POLITECNICO DI MILANO

SCHOOL OF INDUSTRIAL AND INFORMATION ENGINEERING

MASTER OF SCIENCE DEGREE IN ELECTRICAL ENGINEERING – SMART GRID

An Innovative Utilization of Space-Time Activity Graph to Integrate the Electric Vehicles into Smart Electrical Networks

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ABSTRACT

As the world is moving towards adopting more and more cleaner energy, it is evident that the transportation sector is foreseeing a major shift. In the coming future countries worldwide are focusing on a complete ban on fossil fuel driven vehicles. Most of the vehicles dominating the market will be Electrical Vehicles. Not only the vehicles will be driven by electric motors and drives, at the same time it is to be ensured that the electricity used to fuel these vehicles is produced by Renewable Energy Sources. Hence there will be mass deployment of EVs along with the need to serve their charging demand. This in turn requires optimized grid planning and updated forecasting technique for better integration and to satisfy the charging demand of this mass EVs smoothly.

With this mass EV adoption comes the need for better integration of this mass EV, that will be deployed in the future, with the existing grid. The requirement for more advanced and adaptive techniques for predicting precisely in real-time the charging demand of the mass EV that will be coupled to the grid has become prominent. The constant balancing of generation and demand has become a prime area of concern for the Grid Managers Worldwide. The EVs act as an Active load connected to the grid in most of the cases.

Keeping into account the fact that it is becoming a challenge to predict with precision the charging demand of the EVs, it has become evident that the there are various factors which affect the location and time at which these charging demands arise. These factors are majorly dependent on the fact that how an individual plan his activity throughout the day, which defines the exact time and location in order to fulfil the changing needs of the EV. Apart from the human behaviour and the way they plan their journey for the day there are other factors that are dependent on the climate, grid capability parameters and the geographical location of the area of scope. The challenge of load forecasting for meeting EV charging needs varies from developed country and the countries that are developing. For the developed as well the developing countries, the problem is treated differently. In case of developed countries, it is important to study the demand curve carefully as it constantly seeing a great change, what is now called as a Duck Curve. Whereas in the developing countries, there is yet an issue of load shedding and skies in the peak demand during the late evening hours, which affects the demand curve differently as compared to the demand curve in case of the developed countries, the curve here is called the shark curve.

Furthermore, it is required to power these EVs with the electricity that is produced by Renewable Energy Sources. That means, in future it will be seen a high diffusion of the renewable energy source. To cope up with the high deployment of the EVs and their integration with the existing grid, there is obligation of making the grid more optimized and adapted to communicate well to the needs of the fast growing EV. For that an

amalgamation of innovative forecasting methodology coupled with Advanced battery management systems are needed to make the integration of the EVs to the Existing Grid more reliant.

SOMMARIO

Mentre il mondo si sta muovendo verso l'adozione di energia sempre più pulita, è evidente che il settore dei trasporti vedrà cambiamenti importanti. Per il prossimo futuro, i paesi di tutto il mondo si stanno focalizzando sul divieto totale dei veicoli alimentati a combustibili fossili. La maggior parte dei veicoli che dominano il mercato saranno veicoli elettrici. Non solo i veicoli saranno guidati da motori elettrici, ma allo stesso modo ci si assicurerà che l'energia elettrica utilizzata per alimentare questi veicoli sarà prodotta da fonti di energia rinnovabile. Ci sarà quindi un dispiegamento di massa di veicoli elettrici assieme alla necessità di sostenere la domanda di ricarica. Ciò a sua volta richiede una pianificazione e ottimizzazione della rete elettrica e tecniche di previsione aggiornate per una migliore integrazione e per soddisfare senza problemi la domanda di ricarica di questi numerosi veicoli elettrici.

Con questa adozione di massa di EV si crea l'esigenza di una migliore integrazione di questi EV di massa, che in futuro verrà implementata nella rete esistente. Diventa così importante la richiesta di tecniche più avanzate e adattative per prevedere con precisione e in tempo reale la domanda di ricarica di EV di massa che saranno accoppiati alla rete. Il costante bilanciamento tra generazione e domanda è quindi una delle principali aree di interesse per i Grid Managers a livello mondiale. Nella maggior parte dei casi i veicoli elettrici funzionano come un carico attivo collegato alla rete.

Tenendo conto del fatto che sta diventando una sfida prevedere con precisione la domanda di ricarica degli EV, è diventato evidente che ci sono vari fattori che influenzano la posizione e il momento in cui sorgono queste richieste di ricarica. Questi fattori dipendono principalmente dal modo in cui un individuo pianifica la sua attività durante il giorno, che definisce l'ora e il luogo esatti per soddisfare le mutevoli esigenze dell'EV. Oltre al comportamento umano e al modo in cui pianificano il loro viaggio per il giorno, ci sono altri fattori che dipendono dal clima, dai parametri di capacità della rete e dalla posizione geografica dell'area di applicazione. La sfida della previsione del carico per soddisfare i bisogni di ricarica degli EV varia fra paese sviluppato e paesi in via di sviluppo, per cui in ogni paese il problema viene trattato in modo diverso. Nel caso dei paesi sviluppati, è importante studiare attentamente la curva di domanda in quanto si nota costantemente un grande cambiamento, chiamato Duck Curve. Nei paesi in via di sviluppo c'è invece ancora un problema di perdita di carico e vuoti nella domanda di picco nelle ore tarde serali, che influenza la curva di domanda in modo diverso rispetto alla curva di domanda nel caso dei paesi sviluppati. In questo caso la curva è chiamata Shark Curve.

Inoltre, è necessario alimentare questi EV con l'elettricità prodotta da fonti di energia rinnovabile. Ciò significa che in futuro si vedrà un'alta diffusione di fonti di energia

rinnovabile. Per far fronte all'elevato dispiegamento di EV e alla loro integrazione con la rete esistente, vi è l'obbligo di rendere la rete più ottimizzata e adattabile per comunicare meglio alle esigenze dell'EV in rapida crescita. Per questo è necessaria una fusione di metodologie di previsione innovative unita a sistemi avanzati di gestione della batteria per rendere più affidabile l'integrazione degli EV sulla rete esistente.

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CHAPTER ONE

1 INTRODUCTION

1.1 GENERAL OVERVIEW

Climate change is real and so are the effects of it. The side effects are out there and are more prominent then they ever were. In the fast pace of life there has been a negligence that has led us to the situation what the world is witnessing now. The statistical data proves that, the fact that the temperature of the earth is rising is no more a myth. The advancing effects of it are alarming. Europe itself has experienced the hottest summer in 2018. With the climate change, the increase in carbon footprints go hand in hand.

Considering the aspects and scenarios in the countries, for instance Europe, there are factors both external and external that further serve as a driving force for moving towards a cleaner society that's based upon the clean energy. The external factors are as follows:

- 20-20-20 EU Goals
- Electricity Consumption
- Security of Supply
- Implementation of Third Energy Package

The internal factors our country specific and has mostly to do with framework of the country, there consumption and generation rates, amount of renewable energy penetration, provision of active participation of customers in the electricity market and overall infrastructure of the electricity market trends. The goals that are set by the authorities of the countries must work in incompliance with the global norms and targets that have been laid down.

For instance, the countries that are a part of EU must abide by the norms and goals of the EU 20-20-20 goals. As per the vision of European Union's horizon 2020, the focus is on reducing the carbon footprints and increasing the share of RES in the sector of electricity, heating and transportation. There is a need for new network strategic to cope with the new Scenario in order to reach 20.20.20 targets. These network strategies should:

- Be able to grant access to renewable power sources
- Be efficient in operation reducing CO2 emissions and providing the best value
- Have a reliable and self-healing network
- Be flexible to fulfil new customers' needs in terms of both active demand and diffusion electric vehicles making them more and more appealing

Having a deeper insight of the transportation sector, there is a tremendous scope as well as and more than that there is a need for deeper penetration of renewable energy sources in this sector. This in turn will promote and shift to cleaner energy driven vehicles. It is important to make sure that not only the vehicles are fuelled by electric energy but also the production of that electricity is also by cleaner means, i.e. means the electricity production by means of renewable energy sources.

The shift from conventional vehicles to the ones fuelled by cleaner energy requires an intense planning phase along with proper implementation. Firstly, promoting Electric Vehicles should been done keeping into account that there are proper infrastructural requirements that are fulfilled, as the infrastructural framework lays the foundation for the smoother penetration/diffusion of electric vehicles in any area. Secondly, it is equally important to have in-depth analysis of the mobility pattern in that area.

The movement of the people throughout the day is a result of the activities that they have planned during the day along with the margin for some unplanned activities that might come up. The easiness to move as a result of the interaction between human activities and transportation or commonly addressed to as the mobility behaviour in a city or any area helps plan a better layout as to adequately reinforce/reconfigure to cater to the requirements for smooth flow of traffic.

Human activities result in the set of individuals, social, and economic behaviours and interactions that raises travel demand. Considering for instance the case of an individual's routine on a normal weekday; the planned activities include: dropping kids to school/day-care, going for work, eating out for lunch, picking kids from school/day-care and dropping them home, back to work, going to grocery shopping and then back to home. All these activities are performed keeping into account the fixed destinations that cannot be changed in any circumstance. The places that remain fixed in this list of activities to be performed in a day are: Home, School/day-care of the kids, Workplace. Based upon these fixed anchors the individual has the flexibility to plan his/her journey to any supermarket for grocery shopping and restaurant for having lunch. Likewise, the summation of activities of the all the individuals in that area defines the mobility behaviour of that area.

Analysing the mobility behaviour in an area gives an idea as of the factors that affect the pattern and trend as to how the people move throughout the day. These factors are a result of the diversity of culture, occupation, personal choices, climatic changes and much more. Considering the case of metropolitans, specifically major metropolitans across the globe, there are always a mix people from different nationalities residing there, with their varying social, economic and cultural preferences.

As per Einstein's space-time theory, it's the space that we trade for in each duration of time. Drawing inspiration from them, one has a possibility to drive the space-time graphs for the movement a vehicle throughout the day. As mentioned in a small example above that an individual's day can be summarized as mix of small activities that have been carried out in a course of a day as, Home-School/Daycare-Office-Restaurant-School/Daycare-Home-Office-Grocery Store-Home. In order to carry out all these activities, the individual is supposed to also keep in mind the time durations that he must stick to; timings of the school/day-care, office working hours and lunch duration, grocery store timings. These all parameters are equally important as the fixed anchors that were mentioned above i.e. the location home, office, school/day-care and grocery store.

All the above activities can be easily depicted in a space-time graph. Likewise, the space-time graph in an area will help in better understanding of the movement of the vehicles through the course of the day, through that area. In order to generate the space-time graph, the assistance of GIS software and by means of the GPS device installed in the vehicles. Hence by the overlapping of the collective data of the movement of vehicles throughout the day in an area will highlight the specific locations where there is a maximum concentration of vehicles that are currently at standstill. By gather the information about that area, it can be analysed that the following location has a need for reinforcement/reconfiguration of the changing stations to serve the need.

Based upon this analysis, the feasibility study must be carried out in that location to keep a track of the fact that how much is the grid capacity, what is the maximum power drawn in that area, possibility of supplying the proposed charging station in that area. In terms of the grid it is very important to keep into account the aspects of the grid, such as the grid capacity, consumption in that area, how much is the grid loaded; whether it is overloaded. Upon carrying out the feasibility study, a clear result will be obtained for the commissioning of the charging station that are.

In the cases where the feasibility study proposes that the location is experiencing a consumption growth and adding to is the fact that the grid will be overloaded by the commissioning of a new charging station, this creates the possibility of promoting the RES powered charging stations. Furthermore, in some area, if the feasibility study holds successful, microgrids can proposed.

Hence, people move to reach goods, services, activities and destinations: the goal of a competitor of mobility is to meet these needs and manage strategies and improvements that increase transport system efficiency and safety. On the regulatory part, the diffusion of more and more Electric vehicles with smoother mobility management need proper regulations along with tariffs and incentives to be enforced by the bodies and authorities.

1.2 Thesis Outline

1.2.1 Chapter 2

In Chapter 2, the analysis of Mobility Management has been carried out. The concept of smart mobility has been explored in form of car sharing, ride hailing, ride sharing, etc. It has been discussed that the day to day routine is an amalgamation of activities that are undertaken at different locations and at different time intervals.

1.2.2 Chapter 3

In Chapter 3, the aspects related to EVs has been discussed. It has been analysed as to which EV manufacturers and which EV models have dominated the market in 2017 and partially in 2018. The factors relating to the battery capacity, the kilometres travelled in a single charge and the plug type has been compared.

1.2.3 Chapter 4

In Chapter 4, it is proposed the method for developing an algorithm for better integration of mass EV into the grid. In the starting of the chapter the Composite load modelling of EV for the Substation/Busbar and the traditional forecasting means are briefly discussed in order to understand their fallouts that paved the way for an updated forecasting methodology for better integration of EVs. In the development of the algorithm for EV integration, the Space-Time graphs are used by obtaining the data from location-based technologies to develop Spatial-Temporal Activity Model. A case study of a metropolitan city, Milan, has been stated, where the Spatial-Temporal Activity Model has been obtained. Similarly, another case study of a Suburban Region, Aosta, has been stated as well for deeper insight.

1.2.4 Chapter 5

In Chapter 5, the focus has been on the establishment of Virtual Energy Storage System and exploits the opportunities to provide ancillary Services by the ESS. The algorithm developed in this part of the chapters is based upon the Spatial-Temporal Activity Model obtained from the first half of the chapter. The case study of Aosta has been further extended in this part of the chapter to propose the Virtual Energy Storage System zones in Aosta. The Locality concept has been introduced. Also, the integration of GIS in the grid has opened the possibibity to maintain the VESS periodically. An algorithm has been developed to demonstrate the handoff process among the localities.

