 2 in UC 3-4.
Bidirectional operation with the grid are prevented in the first case.
Keeping the same UC distinction, the EV discharging capacity limits are respectively expressed as follows:

$$x_t^{EV,dh} \leq p_t^{EV,dh} \leq P_t^{net} \cdot x_t^{EV,dh} \quad (8)$$

$$x_t^{EV,dh} \leq p_t^{EV,dh} \leq P^{ch,max} \cdot x_t^{EV,dh} \quad (9)$$

Charging operations are instead bounded as follow:

$$P^{ch,min} x_t^{EV,ch} \leq p_t^{EV,ch} \leq P^{ch,max} x_t^{EV,ch} \quad (10)$$

In accordance with the methodology adopted in [8], $P^{ch,max}$ decreases linearly when a deterministic SoC limit is exceeded (Equation 3). This limitation is imposed by the battery management system to prevent excessive degradation and undesired side reactions. In Equation 3, $P^{lim,1}$ corresponds to the minimum capacity limits imposed by the battery and the EVSE.
The purchase and injection of energy into the grid, when possible, are limited by :

$$x_t^{grid,buy} \leq p_t^{grid,buy} \leq P^{grid,max} \cdot x_t^{grid,buy} \quad (11)$$

$$x_t^{grid,sell} \leq p_t^{grid,sell} \leq P^{grid,max} \cdot x_t^{grid,sell} \quad (12)$$

By means of the binary variables x_t^i, simultaneous operations for the same unit are prevented enforcing the following relations:

$$x_t^{EV,dh} + x_t^{EV,ch} \leq 1 \quad (13)$$

$$x_t^{grid,sell} + x_t^{grid,buy} \leq 1 \quad (14)$$

$$\min_{p} \quad \underbrace{\sum_{t=0}^{N^P} p_t^{grid,buy} \cdot C_t^{el} \cdot \Delta t +}_{\text{Cost for electricity}} \; \underbrace{2 \cdot D \cdot \sum_{t=0}^{N^P} p_t^{EV,dh} \cdot \Delta t}_{\text{Cost for battery degradation}} \tag{16}$$

$$\min_{p} \quad \underbrace{\alpha \cdot \sum_{t=0}^{N^P} p_t^{grid,buy} \cdot C_t^{el} \cdot \Delta t + 2 \cdot D \cdot \sum_{t=0}^{N^P} p_t^{EV,dh} \cdot \Delta t}_{\text{Total cost of operation}} + \beta \cdot \underbrace{\sum_{t=0}^{N^P} p_t^{excess}}_{\text{Renewable surplus}} \tag{17}$$

$$\min_{p} \quad \underbrace{\sum_{t=0}^{N^P} p_t^{grid,buy} \cdot C_t^{el} \cdot \Delta t}_{\text{Cost for grid supplied energy}} + 2D \cdot \sum_{t=0}^{N^P} p_t^{EV,dh} \cdot \Delta t - \underbrace{\sum_{t=0}^{N^P} p_t^{grid,sell} \cdot C_t^{el} \cdot \Delta t}_{\text{Revenues injected energy}} \tag{18}$$

Satisfying SoC user requirements is the basis of the optimisation process. Practically, this is accomplished by means of the following condition:

$$soc_{t=N_P} = SoC^{target} \tag{15}$$

2.3. Conditional constrains

Four distinct energy level are defined in the updated protocol for bidirectional charging of EV ISO 15118-20 [9] to regulate operations. Consequently, four SoC region are defined:

- Zone 1 represents a non optimized region in which cycling is not allowed and the charging is rule based. Practically, charging is performed at the maximum available power with respect to the fuse limit until the safety value $SoC^{minimum}$ is reached.
- Zone 2 is an optimized region in which cycling is still not permitted but the charging can be postponed waiting for a more convenient time.
- In Zone 3, charging and discharging can freely take place as resulting from the optimal control strategy.
- Zone 4 corresponds to the region between $SoC^{max,v2X}$ and $SoC^{maximum}$. This region will be entered only if the user defined target belong to it. Discharge is prevented.