1.2.5 CHAPTER 6

In Chapter 6, the Impact of the mass EV adoption on the Existing Grid has been analysed. The prime focus areas of impact due the mass EV adoption has been discussed. The case study of Aosta has been extended further. The grid Simulations has been carried out for the case of Aosta and their results have been evaluated.

1.2.6 CHAPTER 7

In Chapter 7, the Feasibility Study has been carried out and the prominent qualitative and quantitative conclusions drawn from this thesis has been presented. Furthermore, the contributions of the current work will be summed up along with defining the scope for future works.

CHAPTER TWO

2 MOBILITY MANAGEMENT

2.1 TRANSPORT:

People commuting day in and day out across the globe make use of a combination of modes of transport. The dimension of their travel can include various levels of transportation means like the private vehicle or the public transport that might include subway, bus, tram etc.; within the city and as well as outskirts. The long-distance travels may include other available means like airways. There is pre-designed way and set of procedures based on which the system of transportation operates.

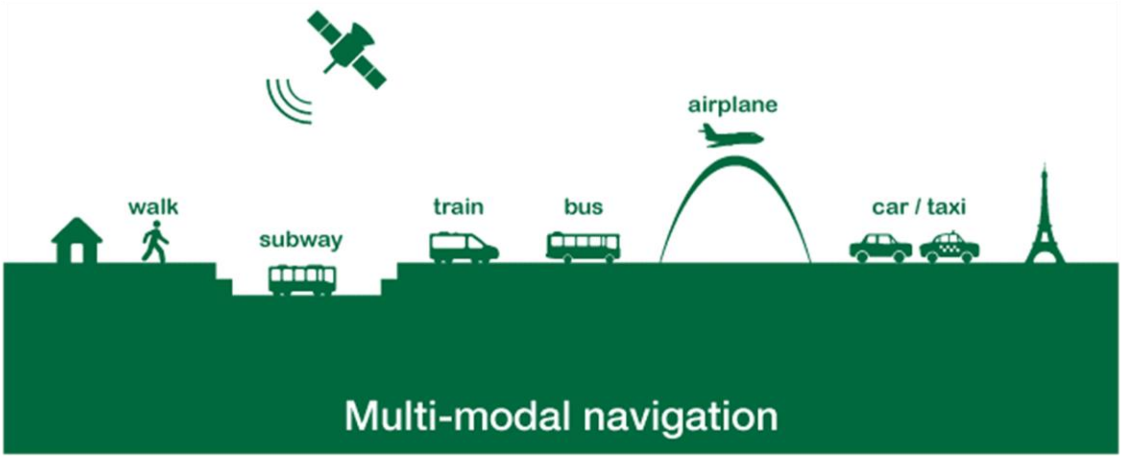


FIGURE 2-1: A REAL TRAVEL IN EACH TIME AS A MULTI MODAL TRIP

Operations deal with the way the vehicles are operated, and the procedures set for this determination, including financing, legalities, and policies. In the transport industry, operations and ownership of infrastructure can be either public or private, depending on the country and mode. Passenger transport may be public, where operators provide scheduled services, or private. Freight transport has become focused on containerization, although bulk transport is utilized for big volumes of durable items [1].

2.2 MOBILITY:

The day to day routine can be perceived as a sequence of activities undertaken at different locations. To perform these activities, we need to make trips; these, in turn, are linked by the sequence of activities over time. Based upon the pattern of an individual's daily routine, they plan their trips within the city or to and from the city. Considering the fact, the commuters who own private cars, there is a possibility to have a database of spatial data as per the movements or journeys they plan. This spatial data is an indicator of their exact spatial location.

FIGURE 2-2: A DAY WITH DIFFERENT ACTIVITIES

Considering the activities of individual persons, interaction may happen with other person. The exposure can be measured by the Social Interaction Potential (SIP) method. The similar nature of work or destination may increase the probability to share the available space of the same vehicles with another passenger. Estimation of this probability can increase the efficiency of the shared mobility. Also, a real-time data collecting, and processing may decrease the limitation of the planning of a journey which is the bottleneck of the mobility service.

The interaction index is the archetypical measure of exposure cited in the literature (Bell, 1954; Lieberson, 1981) [2][3]. Massey and Denton eloquently describe it as “the minority-weighted average of each spatial unit's majority proportion” (Massey and Denton, 1988, 288) [4]. We consider the equation for the vehicles instead of the people ethnicity. By this equation we can find out the segregation of passenger vehicles which can be a key solution to assume the concentration or congestion of the traffic in different zones. Also, it can be used to find the destination-based space availability for the travellers with the same destinations. We may define a vehicle group in terms of its ownership ie. Public or Private; or by the sharing nature, such as Car Sharing, Ride Hailing and Ride Sharing. Borrowing notation from Wong and Shaw (2011) [5] we can measure the exposure of group of vehicle a to group b as:

$$P_{aXb} = \sum_{i=1}^{n} \left(\frac{a_i}{A}\right)\left(\frac{b_i}{t_i}\right)$$

Where a_i, b_i and t_i are the number counts of the two group of vehicles and the total number in zone i respectively, A is the total number of the vehicles of group in one zone, and n is the number of zones of a municipality. This interaction index evaluates the contact probability between two groups within each zone, ignoring the potential for contact with vehicle to vehicle of one group in different zones as its roam around the municipality area. Importantly, this index is extendable to three or more vehicle groups, and reversible, so that measures of isolation can also be obtained.

Upon the determination of the spatial/space-time location, the data is clubbed together as a spatial prism. Space-time prism is a geometric approximation of the set of all space-time paths an individual could potentially traverse between a pair of fixed anchors in space-time. The volume of the prism is traditionally interpreted as a measure of potential accessibility, as it intrinsically captures the amount of time an individual could invest at each desired location. The social interaction potential is a computation of the average space–timelines intersections volume of people in a region [6].

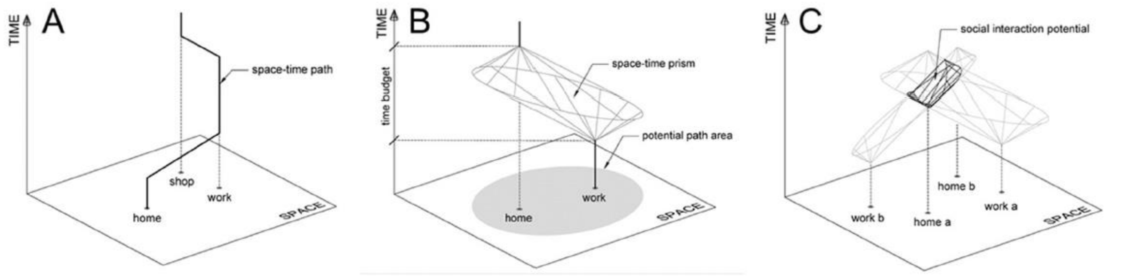


FIGURE 2-3: DEPICTIONS OF A) A SPACE–TIME PATH, B) A SPACE–TIME PRISM AND C) THE INTERSECTION OF TWO SPACE TIME PRISMS, FORMING THE BASIS OF THE SOCIAL INTERACTION POTENTIAL (SIP)METRIC (SOURCE: FARBER ET AL. 2012))

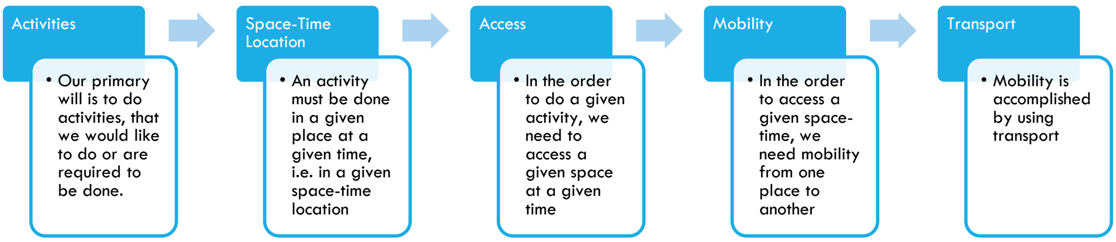


FIGURE 2-4: COMPLETE PROCESS OF MOBILITY AND TRANSPORT

In order to get a deeper insight, we may consider the mobility situation of Milan Metropolitan Area.

Among 3.2 Million of Inhabitants; 1 million people need to move to the city area every day and the overall mobility (trips/day, 2013) is 5,255,000. Out of the total trips 56% trips occur in the city area of Milan and rest 44% trips occur between the city and the metropolitan area. Also, the motorization rate of Milan is 51 cars per 100 inhabitants.

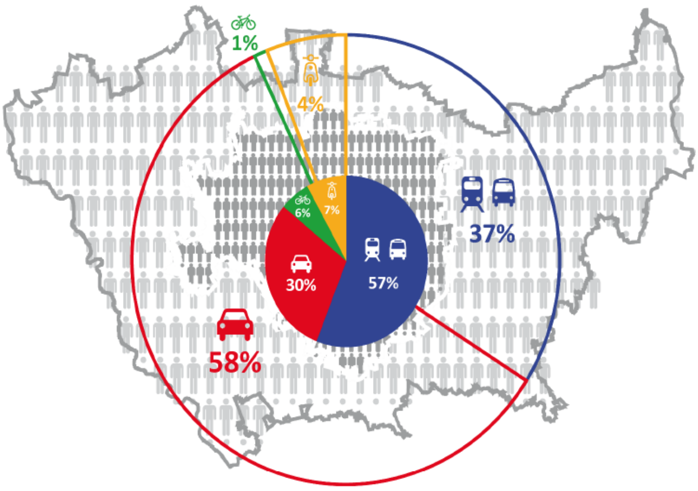


FIGURE 2-5: MOBILITY IN MILAN

2.3 Smart Mobility:

The current transport landscape is experiencing radical changes, as witnessed by the emergence of a multitude of new applications, business models and specializations, as well as by the entry of new players. Innovation in the transport industry is expected from the integration of new technologies and the development of new concepts of mobility.

The so-called ‘Smart Mobility’ is the vision of a revolutionized individual and collective mobility because of emerging technologies such as automated vehicles, peer-to-peer sharing applications and the ‘internet of things’.

Most contemporary imaginings of ‘Smart Mobility’ describe a transition of equivalent reach and significance to that of ‘auto-mobility’, focusing on a range of positive changes to how we travel around. Proponents of the ‘Smart Transition’ outline a vision of the future in which mobility will be framed as a personalized ‘service’ available ‘on demand’, with individuals having instant access to a seamless system of clean, green, efficient and flexible transport to meet all their needs.

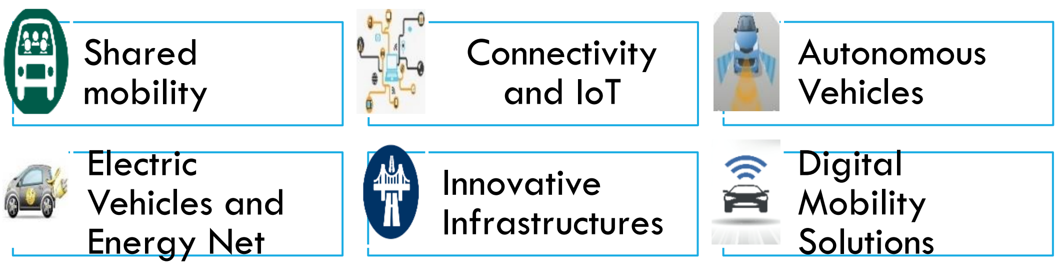


FIGURE 2-6: MOBILITY KEY TRENDS

2.3.1 Shared Mobility:

Shared mobility brings a radical change in transportation. It increases the sale of the mobility instead of cars. The concept if becoming very popular with day by day. The following graph represents European trends for car sharing and it shows how exponentially it's growing with the years [7].

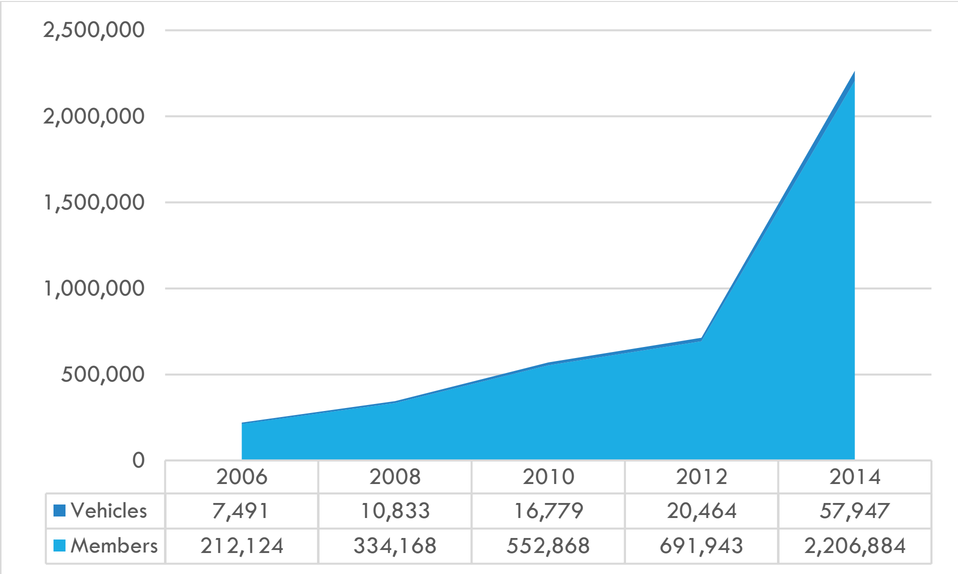


FIGURE 2-7: EUROPEAN CAR SHARING MARKET TREND

The membership growth in the shared mobility rates in Europe were 26%, 29%, 12% & 79% respectively in 2008, 2010, 2012 & 2014. To support the growth of the passenger the fleet number has increased accordingly. The number of fleet growth was 20%, 24%, 10% & 68% respectively in 2008, 2010, 2012 & 2014, which followed the increment of the Member-Vehicle ratio ie 28.3, 30.8, 32.9, 33.8, 38.1 respectively the stated years [8].

2.3.1.1 Car Sharing:

Car sharing (also bike sharing and other vehicle sharing) In its most basic form, car sharing is a car rental by the hour. Providers include commercial entities, as well as private individuals who rent out their own vehicles through peer-to-peer car sharing programs. These services give consumers all the benefits of car ownership without its attendant costs, including purchase cost, insurance, maintenance, and parking. Nowadays, they are all supported by mobile apps.

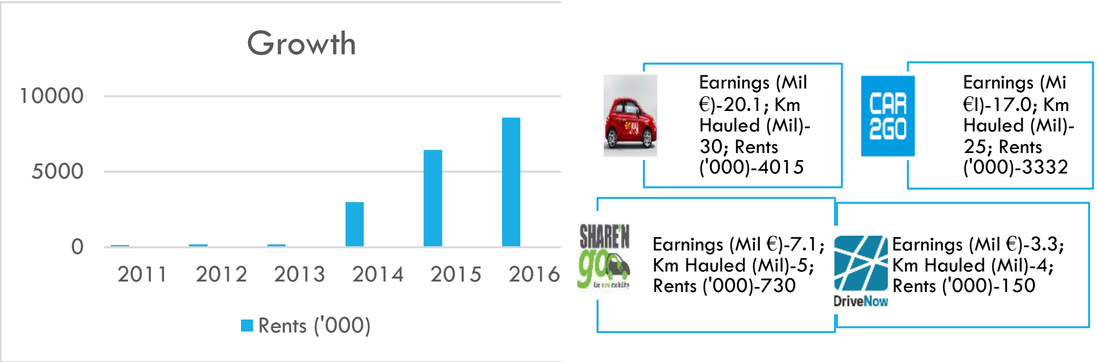


FIGURE 2-8: CAR SHARING IN ITALY

The shared mobility market in Italy has got a boost already and the growth curve indicates 125% increase of the market for the car sharing in Italy.

2.3.1.2 RIDE HAILING:

Ride hailing (also called ride sourcing, or on-demand ride service) These are online platforms developed by transportation network companies that allow passengers to "source" or "hail" rides from a pool of drivers that use their personal vehicles [9].

2.3.1.3 RIDE SHARING:

Classic ridesharing is simply what was previous called the carpooling: two or more travellers sharing common, pre-planned trips made by private automobile. In recent years, thanks to GPS and mobile technologies, ridesharing has evolved into a real-time or dynamic ridesharing that can match drivers with riders in real time without planning. This ride-matching process is conducted through mobile apps that connect drivers with passengers traveling similar routes, in real time, at predesignated pickup locations (commonly called casual carpooling or "slugging").

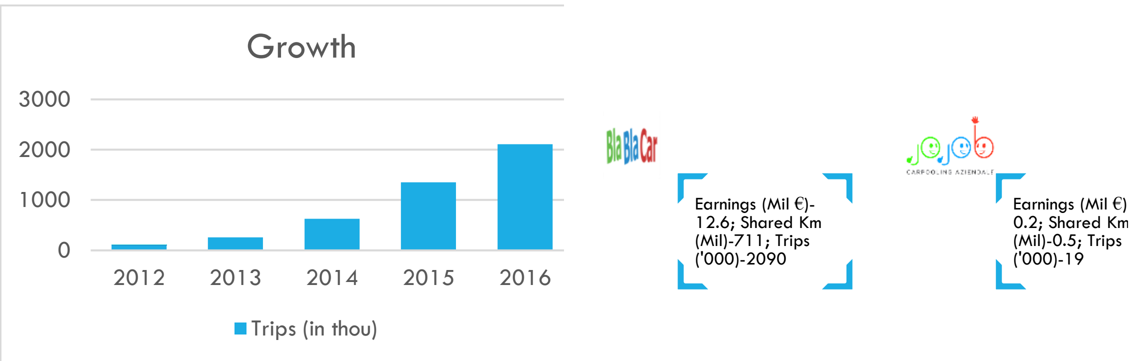


FIGURE 2-9: RIDE SHARING IN ITALY

The ride sharing is one of the most vital competitors of car sharing business model. The above-mentioned graphical representation shows the growth of 113% in Italy for the ride sharing market.

2.4 Electric Vehicles and Energy Net

An electric vehicle (EV) is a vehicle that is powered, at least in part, by electricity. Apart from the traditional electrified vehicles (e.g. rail rolling stocks), road electric vehicles are now a real choice. To power up these vehicles we need the access of the energy from the grid and as it's a sophisticated (in terms of mobility and high charging current requirement) new mobile load to the system. The requirement to define a standard of the new load fleets is a must and that's why the International Electro Technical Commission (IEC) Technical Standard 61851 defines 4 modes of conductive charging which'll be described in the next chapters.

2.5 Connectivity and IoT:

Connected vehicles are vehicles that use any of several different communication technologies to communicate with the outside world using on board sensors and Internet connectivity. This allow the vehicle to enhance the in-car experience, optimize its own operation and maintenance as well as the convenience and comfort of passengers. It works in different communication Vehicle-to-driver, vehicle-to-vehicle, Vehicle-to-infrastructure, Vehicle-to-internet.

The "Internet of Things" (IoT) is defined by three characteristics: the presence of sensors, connectivity to networks, and the ability to rapidly compute incoming data. IoT applications are quickly spreading into mobility, so that vehicles could be part of IoT [10].

2.6 Autonomous Vehicles:

An autonomous vehicle is one that can drive itself from a starting point to a predetermined destination in "autopilot" mode using various in-vehicle technologies and sensors, including adaptive cruise control, active steering (steer by wire), anti-lock braking systems (brake by wire), GPS navigation technology, lasers and radar [11].

2.7 Innovative infrastructures

Taking initiative to create modern structures is a demand to underpin the smart mobility and a good deal of things are considering raising the infrastructure. The major initiatives are Electric Vehicles charging infrastructures, Hyperloop, Smart roads, E-highways etc.

Among all of them the EV charging infrastructures are the first step to boost up the Electric vehicle uses. Directive 2014/94/EU on the deployment of alternative fuels infrastructure lays down rules to ensure the build-up of alternative refuelling points across Europe with common standards for design and use, including a common plug for recharging electric vehicles. In 2016, there were about 120’000 charging positions in Europe and 300’000 in the world.

2.8 Passenger Car using trend

This increase in motorization results from the rising income levels in developing countries. The stock of passenger cars grows from approximately 1 billion in 2015 to around 1.7 billion in 2030 and 2.4 billion in 2050 in the baseline scenario. While some developed economies have reached saturation in terms of car ownership, and some urban areas are witnessing a decrease in the number of cars per inhabitant, population and economic growth in developing economies will continue to bring more cars onto the roads in these regions. By 2050, developing countries will own over three-quarters of the world’s vehicles, compared with slightly less than half in 2015 [7].

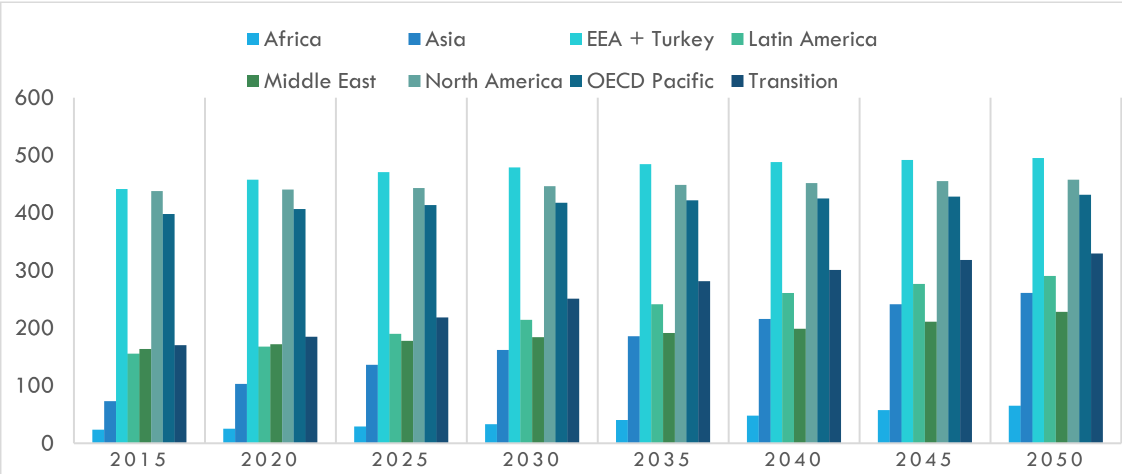


FIGURE 2-10: PASSENGER CAR OWNERSHIP BY REGION

If we narrow down the number of the vehicles of the EU, we’ll noticed a steady growth from the current period. To making the cites more sustainable by means of smart city concept, reducing carbon footprint European Union (EU) Horizon initiated the 2020 strategy. Transportation forms one of the vital pillars of the EU Horizon 2020 framework. Hence there has been derived a concept of smart mobility, which translates to increasing the sustainability of transport as well as the efficiency and effectiveness of the transport system, primarily through connectivity. At the grassroot level there is a need to conduct the mobility study to lay the foundation for the EU Horizon 2020 target, considering transportation section into mind.

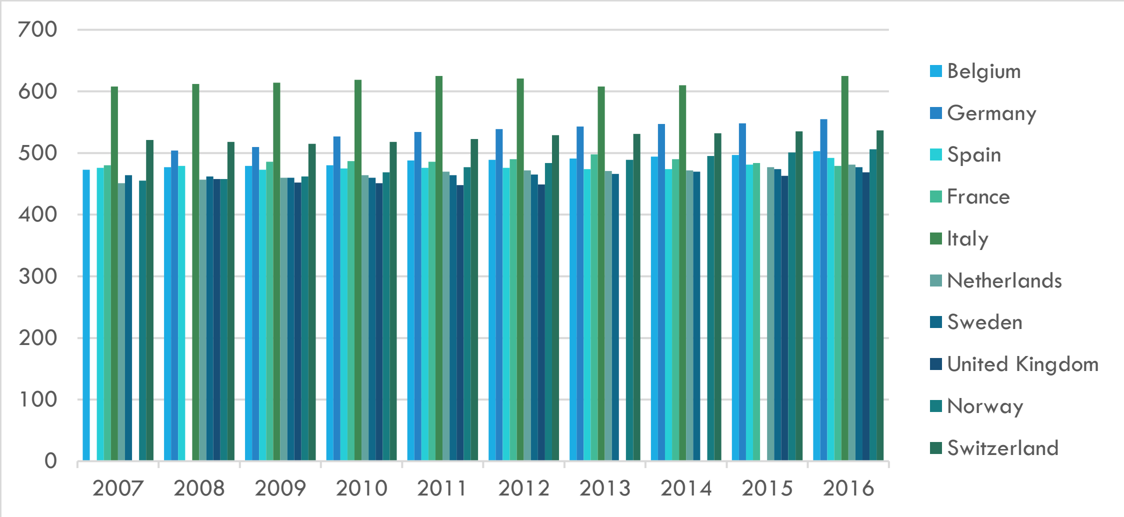


FIGURE 2-11: PASSENGER CARS PER 1000 INHABITANTS [ROAD_EQS_CARHAB]; [SOURCE: EUROSTAT; 15.03.18]

Amongst major EU Member States with the highest motorization rates, i.e. passenger cars per thousand inhabitants, there are several countries with a high motorisation rate include Italy (625 cars: 2016 data), Germany (555 cars) and Norway (506 cars).

Figure 2-12 shows that in 2016 more than 51% of the cars were petrol driven in 9 of 23 EU Member States for which data were available (The data of Netherlands isn't available here). The highest percentage of petrol-driven cars was reported by Germany (65%), followed by Sweden (62%) and United Kingdom (61%). Diesel driven cars exceeded the 50% threshold in France (69%), Belgium (60%) and Spain (57%). The contribution of alternative fuels was significant in Italy (8%), Sweden (6%) and Norway (4%) in 2016 [12].

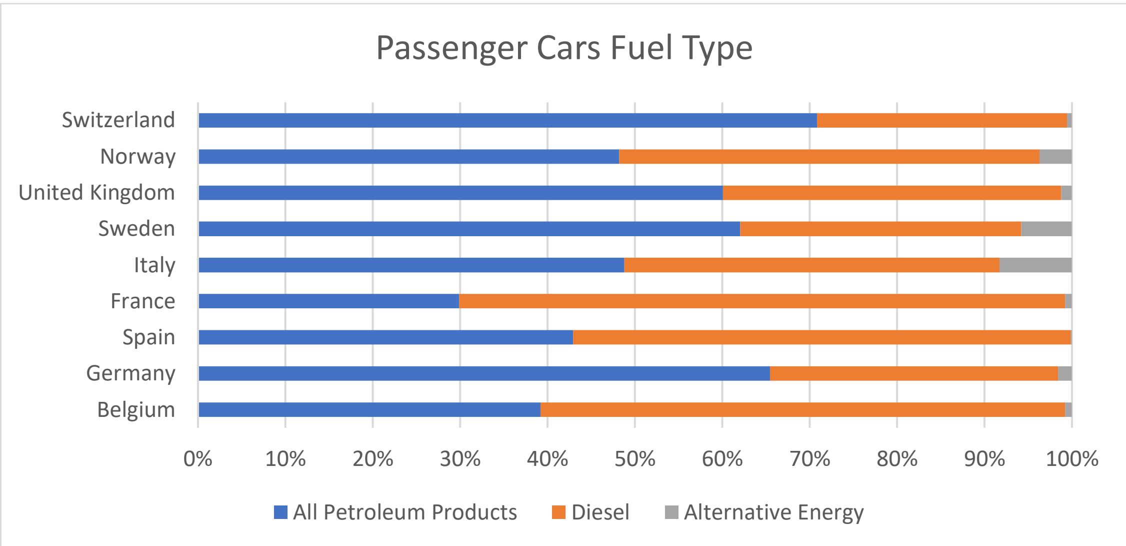


FIGURE 2-12: SHARE OF PASSENGER CARS, BY FUEL TYPE, 2016 [ROAD_EQS_CARPDA]; SOURCE: [EUROSTAT; 13.03.2018]

2.9 Smart digital mobility solutions

Linking all the facilities in the same platform will lead to the ultimate success of the smart mobility. There're several applications related to mobility which categorized as Mobility Apps, Smart parking apps, Vehicle connectivity apps, Courier network services, Complementary apps. It's also possible to integrate V2G in the same platform which may lead us a complete interaction for vehicle to grid in terms of the communication and power. The possibility of such solution will describe in the one chapter.