Correspondence between boolean algebra and constrains has been used to enforce the logic above. Binary variable $x_t^{zone,i}$ are used to monitor the SoC and eventually prevent operation. Necessary formulations for the implemented logic operators are inspired by [10, 11]

2.4. Objective functions

Boundary conditions differences in each UC directly affect the explicit form of the objective functions. Moreover, user may be interested not only in reaching economical benefits (Equation 16) but also in self consuming the highest share of on site renewable production (Equation 17). Injection of power into the grid with different valorisation corresponds instead to Equation 18 where C_t^{el} may correspond to the retail price or to an arbitrary FIT. The aforementioned frameworks are directly connected with the UCs presented in Table 1
Note that a differential logic has been implemented to account for degradation: charging the vehicle up to a target SoC represents a benchmark, an inevitable deterioration of battery performances induced by the simple car use and therefore it should not affect the optimization scheduling. For this reason, the optimal charging schedule is affected accounting for two times the discharged energy, considered as the deviation from the reference unidirectional charging process.

2.5. Economic Model Predictive Control

The deterministic scheduling detailed above is incorporated in an iterative and predictive framework of operations. At each sampling time, the state of the system is updated with current values while the prediction window is reduced as the result of a fixed condition on the departure time (Equation 15). This peculiar iterative control technique falls under the name of Shrinking Horizon MPC. Computational burden decrease progressively as a result of the decreasing number of decision variables.

3. Case studies

A grid-connected household located in Gothenburg, Sweden, with solar panels on the roof and bidirectional EVSE and EV has been chosen as object of the investigation.
LoadProfileGenerator [12] was use to estimate the domestic load demand of a family with two working parents and one child while PV resource has been generated using PVsyst [13] for a PV with a 3 kW rated power.
A hourly discretized ToU tariff, taken from Nordpool day ahead market price [14], has been considered in line with related studies [3, 4]

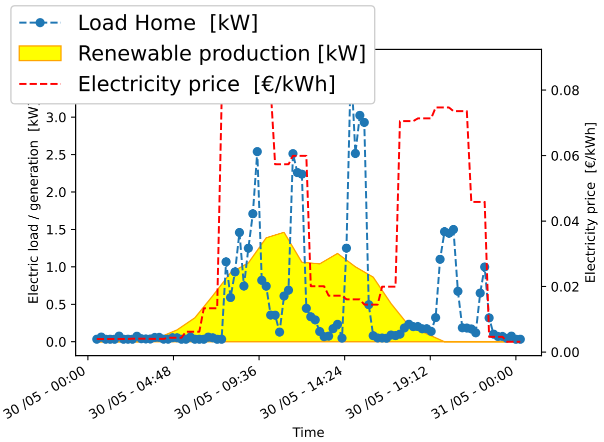

Figure 2: Forecasted trends the 30 of May 2023

A discretization time step Δt of 15 minutes wasassumed while EV model is Volvo XC40 with a battery capacity of 69 kWh. The same retail price has been used to quantify revenues from sold energy in UC 3.
Other relevant assumptions are listed below:

Table 2: Relevant input values

$\eta^{ch/dh}$	$\hat{C}^B$	$P^{ch,min}$
0.9	100 €/kWh	2.3 kW

$P^{lim,1}$	Hours	$P^{grid,max}$
11 kW	30 h	11 kW

According to common practice [5, 15] and to ensure clear representation of the interdependencies within the system, this stage of the research intentionally excluded uncertainty in the load and PV profiles. This represents the most optimistic solution in economic terms. However it represents a valid reference benchmark to assess system's performances.

4. Results

Bearing in mind general assumptions in Table 2 and assuming $SoC^{arrival}$ and SoC^{target} respectively equal to 0.35 and 0.7, optimHome performances are compared to uncontrolled charging, also referred as dumb charging. Savings can reach up to 90 % for UC 1 at the expenses of an increasing battery and grid utilization (respectively 37.2 % and 25.2 %). It is relevant to point out that cost reduction is related to the charging period at which dumb charging is performed. Results are related to a peak price period, typical for 17:00-18:00, and, for this reason, saving are potentially extremely high.
Only at this stage, an additional limitation on the total discharged energy has been added to simulate the tentative of automakers to prevent a fast and excessive battery deterioration. Results for UC 1 are not changing as the limit was not saturated.