The advent of new transport solutions or radically different technology could also overhaul current mobility systems and lead to achieve the target. In the urban sector, for instance, making ride-sharing the norm rather than the exception would completely change the role of cars in urban. In addition, by enabling the right interaction between vehicle and grid may open a new horizon of the Electric Vehicle (EV) and the electricity & smart grid market. The interaction should be in real time with the consideration of the position of the vehicle as it's crucial to activate the power sharing. GIS can be the platform for it as transportation and electric utilities have an extended dimension of uses of this technology.

Looking at the environmental impact, the CO2 emissions are expected to decrease by 10% to 17% and the energy consumption is expected to see a decrease of 12%. Considering the above-described facts and figures there is a need for smart mobility alongside sustainable mobility, with the primary concern to:

- Decouple mobility needs and the use of private cars
- Improve the quality of public space by reducing the share allocated to infrastructure
- Expanding proper safety incorporated measures for pedestrians, cyclists and vehicle sharing models
- Encourage, integrate and innovate low-impact transport services and modes
- Making free urban spaces by making car sharing and bike sharing attractive
- Develop practices of smart mobility alongside sustainable mobility promoting efficient use of energetic resources
- Paying emphasis on developing better and innovative charging infrastructure that serves multiple needs for both private vehicle owners as well the vehicle sharing models

CHAPTER THREE

3 OUTLINE OF ELECTRIC VEHICLE

3.1 INTRODUCTION

The demand of vehicles is increasing to catch up with the fast pace of life, it is the roads which are getting filled with new vehicles at a rapid pace. Consequently, the world is experiencing the alarming increase in the pollution. The industry has already started shifting to the electric power for the purpose of manufacturing and various other industrial works, but those are the vehicles which still rely mostly on the IC engines as their propelling force. Though with the growth of technology, the IC engines are also getting lesser and lesser polluting with every passing moment, but still looking at the data available from various studies, the IC engines are still amongst the major source of pollution worldwide. This for sure has led to a tremendous shift towards the means of transport powered by electricity, which in turn is generated by the both programmable as well as non-programmable non-conventional energy sources. Hence looking at the demand of the cause, it is the electric vehicles, moved by an electric Drivetrain, which is ridden by the storage power from a rechargeable battery bank or from a portable, refillable electrical energy source, which is being worked on throughout the world.

Over the recent years concerning the drive towards clean energy in the sector of transportation has shown various trends that emerged as the governing aspects. In the past five years, there has been a shift in these trends as to which will be dominating and seeking the major percentage of attention executives in the transportation sector. The figure shows the pattern of order how these trends have dominated. Amongst these trends, the trends which have been the major highlights and ranked amongst the top 10 have been: Battery electric vehicles(BEVs), Connectivity and digitalization, Hybrid electric vehicles(HEVs), market growth in emerging markets, Increasing use of platform strategies and standardization of modules, creating value out of big data of vehicle and customers, Mobility-as-a-service/car sharing, Autonomous and self driv8ng cars, OEM captive financing and leasing and Innovative urban design concepts. As the need of the hour, regulatory pressure pushes awareness for electrification, with Battery Electric Vehicles dominated the trend in 2017.

Source: KPMG's Global Automotive Executive Survey 2017

FIGURE 3-1: KEY TREND OF THE VEHICLE TILL 2017

Regulatory pressure pushes awareness for electrification, battery electric vehicles are this year's number one key trend.

3.2 Types of Electric Vehicle

Moving forward to have a deeper insight of the electric vehicles will, in turn, reflect upon the current technologies and actors dominating the market. Electric vehicles can be segregated into three major categories.

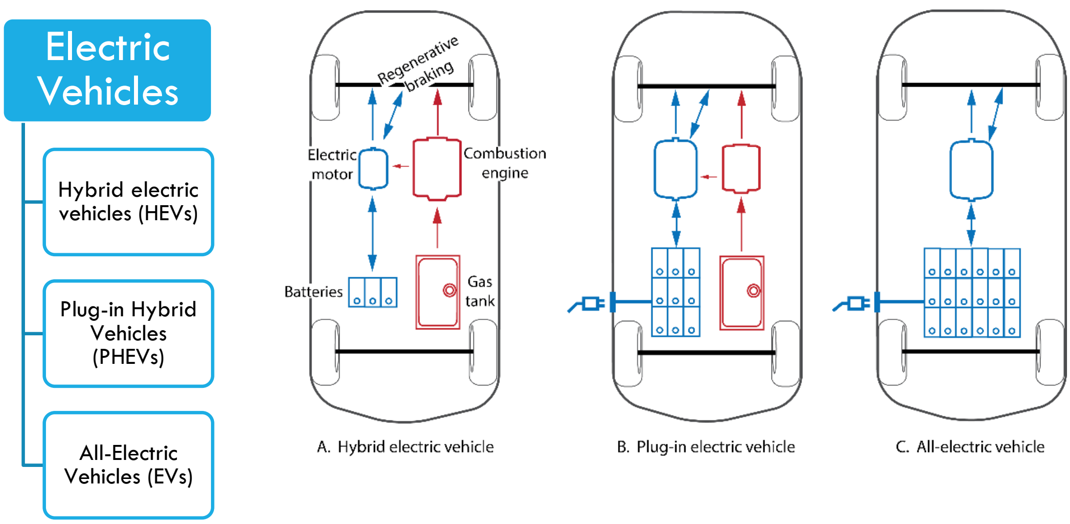


FIGURE 3-2: TYPE OF ELECTRIC VEHICLES

3.2.1 Hybrid

Hybrid electric vehicles (HEVs) combine the benefits of petrol engines and electric motors. They are projected to take on different ends, such as better fuel economy or more power [13].

Most hybrids use several innovative engineering technologies:

3.2.1.1 *Regenerative Braking.*

Regenerative braking recover energy normally lost during coasting or braking. It uses the forward motion of the wheels to turn the motor. This generates electricity and helps slow the vehicle.

3.2.1.2 *Electric Motor Drive/Assist*

The electric motor supplies power to assist the engine in accelerating, going across, or hill climbing. This allows a smaller, more-efficient engine to be used. In some hybrids, the electric motor alone propels the vehicle at low velocities, where gas engines are least effective.

3.2.1.3 *Automatic Start/Stop.*

Automatically shuts off the engine when the vehicle comes to a stop and restarts it when the accelerator is pressed. This prevents wasted energy from idling.

3.2.2 Plug-in Hybrid

Plug-in hybrids or Plug-in Hybrid-Electric Vehicles (PHEVs), are hybrids with high-capacity batteries that can be charged by plugging them into an electrical outlet or charging station. They can store enough power to significantly reduce their fossil fuel use under typical driving conditions [14].

There are two basic plug-in hybrid configurations:

3.2.2.1 *Series plug-in hybrids*

Also called **Extended Range Electric Vehicles (EREVs)**. The wheels are driven by the electric motor and the electricity is generated by the fossil fuel engine only. The motor can drive the car solely on electricity until the battery runs down. The petrol engine then generates electricity to power up the electric motor. For short ranges, these vehicles might use no fossil fuel at all.

3.2.2.2 Parallel or Blended Plug-in Hybrids.

Both the engine and electric motor are connected to the wheels and propel the vehicle under most driving conditions. The electric-only operation usually occurs only at low speeds.

3.2.2.3 Benefits and Challenges

Some plug-in hybrids have higher-capacity batteries and can go further on electricity than others. PHEV fuel economy can be sensitive to driving style, driving conditions, and accessory use.

- Lower use of petroleum. Plug-in hybrids use roughly 30% to 60% less petroleum than conventional vehicles. Since electricity is produced mostly from domestic resources, plug-in hybrids reduce fossil fuel dependence

- Lower GHG emission. Plug-in hybrids typically emit less GHG than conventional vehicles. Nevertheless, the amount generated depends partly on how the electricity is made. For example, nuclear and hydroelectric plants are cleaner than coal-fired power plants. Moreover, renewable energy has the clean sheet to produce the power.

- High initial investment and low travel cost. A plug-in hybrid can cost roughly €2 to €6 thousand more than a comparable non-plug-in hybrid. Using electricity is normally less expensive than using petrol, sometimes a lot more cost effective. Nonetheless, fuel savings may or may not offset the higher vehicle cost. It depends on the vehicle, the share of miles operating on electricity, fuel costs, and ownership length. Several countries facilitated the owner by tax incentives for qualifying plug-ins.

- Electricity charging takes time. Recharging using a 230VAC household outlet can take several hours. A "fast charge" to 80% capacity may require as short as half an hour. Even so, these vehicles don't have to be plugged in. They can be filed only with gasoline but will not reach maximum range or fuel economy without charging.

3.2.3 All-Electric

All-electric vehicles (EVs) run on electricity alone. They are propelled by one or more electric motors powered by rechargeable battery packs or from a portable, refillable, electrical energy source (like the fuel cell, PV modules). EVs have several advantages over conventional vehicles:

3.2.3.1 Benefits and Challenges

- More energy efficient. EVs convert about 85% of the electrical energy to power up the wheels. Besides ICE (include hybrids) based vehicles only convert about 20-35% while driving. Conventional gasoline vehicles only convert about 17%–21% of the energy stored in gasoline to power at the wheels. Despite the losses in other processes, the EVs are more efficient (ie about 26-43%) than the ICE engine-based vehicle (ie about 16-29%). Besides its usual to turn off the motor in traffic jams if needed, which isn't convenient in the conventional one [15].

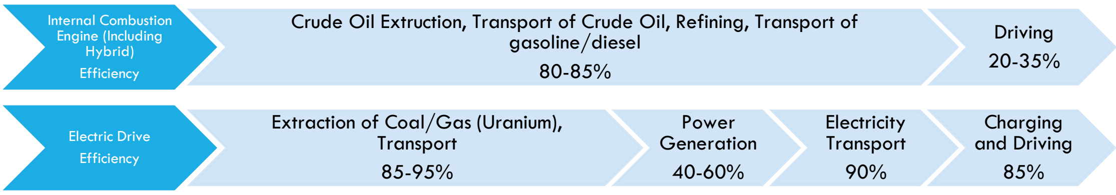


FIGURE 3-3: WELL TO WHEEL EFFICIENCY

- Safe and environmentally friendly. No tailpipe made its emission, zero! The result is no pollutants. Zero CO_2, SOx, NOx and other foreign particles. EVs emit no tailpipe pollutants, although the power plant may emit them cause of electricity. Of course, the emission depends on the source of the electricity and the world is already moving towards more renewable. Consequently, it'll be a dynamic shift for the car industry to move towards EVs completely. Moreover, electricity from nuclear, hydro, solar, or wind-powered plants have no air pollutants. So, EVs have no pollutants as the conventional vehicles. In addition, the overall heat dissipation is lesser than ICE and this feature saves energy by cooling inside the car.

- Better performance. Electric motors provide smooth, quiet performance and a top-notch acceleration and require less maintenance than the ICEs.

- Regenerative Braking. The electric motor of the EVs acts like a generator while breaking. It generates electricity from the kinetic energy and stores it to the battery, where it can be utilized later to drive the vehicle.

- Energy diversity. EV takes the power from the electricity source and that makes it less energy dependence from a single source. Electricity is the best form of energy to drive the machines. The source of electricity can be switched by the willingness of the government. The fuel flexibility of EVs created more challenges to the ICE.

However, EV’s facing significant battery-related challenges. It has a direct effect on driving range, recharging time, the replacement cost & weight. The typical range of the EVs is limited to 100 to 200 Kilometres on a full charge although a few models can go up to 300 to 500 Kilometres. To recharge the battery can take 4 to 8 hours, even a ‘fast charge' up to 80% may lead 30 minutes. Moreover, the energy density of the battery is still in a challenge, and it causes these packs heavy and occupies considerable space. Despite the issues, Researchers are working on improved battery technologies to increase driving range and reduce charging time, weight, and cost. These genes will ultimately shape the future of EVs. Also, exploring more prospects for the fuel cell may lead on board charging convenient and reduce carbon footprint.

3.3 EU Market Scenario

Talking about the market aesthetics, a clear picture can be seen as to which vehicles/models have dominated under the categories of PHEVs and PHEVs till 2017. The figure shows the percentage of the various PHEV models that dominated the market in the year 2017. For instance, it can be noted that there have been vehicles with quite a comparable share in the market, on an average the share of Volkswagen Golf GTE, Passat GTE, BMW 225xe Active Tourer, BMW 330e and Mercedes GLC350e has ranged between 6%-9%. Amongst all the PHEVs available, Mitsubishi Outlander has dominated, though it had a share of 12%.

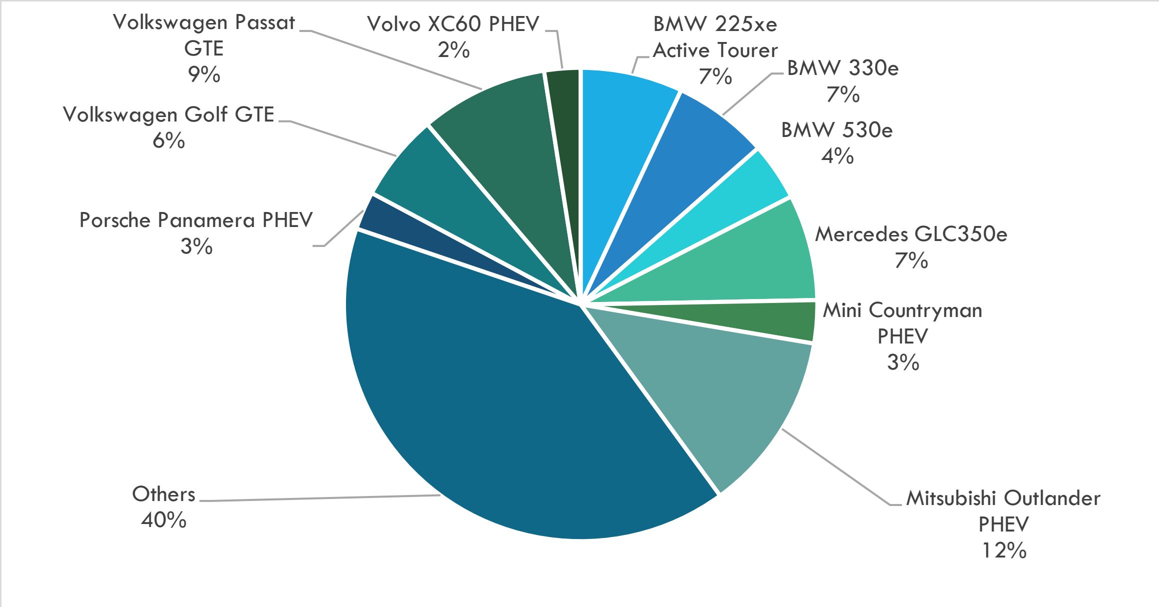


FIGURE 3-4: TOTAL PHEV IN EU (TILL 2017) (SOURCE-ACEA)

The figure shows the percentage of the various BEV models that dominated the market in the year 2017. Renault Zoe has dominated the market with the market share of 23%. The BEVs like Volkswagen e-Golf, Tesla Model S, BMW i3, Smart Forto ED, Smart Forfour ED, Kia Soul EV, Hyundai Ionic, Nissan Leaf, and Renault Zoe have captured 81% of the market. In the figure, it is depicted the combined share of the EVs dominated the market, be it PHEVs or BEVs. Even in the overall statistics, Renault Zoe has dominated the EV market by 11% in 2017.

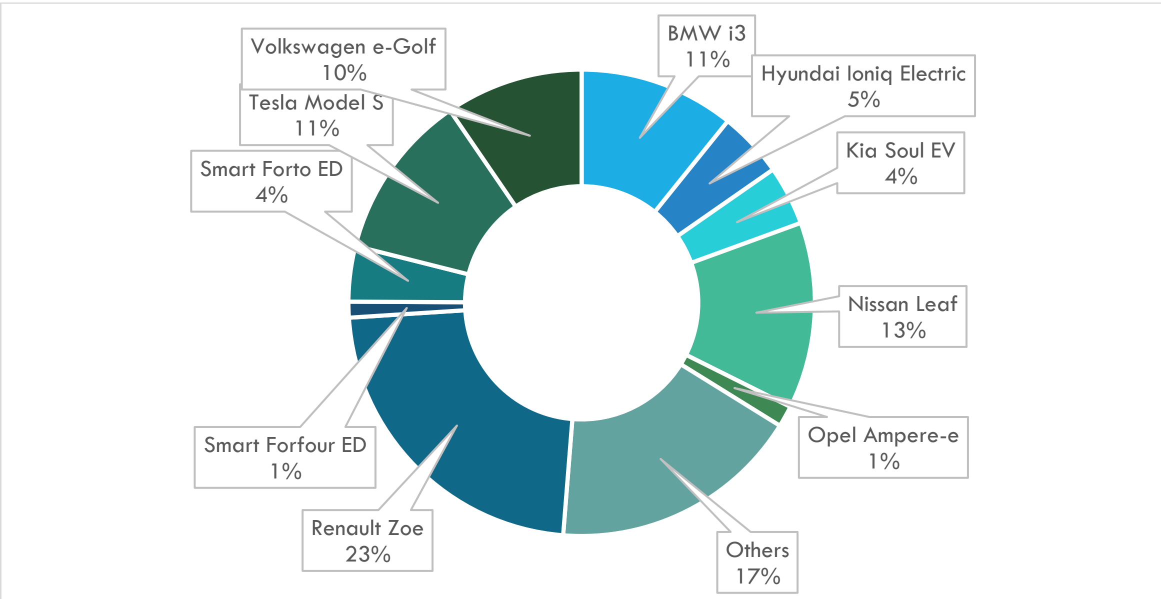


FIGURE 3-5: TOTAL BEV IN EU (TILL 2017) (SOURCE-ACEA)

3.3.1 The Top Five EV in EU

The top five models are holding 34% market share of the EU. These fives are Renault Zoe, Mitsubishi Outlander, Nissan Leaf, Tesla Model S and BMW i3. All the EVs are BEV except the Mitsubishi Outlander.

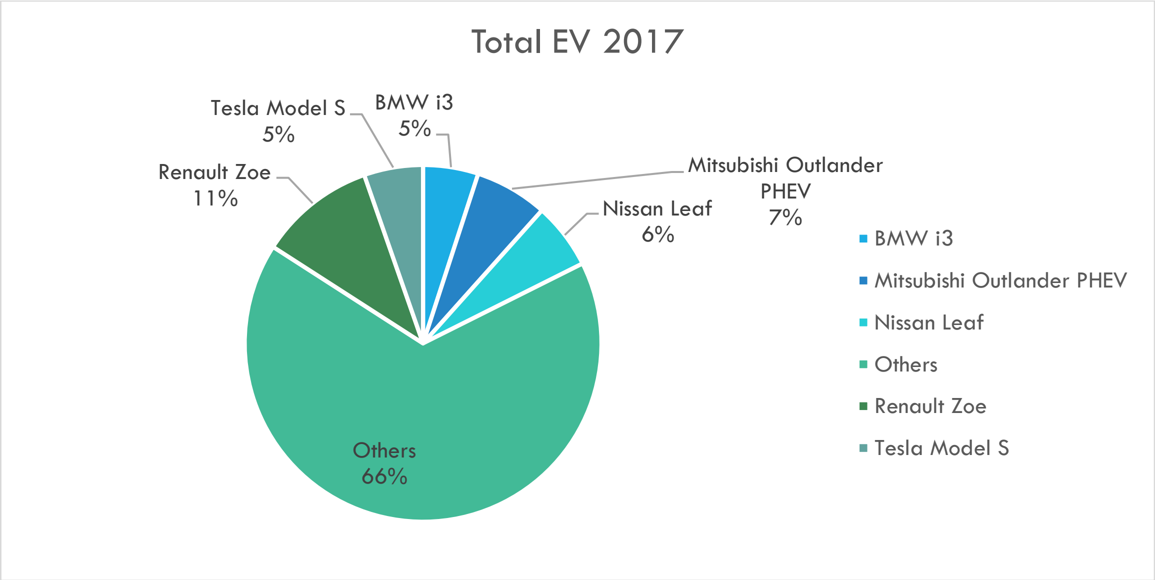


FIGURE 3-6: TOTAL EV IN EU (TILL 2017) (SOURCE-ACEA)

3.3.1.1 Renault ZOE

Renault ZOE is the Europe's best-selling electric car till 2017. The newest 2018 entry model runs about 400 km on a single charge. The standard model (R90) reaches 255 km on a single charge. The range depends on the speed, driving behaviour, weather and road conditions. The prices start at €32,580 (R90) [16].

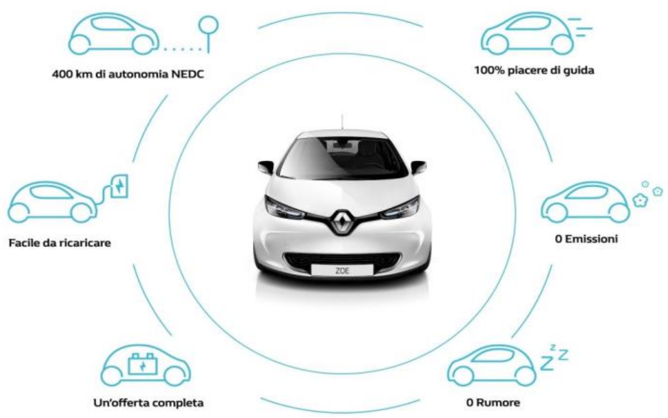


FIGURE 3-7: RENAULT ZOE

3.3.1.2 *MITSUBISHI OUTLANDER*

Mitsubishi Outlander 2016 is in the leading spot in the category of PHEV and second in overall EVs selling in Europe. It was completely redesigned in 2016 with greater capability. Moreover the 2018 model brings fast charging capability through the CHAdeMO DC fast charging, which increase the capacity of the PHEV to continue the race with BEV. The new features shrink the charging time dramatically and it's possible to charge up to 80% capacity in approximately 25 mins [17].

FIGURE 3-8: MITSUBISHI OUTLANDER 2018 & NISSAN LEAF

3.3.1.3 *NISSAN LEAF*

Nissan LEAF has topped the best-selling list of electric cars worldwide, ever since its release in 2011. Its 2017 model runs 170 km on a single charge. The 2018 LEAF is expected to provide +200 km of range to compete with the Chevrolet Bolt. Prices for the LEAF start from €33,600 [18].

3.3.1.4 *TESLA MODEL S*

The revolutionary Tesla Model S is one of the best-selling electric cars across Europe and the US. It comes in three versions: a standard model that goes 370 km on a single charge, an extended range all-wheel drive model that runs 380 km on a single charge, and an extended range high-acceleration model that reaches 465km on a single charge. Prices start at €81,285 (standard model) [19].

FIGURE 3-9: TESLA MODEL S & BMW I3

3.3.1.5 BMW i3

The 2017 BMW i3's battery yields a 33.2-kWh capacity, with the same external pack dimensions as the previous i3 version. In the winter, BMW i3 reaches between 120-175 km on a single charge. In the summer, BMW i3 reaches between 155-265 km on a single charge. Prices start from €38,300 [20].

3.3.2 Battery Capacity Summary

The battery capacity of the top five (by trading in EU) EVs is different and the chart shows the comparison of the standard models of each ace. The stock edition of Renault Zoe has a battery capacity of 41 kWh in which 37 kWh is usable. Nissan Leaf has slightly less battery capacity (40 kWh) comparing with Renault Zoe with slightly better usable capacity ie. 38 kWh. Whereas Tesla Model S has a larger battery capacity (100 kWh) comparing with other twos; also, usable capacity is 94 kWh for Tesla. BMW i3 has a smaller battery capacity (33.2 kWh) comparing with the other three top selling BEVs and it comes with a usable capacity of 27.2 kWh. Without wonder the Mitsubishi Outlander has the smallest battery capacity, i.e. 12 kWh as it has the alternative machine to drive the car as well as charge the battery parallelly.

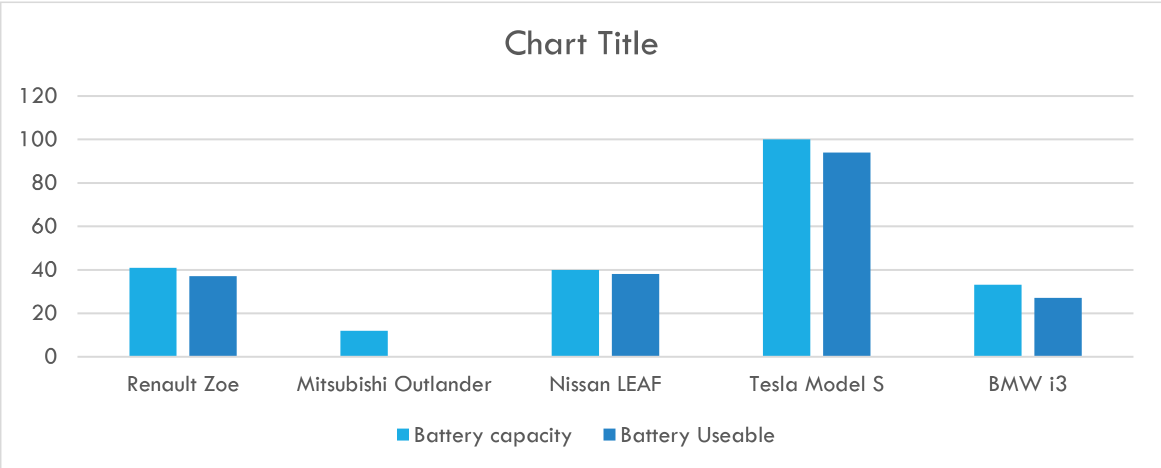


FIGURE 3-10: BATTERY CAPACITY COMPARISON

3.3.3 Charging Plug & Capacity Summary

These top five EVs are compatible with AC charging. Renault Zoe, Nissan Leaf and BMW i3 can be interfaced with 'Type 2' charging plugs, as well as the usual charging capacities are 22 kW, 6.6 kW and 11 kW with single or three phase AC power. Respectively the fast charging can be done by the capacity of 40kW (plug: type 2), 50 kW (plug: CHAdeMO) and 50 kW (plug: CCS) of DC power supplies. On the other hand, TESLA has a different infrastructure for its charging facilities, though it's possible to charge the Tesla cars through the usual home used AC plug. Tesla cars can be charged through Type 2 plug (17 kW AC) and fast charging (120 kW DC) can be done through 'Supercharger', a unique innovation of TESLA itself. Mitsubishi Outlander is one of the best-selling models in PHEV category, and it's improving its feature distinctively. In 2018 model Mitsubishi has added CHAdeMO plug for fast charging though it's using 'Type 1' (2.3 kW AC) plug for usual charging.