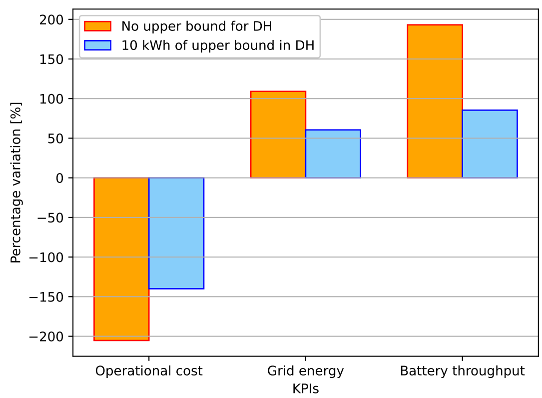

Figure 3: Comparison of percentage variations with the added limitation in discharge for UC 3

Testing UC 2, α and β in Equation 17 have been progressively changed in order to explore different conditions for renewable penetration. This capability is enabled shifting the EV charging process to integrate renewable over-generation. Note that the economic trade-off condition is imposed by the additional offset, bought from the grid in an non-optimized moment, to effec-

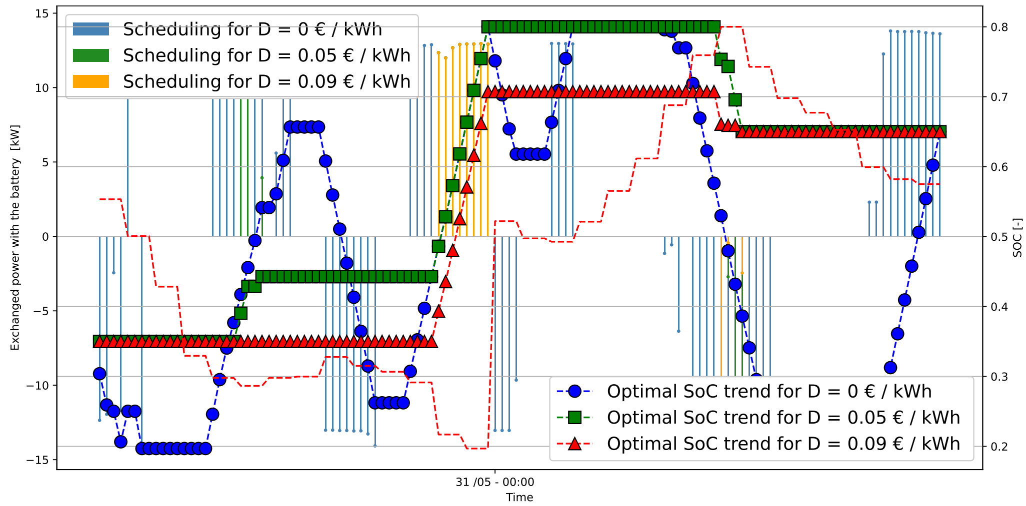

Figure 5: Optimal charging schedule as a function of degradation coefficient D

tively exploit overproduction to charge the EV at $P^{ch,min}$. Pure economic solution, obtained for $\beta = 0$, corresponds to a cost reduction of 80 %. However, intermediate solutions, obtained properly tuning the coefficients, assure an high degree of renewable integration with reasonable savings (Figure 4).

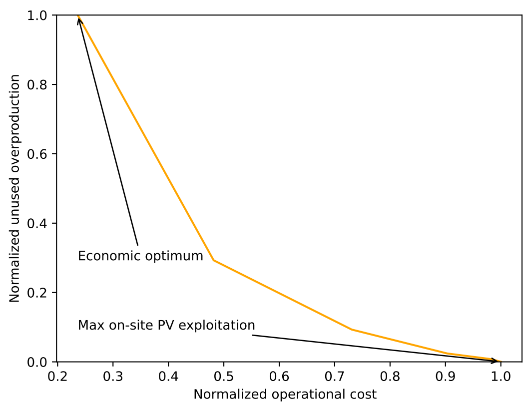

Figure 4: Pareto front reporting normalized non dominated solution

A sensitivity analysis for the fuse limit economic impact has been performed. Higher capability to interact with the grid results in faster and often cheaper operations with the battery. In order to exclusively test the influence of the peak power, EVSE maximum admitted power has been increased to 22 kW.
The total cost of operations varies non-negligibly ($\pm$ 10 %) and imposes a trade-off condition between decreasing operational costs and the additional fixed costs in electricity bills imposed by distributors to take advantage of a higher power availability.