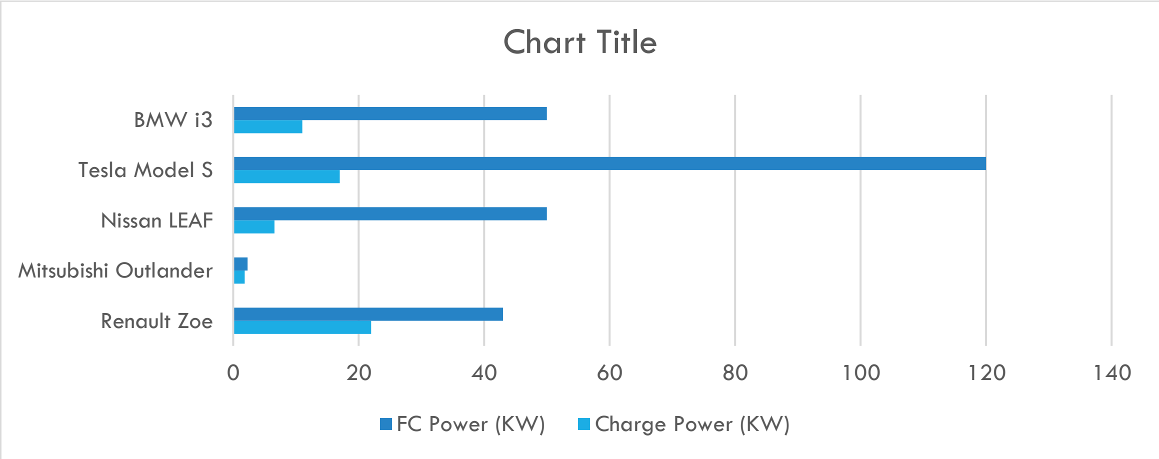


FIGURE 3-11: CHARGING CAPACITY SUMMARY

3.3.4 Other Charging Parameters Summary:

TABLE 1: SUMMARY OF THE TOP FIVE EV CHARGING INFORMATION

Model	Charge Time	Charging Speed	Electric Range
Renault Zoe	Charge Time (0->145 mi): 2 hours FC Time (15->116 mi): 45 min	Charge Speed: 73 mph FC Speed: 130 mph	145 mi
Mitsubishi Outlander	F 25 (up to 80% capacity)		
Nissan Leaf	Charge Time (0->150 mi): 7 hours FC Time (15->120 mi): 35 min	Charge Speed: 22 mph FC Speed: 180 mph	150 mi
Tesla Model S	Charge Time (0->305 mi): 6 hours 45 min FC Time (31->244 mi): 35 min	Charge Speed: 46 mph FC Speed: 360 mph	305mi
BMW i3	Charge Time (0->105 mi): 3 hours FC Time (11->84 mi): 25 min	Charge Speed: 36mph FC Speed: 179 mph	105 mi

The parameters related to the types of Charging Plugs; Location on charger, Types of power levels, Typical usage, Interface for Energy Supply, Expected Level of Power, have been descried in the table below, this comparison of the various plug types has been carried out Salman Habib and Muhammad Mansoor Khan [21].

TABLE 2: THE PARAMETERS RELATED TO THE TYPES OF CHARGING PLUGS

Types of Power Levels	Location for Charger	Typical Usage	Interface for Energy Supply	Expected Level of Power (P:kW)
SAE STANDARDS: AC and DC Charging				
Level 1: Continent **V_{ac}: 230 (EU)** **V_{ac}: 120(US)**	**Single Phase** On-board	Office and Home base Charging	Any Convenient Outlet	**P:** 1.4 (**12A**) **P:** 1.9 (**20A**)
Level 2: Main **V_{ac}: 400 (EU)** **V_{ac}: 240 (US)**	**Single phase/Three Phase** On-board	Privately & Publicly base Charging	Electric Vehicle Supply Equipment	**P:** 4 (**17A**) **P:** 8 (**32A**) **P:** 19.2 (**80A**)
Level 3: Fast **V_{ac}: 208-600**	**Three Phase** Off-board	Like a filling Station, Commercial Point	Electric Vehicle Supply Equipment	**P:** 50 **P:** 100
DC Power Level 1 **V_{dc}: 200-450**	Off-board	Dedicated Charging Stations	Electric Vehicle Supply Equipment	**P:** 40 (**80A**)
DC Power Level 2 **V_{dc}: 200-450**	Off-board	Dedicated Charging Stations	Electric Vehicle Supply Equipment	**P:** 90 (**200A**)
DC Power Level 3 **V_{dc}: 200-600**	Off-board	Dedicated Charging Stations	Electric Vehicle Supply Equipment	P: 240 (**400A**)
IEC STANDARDS: AC and DC Charging				
AC Power Level 1	**Single Phase** On-board	Office & Home base Charging	Any Convenient Outlet	**P:** 4-7.5 (**16A**)
AC Power Level 2	**Single phase/Three Phase** On-board	Privately & Publicly base Charging	Electric Vehicle Supply Equipment	**P:** 8-15 (**32A**)
AC Power Level 3	**Three Phase** On-board	Like a filling station, Commercial Point	Electric Vehicle Supply Equipment	**P:** 60-120 (**250A**)
DC Rapid Charging	Off-board	Dedicated Charging Stations	Electric Vehicle Supply Equipment	**P:** 1000-2000 (**400A**)
CHAdeMO Charging Standard				
DC Rapid Charging	Off-board	Dedicated Charging Stations	Electric Vehicle Supply Equipment	**P:** 62.5 (**125A**)

Chapter Four

4 Development of EV Load Forecasting Technique

4.1 Overview

One of the major challenges from the angle of distribution grid operators remains to foresee location and time of EV charging events to guarantee a continuous supply of energy and install enough power capacity within each service area of the distribution grid [22]. This is especially important as EV adoption patterns might result in spatial-temporal clustering of charging demand which could cause unexpected overloads at secondary distribution levels [23]. The above-mentioned details become even more crucial for the fact that it a necessity to keep into account the impact of mass EV adoption on the existing grid so that the measures taken can fully work at power to cope up with these effects.

The facts and the norms set forth clearly state that in the coming future there will be a strong shift from the conventional/fossil fuel driven vehicles, and they will be completely eradicated from the roads. On the brighter aspects, this change will help combat the alarming carbon footprint increment in a much broader sense. Although the diffusion of EVs at a fast pace will benefit the society and the environment greatly, it is important to consider also the effect this huge diffusion of EVs will have on the existing grid infrastructure: network infrastructure, grid capacity, increasing demand for electricity as a result of the constant growth of its consumption. The deployment of EVs in huge numbers will create a need for equally available charging facilities. This wide increment in the electric vehicles due to a complete ban of the conventional fossil fuel driven vehicles will create a huge impact on the traditional grid. It will lead to an urgent requirement for the modifications in the traditional grid planning.

As a matter of fact, energy can be stored in different forms but electricity itself can't be stored. On the contrary, the production and consumption of electricity are needed to be balanced continuously in every instance. The gap between production and consumption of electricity makes an effect on the electricity system parameters like voltage and frequency. Maintaining system frequency is one of the major fundamental drivers of power system reliability. Similarly, the variation of voltage is one of the key elements characterizing of quality of service. Even the frequency of the power system must be kept within the nominal values i.e. 50/60 Hz. Automatic control systems are necessary for power systems to respond to the mismatch between the power generation and loads, otherwise, it can hinder the devices of the power system. For the same reasons, the frequency control is applied in three layers as Primary, Secondary and Tertiary.

On the other hand, consumers feel satisfied when the system operates at its best in terms of performance & continuity with energy being supplied at the nominal voltage. Fluctuations beyond the set limits can have an adverse effect, thus hindering the system performance. This voltage variation is caused by the disturbances and control actions of reactive power sources in the grid. The disturbances may be the variation of load and variation of the system structure. So, to respond to these variations, voltage regulation is done, through which voltage is controlled in the grid by HV/MV transformers with On Load Tap Changer (OLTC) and MV/LV transformers merely with No Load Tap Changer

In recent days the increasing of non-programmable renewable energy-based power plants are significant. Load varies throughout the day; conventional generation can often deviate the schedule, besides the non-programmable power plants outputs vary on different time scales based on the weather. So, it is not possible to predict the non-programmable power plants generation with perfect accuracy. Similarly, the contingency of programmable power plants is unexpected, even the load forecast errors are unexpected.

The traditional grid planning is already focused on coping with the tremendous increase in the consumption of electricity and meeting these needs, that are a result of the internal factors on the country-wise basis. Analysing the effect of coupling the huge number of EVs to the grid for charging purposes, thus becomes more and more important. In order to carry out this analysis precisely, it is important to understand the load profile of these EVs that have charging requirements based upon their spatial-temporal locations. This is important because the diffusion of EV result in an increase in charging demand. As a result, the increasing charging demand will lead to the overloads at the distribution system levels.

Before focusing of the Load forecasting technique, it’s necessary to classify the load characteristics to understand the relationship between real or reactive power and system parameters such as voltage and frequency. The load characteristics influence is significant for both steady-state and dynamic state. Thus, appropriate load modelling is one of the most important tasks to represent the performance of those loads, which lead to suggest the planning and operation in power systems. The actual load modelling is finalized from the number of historical events which lead to component outages, voltage collapse, and system instability. We want to describe these events in terms of Electrical Vehicles, and it will lead us to respond adequately to the Energy Demand Management next.

- **Outage:** A power outage (also called a power cut, a power out, a power blackout, power failure or a blackout) is a short-term or a long-term loss of the electric power to an area. Typically, the required generation use to simulate the standard dynamic load database and when it doesn't match, the outage occurs. Most of the time the event happened for the most optimized situation. A mass number of Electric Vehicle integration in the grid may make the grid more vulnerable and outage can take place frequently if the simulation results with the recorded response do not match. Therefore, regular load modelling is a must to avoid interruption.

- **Low Frequency Oscillation:** Different load models such as a composite load model, the dynamic load model and the exponential load model are required to handle low frequency oscillation and damping. Many studies show that the effects are different on the power system stability for the different load models.

4.2 Load Modelling Approaches

It is necessary to model the load with its characteristics. The load models are described as the following classifications and all types of loads make the composite load for a substation and by study these models, we can control and monitor the voltage and frequency precisely of the busbars in a substation, as many loads are dependent on voltage (lighting, heating etc.) and many of them have dependency of frequency (induction motors).

For analysing the load profile, it is necessary to have a deeper insight into the traditional forecasting techniques. Considering from the broader perspective, Load forecasting without a hint of doubt is crucial for utilities and other participants in electric energy generation, transmission, distribution and markets. Thus, to overview the load forecasting techniques in detail to have a better understanding as to whether they will cater sufficiently to the tremendous charging demand of the fast-growing EV and the effect of coupling the EVs to the grid for charging purposes.

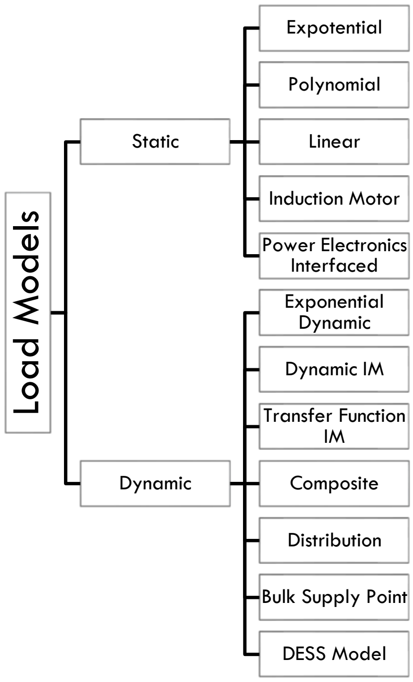


FIGURE 4-1: TAXONOMY OF THE LOAD MODELS

4.2.1 ELECTRIC VEHICLE AS A LOAD

By the definition of the most commercial battery types it is well known that those are chemical storage devices and the charging and discharging characteristics depends on the types of chemical characteristics. Most of the time they are exponential functions over time. Considering the top selling models of EV's battery as described in the previous chapter we can analyse the following exponential formula for the battery systems for the instantaneous charging. [24]

$$P_{EV}(t) = P_{EV,max} \cdot \left(1 - e^{-\frac{\alpha t}{t_{max}}}\right) + P_{EV,0}$$

Where,

$P_{EV,0}$ is the initial status of battery system while charging
$P_{EV,max}$ is the maximum power capacity of the Electric Vehicle
t_{max} is the maximum charging time.
α is the constant parameter declared by the EV manufacturers

Additionally, considering the unity constant power factor of the EV's battery system the reactive power demand is zero, [24] which implies

$$Q_{EV.DEM} = 0$$

The equations prove that Electric Vehicle is an active load.

4.2.2 COMPOSITE LOAD IN A SUBSTATION

Considering the EVs as an active load; now it is easier to form a composite model by aggregating all the loads under a busbar. As the utility service provider categorized the loads as residential, commercial and industrial; we may include the new EV loads in the load table. A hypothetical example of the load model's chart has mentioned below.

TABLE 3: A COMPOSITE LOAD FOR A SUBSTATION

Type	% Large IM	% Small IM	% Lighting	% EV	%Tx	% Constant MVA	% Mixed Load
Residential	0	20	5	45	1	4	25
Commercial	0	20	40	30	1	4	5
Industrial	55	10	10	20	1	5	4

By examining the above data, it is easier for a Utility service provider to find the ratio of different categories of the load in a busbar or in substation. Following the ratio, they may create the composite load models for the busbar too. As different types of loads are connected to the busbar, the aggregation of such loads create a composite load model for the busbar considering the characteristics of the voltage and frequency dependency of the composite load. The following figure has shown such a model.

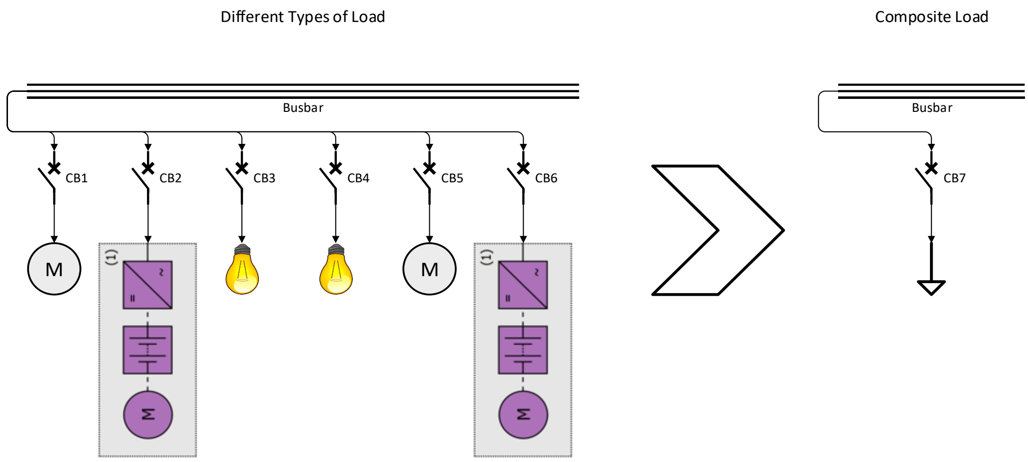


FIGURE 4-2: A COMPOSITE LOAD

In usual cases of steady state analysis i.e. the load flow analysis it can be either the constant power loads i.e. P & Q remain constant or it can be constant MVA Load. On the other hand, for the transient stability analysis the load models usually are modelled as constant impedance load which is connected as constant impedance at the bus. So, with the change in voltage the power drawn by the load changes; also, the power drawn by the load changes because of the change in frequency. In addition, the induction machine loads are modelled as constant current loads in transient stability analysis. At the end when we sum up all the loads as composite, we may find those sensitive with respect to the voltage and the frequency. So, the general equations for the load can be considered as below:

$$P = P_0 \times p_{vs} \times p_{fs}$$
$$Q = Q_0 \times q_{vs} \times q_{fs}$$
$$p_{vs} = k_1 + k_2V + k_3V^2$$
$$p_{fs} = 1 + k_4f$$
$$q_{vs} = k_5 + k_6V + k_7V^2$$
$$q_{fs} = 1 + k_8f$$

Where;

P is the active power at any voltage and frequency
P_0 is active power at the rated voltage and frequency
Q is the reactive power at any voltage and frequency
Q_0 is reactive power at the rated voltage and frequency
p_{vs} voltage sensitivity of the active power
p_{fs} frequency sensitivity of active power
q_{vs} = voltage sensitivity of the reactive power
q_{fs} = frequency sensitivity of reactive power

The higher order terms of frequencies are avoided as the band of frequency is very small and the voltages are taken up to square as the constant impedance loads are where in the real power varies as per square if the voltage.

Here, K_1 to K_8 are the constants for the different types of the loads and these values come from the percentage of various kinds of load in a busbar. By choosing different values of K_1 to K_8; we can model the loads as a composite load model.

Again, if we decoupled the EV loads from the composite model to analyse separately we just need to solve the load flows for the active models for it, but the percentage of the different loads on the busbar will roll back to the past values without the EV. So, it is certain that the new load is needed to be handled properly before it creates new issues in the power system.

As Location wise most of the loads are static; but the EV changes its position dynamically considering the psychology and movement of the users. The probability is higher to be connected in the same busbar for the conventional loads comparing the Electric Vehicle. This is one of the reasons to implement the Time-Space Theory concept to plot the graph of the stationary time of the EVs in certain places. It helps to predict the possible consumption or dispatch (V2G) the power to a busbar.

To secure the load model in more effective way it is now needed to integrate the Geographic Information Systems (GIS) to the busbar. This integration leads the busbar to specify the location with proper data i.e. line/cable data, load/generation data and GPS Coordinates/schematic diagram information.

In order to analyse the proper implementation of the above mentioned, it is important to first study the existing load forecasting techniques and evaluate their pros and the challenges. This in turn will lead the path for the updated Spatial-Temporal based load forecasting that forms one of the prime focus of the whole research.

4.3 Load forecasting

A prediction of electrical power required to meet the short term, medium term or long-term demand is load forecasting. Looking at the forecasting methods, the most typical way of characterising them is whether they are quantitative methods, or they are qualitative methods. Quantitative forecasting methods focus on collecting the historical data or time series and correlation data, analysing these data to obtain the forecasts as to what predictably can be the load profile in the future. On the other hand, there are the qualitative forecasting techniques, which focus on gathering opinions of the experts, policy makers, customers as to see that how the demand will be in the coming future in a specific situation.

There is a further classification of the load forecasting techniques based upon the duration as; short-term forecasting, medium-term forecasting and long-term forecasting. Keeping at par with carrying out the forecasting in the respective durations, as a matter of fact, will, in turn, achieve maximum savings. This will eventually be the interest of both the generator, distribution and consumer of electricity, because if the forecasting is not carried out adequately then the resulting forecasting errors will increase the operation cost for power generation. Because of the operation cost increasing for the power generation, the other sectors of electricity transmission and distribution will also have to bear the consequences.

The forecasting leads the utility companies to maintain the desired generation, expected operation & maintenance, and meet the demand of their customers. Electrical load forecasting is one of the most necessary process to the utility service providers which can increase the efficiency and revenues of the organizations. It assists them to plan on their capability and operations to supply all consumers with the utmost reliability.

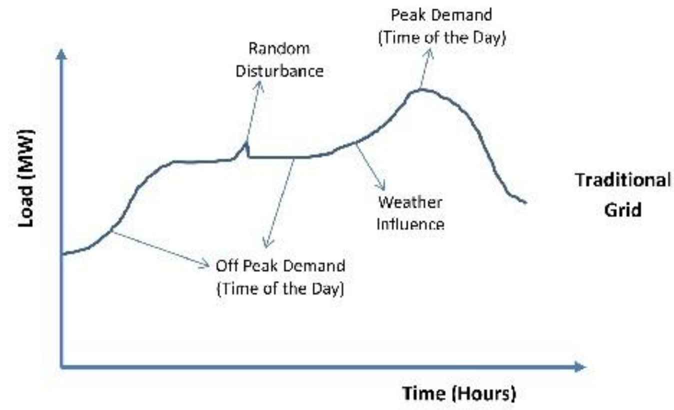


FIGURE 4-3: TYPICAL DAILY LOAD FORECAST

To get the benefit of load forecasting it's always needed to predict the real-time demand utmost. For this reason, different techniques have been adopted till now. Among many factors, the weather itself has big impact in load forecasting, and weather specialists' efforts are significant to forecast it closer to the real one despite sometimes the weather is unpredictable and depends on many other factors. In addition, the past data of the load consumptions is also a major consideration for the load forecasting but in recent days the emerge of large number of EV is stressed the past load consumption data a lot. The vehicle was never been a part of the Electric grid earlier, but the scenario is changing dramatically.

The traditional load forecasting techniques are also getting shaped from the manual technique to database system. Specially the smart meter is also getting to play in a major role for future load casting technique. Despite of the continuous improvement of load forecasting technique there're still challenges and connecting EV in the grid is increasing the challenges more. So, we need to build a solution by discussing the evaluation of the classical and modern approach of the Load forecasting techniques. The solution should minimize the complexity to add the new loads in the current load forecasting process.

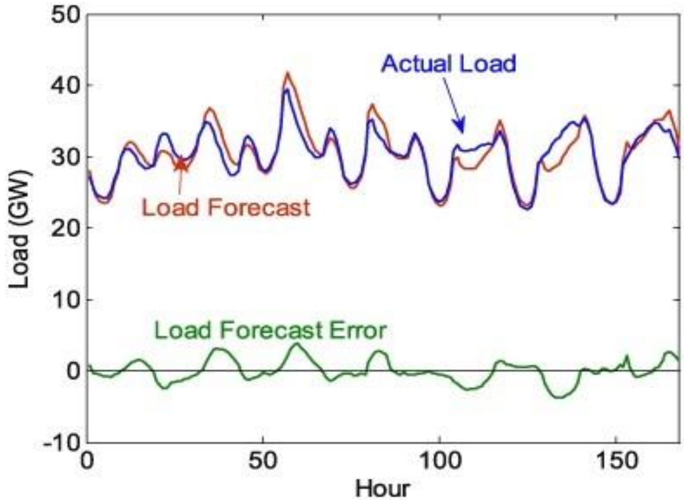


FIGURE 4-4: TYPICAL LOAD FORECAST ERROR PLOT | IMAGE: CDN.IOPSCIENCE.COM

Load forecasts can be split into three categories: short-term load forecasts which are usually from one hour to one-week, medium-term load forecasts which are usually from a week to a year, and long-term load forecasts which are longer than a twelvemonth. The load forecasts for different time horizons are significantly important for variety of operations within a utility service provider [25]. To integrating the electric vehicles in the load forecasting we're more interested to the short-term load forecasts as the movement of the electric vehicles vary by the desire and day to day activities of the users.

4.3.1 Short Term Load Forecasting

A large variety of statistical and artificial intelligence techniques have been developed for short-term load forecasting and we're interested to integrate an algorithm by which we can integrate the Electric Vehicle as a load with the precise direction. At the very beginning of discussing we segregate the STLF in two parts. The traditional and modified traditional techniques of STLF has mentioned below with different methods. These definitions will lead us to develop the concept of the new method to integrate the large number of electric vehicles in the load forecasting techniques.

4.3.1.1 Traditional Forecasting Techniques

4.3.1.1.1 Regression Method

Regression is one of the most widely used statistical techniques and it is often easy to be implemented. The regression methods are usually employed to model the relationship between load consumption and other factors such as weather conditions, day types and customer classes. This method assumes that the load can be divided between a standard load trend and a trend linearly dependent on some factors influencing the load [26]. The method accuracy relies on the adequate representation of possible future conditions by historical data but a measure to detect any unreliable forecast can be easily constructed. The proposed procedure requires few parameters that can be easily calculated from historical data by applying the cross-validation technique. In order to forecast the load precisely throughout a year, one should consider seasonal load change, annual load growth and the latest daily load change. To deal with these characteristics in the load forecasting, a transformation technique is presented. This technique consists of a transformation function with translation and reflection methods. The transformation function is estimated with the previous year's data points, in order that the function converts the data points into a set of new data points with preservation of the shape of temperature-load relationships in the previous year.

4.3.1.1.2 MULTIPLE REGRESSION METHOD:

Multiple Regressions is the most popular method and often used to forecast the load affected by several factors ranging from meteorological effects, per capita growth, electricity prices, economic growth etc. Multiple Regression analysis for load forecasting uses the technique of least square estimation [26]. Mbamalu and El-Hawary used the following load model for applying this analysis [27].

$$Y(t) = V_t a_t + e_t$$

Where,

t is sampling time,
$Y(t)$ is the total measured load system
V_t is a vector of adapted variables such as time, temperature, light intensity, wind speed, humidity, day type (workday, weekend), etc.
a_t is transposed vector of regression coefficients and it is the model error at time t.

The Polynomial degree of influence of the variables from 1 to 5 can be selected by the data analysis program.

4.3.1.1.3 EXPONENTIAL SMOOTHING:

In this method, the first load is model based on previous data, then to use this model to predict the future load. In Moghram and Rahman's exponential smoothing model, the load at time t, y(t), is modelled using a fitting function and is expressed in the form [28];

$$y(t) = \beta(t)^T f(t) + \varepsilon(t)$$

Where,

$f(t)$ = Fitting function vector of the process,
$\beta(t)$ = Coefficient of a vector,
$\varepsilon(t)$ = A White noise and
T = Transpose operator.

The Winter's method is one of existing exponential smoothing methods having the capacity to analyse seasonal time series directly. It is based on three smoothing constants for stationary, trend and seasonality.

4.3.1.1.4 Iterative Reweighted Least-Squares

Mbamalu and El-Hawary [27] used iteratively reweighted least-squares procedure to identify the model order and parameters. The method uses an operator that controls one variable at a time and determines an optimal starting point. Autocorrelation function and the partial autocorrelation function of the resulting differenced past load data is utilized to identify a suboptimal model of the load dynamics. A three-way decision variable is formed by the weighting function, the tuning constants and the weighted sum of the squared residuals in identifying an optimal model and the subsequent parameter estimates.

4.3.1.2 Modified Traditional Techniques

4.3.1.2.1 Adaptive Demand Forecasting

Demand forecasting model parameters are automatically corrected to keep track of the changing load conditions. Hence Demand forecasting is adaptive in nature and can also be used as an online software package in the utility control system. Next state vector is estimated using current prediction error and the current weather data acquisition programs. The state vector is determined by total historical data set analysis. Switching between multiple and adaptive regression analysis is possible in this mode.

4.3.1.2.2 Stochastic Time Series

The Time series methods appear to be among the most popular approaches that applied to STLF. Time series methods assume that the data have an internal structure, such as autocorrelation, trend or seasonal variation. The first impetus of the approach is to accurately assemble a pattern matching available data and then obtain the forecasted value with respect to time using the established model. There are further three sub-methods clubbed under it; Autoregressive (AR) Model, Autoregressive Moving-Average (ARMA) Model, Autoregressive Integrated Moving-Average (ARIMA) Model.