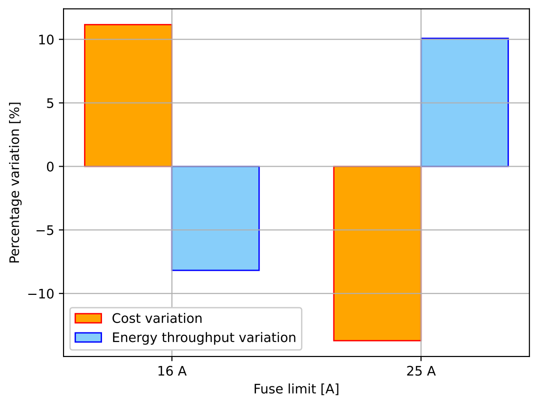

Figure 6: Percentage variation of cost and energy throughput with respect to 20 A

Sensitivity on the degradation coefficient D suggested the relevance of local peak to valley local difference in the price profile. Increasing D, exploited variability reduces and cycling is performed only in correspondence of global peaks (Figure 6). Extreme solution with high D results in unidirectional smart charging as optimal trend.

5. Conclusions and Future Developments

Economic MPC was introduced as a method for integrating the EV charging in household energy management in presence of a ToU tariff. EV's

arrival SoC, charging limitations, departure time and desired SoC have been identified as the most relevant parameters to be communicated to perform the optimization. Optimization-based approach was found effective in the optimal scheduling of operations within the household. The EV, considered as a controllable and bidirectional load, was successfully operated aiming at minimizing user-defined objectives. Moreover, the MPC-based technique was proven valid when dealing with uncertainty and user inputs' variations in time.
Future works may address the inherent stochastic character of the net load demand, as well as heat pumps as an additional controllable load.

6. Acknowledgements

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List of acronyms

EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
FIT	Feed in Tariff
HEMS	Home Energy Management Systems
MILP	Mixed Integer Linear Programming
MPC	Model Predictive Control
PV	Photovoltaic
RES	Renewable Energy Sources
SoC	State of Charge
ToU	Time of use
UC	Use Case

Nomenclature

Variables

$p_t^{grid,buy/sell}$	Power exchanged with grid [kW]
$p_t^{EV,ch/dh}$	Power exchanged with EV [kW]
p_t^{excess}	Renewable overproduction [kW]
$x_t^{grid,buy/sell}$	Binary variable for grid mode
$x_t^{EV,ch/dh}$	Binary variable for EV mode
$x_t^{zone,2}$	Binary variable for Zone 2
$x_t^{zone,4}$	Binary variable for Zone 2
soc_t	State of charge of EV [-]

Parameters

P_t^{PV}	PV power [kW]
P_t^{load}	Load demand [kW]
P_t^{net}	Net demand [kW]
$P^{grid,max}$	Grid maximum power [kW]
$P^{ch,min}$	Minimum charging power [kW]
P^{avg,I_C}	Average EV power [kW]
SoC^{highP}	SoC threshold for power limit [-]
$SoC^{arrival}$	Arrival SoC [-]
SoC^{target}	SoC Target [-]
$SoC^{max,V2X}$	SoC maximum for V2X [-]
$SoC^{maximum}$	Maximum admitted SoC [-]
$SoC^{minimum}$	Minimum admitted SoC [-]
C^{EV}	Battery capacity [kWh]
C^{el}	Electricity price [€/kWh]
Δt	Discretization time-step [min]
N^P	Prediction horizon [h]
D	Degradation coefficient [€/kWh]
q	Percentage capacity loss [%]
$\hat{C^B}$	Specific battery cost [€/kWh]
φ	Remaining capacity at end life [-]