4.3.1.2.2.1 Autoregressive Model:

An autoregressive model is used if the load is assumed to be a linear combination of the previous loads [29]. A short-term load forecasting approach using an autoregressive model with optimal threshold stratification is presented in [30]. This model can derive the minimum number of parameters required for the representation of the stochastic components, which removes the subjective judgement and therefore improves the accuracy of the prediction.

4.3.1.2.2.2 Autoregressive Moving average Model:

An autoregressive moving-average (ARMA) model is used if the current value of the load time series is expressed linearly in terms of its values at previous periods and the previous values of a white noise. The non-linear regression approach such as the maximum-likelihood approach can be used to identify the parameters of an ARMA.

4.3.1.2.2.3 Autoregressive Integrated Moving Average Model:

An autoregressive integrated moving-average (ARIMA) model is used if the load variation process is considered as a non-stationary process. In this model, before the forecasting starts, the time series should be transformed into the stationary form [31]. An ARIMA short term load forecasting approach is proposed in [32], and the mean absolute percentage error ranges from 6% to 9% depending on the season.

4.3.1.2.3 Fuzzy Logic:

The fuzzy logic approach is also widely applied to load forecasting, and it works in two stages: the training stage and the forecasting stage. In the training stage, large quantities of historical load data are used to train a fuzzy logic-based forecaster to generate the pattern database and the fuzzy rule. After training and once validated, the trained forecaster is used for on-line prediction. If the most probable matching pattern with the highest possibility can be found, then an output pattern will be generated through a centroid defuzzifier. More details about fuzzy logic can be found in [33]. A fuzzy logic-based model for short-term load forecasting is presented in [34], and Tabu search is used to optimise the fuzzy model structure. The mean square error in this case ranges from 4% to 7%. Similarly, Paper [35] proposes a fuzzy logic-based methodology, with a root mean square error of about 4%.

4.3.1.2.4 Artificial Intelligence Based Approach

Due to the complexity and relatively low prediction accuracy of regression models and time-series stochastic models, and subjectivity about the selection of the membership function of fuzzy logic-based models, approaches based on artificial intelligence (AI) techniques are gaining more and more attention.

They are now rapidly developing because of their high accuracy. Some of the AI based methodologies for load forecasting have already been adopted and widely used by the industry, and the two most widely used AI techniques are the artificial neural network (ANN) and adaptive neuro-based fuzzy inference system (ANFIS) [36].

4.3.1.2.5 Artificial Neural Network

An artificial neural network (ANN) is an interconnected assembly of simple processing elements, units or nodes, whose functionality is inspired by animal central nervous systems. The processing ability of the network is stored in the inter-unit connection weights, obtained by a process of adaptation to a set of training patterns. It is now widely applied to several areas such as prediction, curve fitting, optimization and clustering etc., because of its capability of learning. Like fuzzy logics, it also works in the training stage and the on-line prediction stage. The mean absolute square error (MAPE) of the prediction ranges from 2% to 5%, depending on different locations and utilities. In [37], an ANN approach trained with generalized delta rules (DR) is adopted to forecast demand, and the mean absolute percentage errors are from 1% to 4%. In [38], a wavelet neural network is adopted for short-term load forecasting of a commercial load, in which different training algorithms are adopted and compared by processing time. The mean absolute percentage errors in this case range from 0% to 5%. A neural network load forecasting approach with weather ensemble predictions for one day to several days ahead of load forecasting is proposed in [39]. The distribution of the load scenarios is used as an input for the estimation of the uncertainty in the forecasting. The mean absolute percentage error in this case ranges from 1.5% to 3%, depending on the number of days in advance that is required to forecast the load.

Apart from short-term load forecasting for real power prediction, the ANN-based approach can also be used for the prediction of reactive power (although it has been applied to only a few cases). A similar ANN-based approach for reactive power prediction is presented in [40], although the reactive power prediction does not acquire the same interest as real power prediction. The mean absolute percentage error ranges from 8% to 17%, depending on the utilities and how long ahead the prediction is (e.g. hours ahead, one day ahead etc.).

4.3.1.2.6 Adaptive Neuro Based Fuzzy Inference System

The adaptive neuro-based fuzzy inference system (ANFIS) is a Sugeno fuzzy inference system (FIS) [41], whose input membership functions are adjusted by either a backpropagation algorithm or hybrid algorithm (a combination of backpropagation and least squares) and output membership functions are either the constant or linear combination of inputs. It is a hybrid approach that incorporates the artificial neural network and fuzzy logic, and is also one of the latest methodologies applied to load forecasting Load prediction based on ANFIS with Gaussian-shaped input membership function, constant output function and hybrid training algorithm is presented and compared with the linear regression approach in [42], and a multi ANFIS for short-term load forecasting for different seasons and different types of days (working days, holidays) is presented in [43]. The mean absolute percentage errors in both cases are up to 3%, in contrast with those for the linear regression approach which, in the same operating environment, are up to 6%. Additionally, in [44], an ANFIS predictor is developed for medium term load forecasting, and the mean absolute percentage error in this case is lower than 2%.

4.4 General Framework for A-I based Short-term Load Forecasting (STLF)

In the case of the electric vehicle scenario these days, GIS-based forecasting will provide the desired results with utmost accuracy. Because data needed for forecasting is updated on a real-time basis, this will ensure a real-time forecasting for Electric Vehicle charging loads. In Figure 4-5 The model for implementation of GIS-based Spatial-Temporal forecasting has been shown.

The proposed charging scheme is based upon the parameters of an electric vehicle; mileage and battery capacity, and the data related to the battery charging; charging power and efficiency. The types of charging schemes and details related to the battery of the Electric vehicle will be discussed in the further chapters. The Spatial-Temporal model is obtained through the information about the activates, their duration and time, and their location.

4.4.1 Spatial-Temporal Activity Model

Let us discuss the Spatial-Temporal Model in detail. As it can be understood from the Model for GIS-based Spatial-Temporal Load Forecasting for EV Charing Load in figure 1., one of the main parameters is the Spatial-Temporal activity model. In order to obtain the model for the Spatial-Temporal activity, it is required to analyse the concept of Space-Time paths.

Based upon the information and communication technology devices, there are a handful of ways to generate these temporal sequences, such as; Event-based recording, Time-based recording, Location-based recording, Change-based recording.

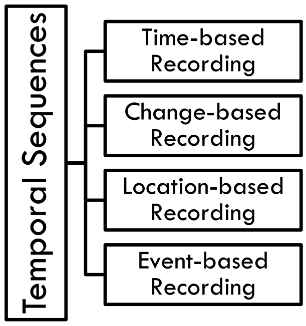


FIGURE 4-5: TYPES OF METHODS FOR OBTAINING THE TEMPORAL SEQUENCES

4.4.1.1 SPACE-TIME PATH

As per Time geography and space-time prism by Harvey J. Miller, The Ohio State University, USA, "Activities such as personal and domestic maintenance, work, shopping, healthcare, education, and recreation are sparsely distributed in time and space; they are available for a limited duration at relatively few locations. Participating in activities requires trading time for space to access these locations at their available times. The space-time path highlights these requirements."

Harvey J. Miller explained the further categorization of the activities into fixed and flexible activities, depending upon the individual's flexibility. Fixed activities are those that cannot be easily rescheduled or relocated (e.g., work, meetings), while flexible activities can be more easily rescheduled and/or occur at more than one location (e.g., shopping, recreation) [45].

Fixed activities act as space-time anchors because other activities such as the flexible activities must occur at the temporal gaps between fixed activities. As it is seen from the graph below, the cylinders depicting work, home, market are the fixed anchors corresponding to the fixed activities while the cylinder for child's school shown by the dotted line represents the flexible activities.

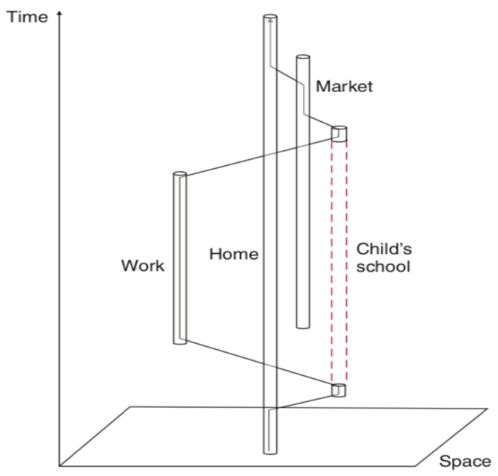


FIGURE 4-6: SPACE-TIME GRAPH

4.4.1.2 SPACE-TIME PRISM

Each anchor has an area defined within its reach based upon its maximum speed. This area is also dependent upon the time budget, as we are trading time for space. Simultaneously the areas corresponding to the two fixed anchors for same time budget forms the space-time prism.

Figure 4-7 illustrates a planar STP. In this case, two space-time anchors frame a prism. Anchors correspond to known locations and time. The spatial footprint of the STP is the potential path area (PPA); this is the region in space that is accessible to the moving object.

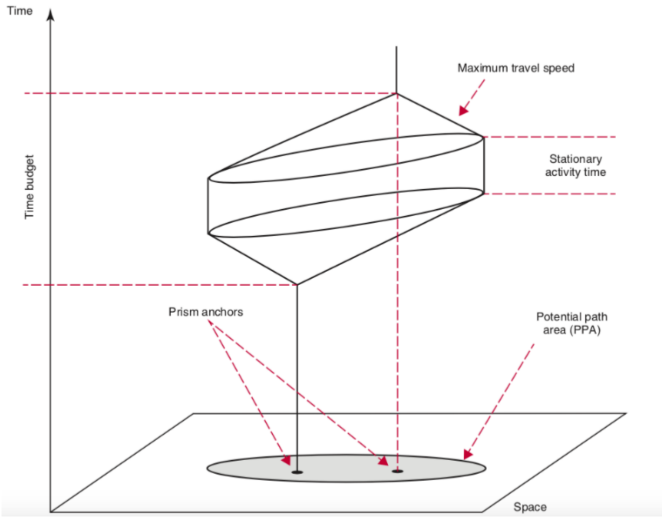


FIGURE 4-7: A PLANAR SPACE-TIME PRISM

The prism in Figure 4-7 is general since it accounts for stationary activity time and has two anchors that are spatially separate. The STP measures accessibility: the ability for an individual to travel and participate in activities and the amount of time available for active participation at locations. An activity at a station is not feasible unless that station intersects with the prism spatially and temporally, the latter for at least as long as the minimum activity time required. This delimits the subset of opportunities in an environment that is available to a person based on their STP constraints.

4.4.1.3 BUNDLING AND INTERSECTIONS

Bundling refers to the convergence in space and time of two or more paths. Path bundling is necessary (although not enough) evidence of shared activities and individuals meshing their space-time activities to participate in projects. Bundling can occur when objects are in motion or stationary; examples of the former include public transportation and ride-sharing.

The intersection is the condition of two or more-time geographic features sharing some locations in space with respect to time. Bundling and intersections are necessary conditions for the emergence of broader space-time activity systems, such as a university or a city. Bundling and intersections require individuals to synchronize over time and space. The rise of geographic information systems (GIS) motivated renewed interest in time geography, particularly in relaxing strict assumptions such as the maximum speed constraining an STP being uniform in space and time.

Location-aware technologies do not generate space-time paths directly; they generate a temporal sequence of spatial locations that are used to construct the path. There are several ways to generate this temporal sequence. The event-based recording captures the time and location when a specified event occurs. The time-based recording captures mobile object positions at regular time intervals. In a change-based recording, a capture occurs when the position of the object is sufficiently different from a previous location. Location-based recording occurs when a mobile object comes close to locations where sensors are located.

The simplest and most common way to generate a path is linear interpolation: assume the object followed the straight-line segment between recorded locations. This works well for time-based and change-based recording with high capture frequencies. Event-based recording creates more issues since events are often not very frequent, and the spatial resolution can be coarse and variable.

The ease of collecting space-time path data from location-aware technologies often comes at the expense of path semantics: details about the moving objects such as the reasons for mobility behaviour. Semantics can be recovered by overlaying paths with other georeferenced data.

Methods for recovering path semantics include decomposing the trajectory into a sequence of moves and stops and annotating these sequences based on map matching with background geographic information.

4.5 Implementing the Spatial-Temporal Activity Model for Mobility Purposes

The Time-Space graphs can be implemented in order to analyse the movement of the vehicles throughout the course of the day. The data obtained from the ICTs devices like GIS, GPS will provide the time and locations. By generating the plots through this data will provide us with clear pictures of the fixed and flexible anchors. Though these location-based information and communication technologies do not auto-generate the space-time paths/graphs, rather they generate the temporal sequence of locations that can further be used to construct the path.

4.5.1 Space Time Activity Graph: Urban Area (Milano)

For explanation, the example of the city of Milan has been considered. First and foremost, it is important to understand that how the commuters travel across the city throughout, day in and day out. The basic structure of transportation in any city is comprised of the public transportation system and privately-owned vehicles. In Milan there is three main type of public transport means, they are listed as below:

- Metro Lines: There are five lines; M1, M2, M3, M4 (still under construction) and M5
- Surface Lines: The surface lines consist of the buses, trams and filo buses.
- Suburban Lines: The suburban lines connect the suburban areas of the city to the main city centre.

The map below obtained through GIS gives a clear picture of how this public network is spread across the city.

The below map shows the density of public transport in Milan. It displays all the possible routes of the buses, trams, metro and suburban trains; along with their respective coordinates. The purple dots in the graph refer to all the possible bus/tram /metro stops across the city. On the other hand, the white and red squares refer to the main railway stations in the city.

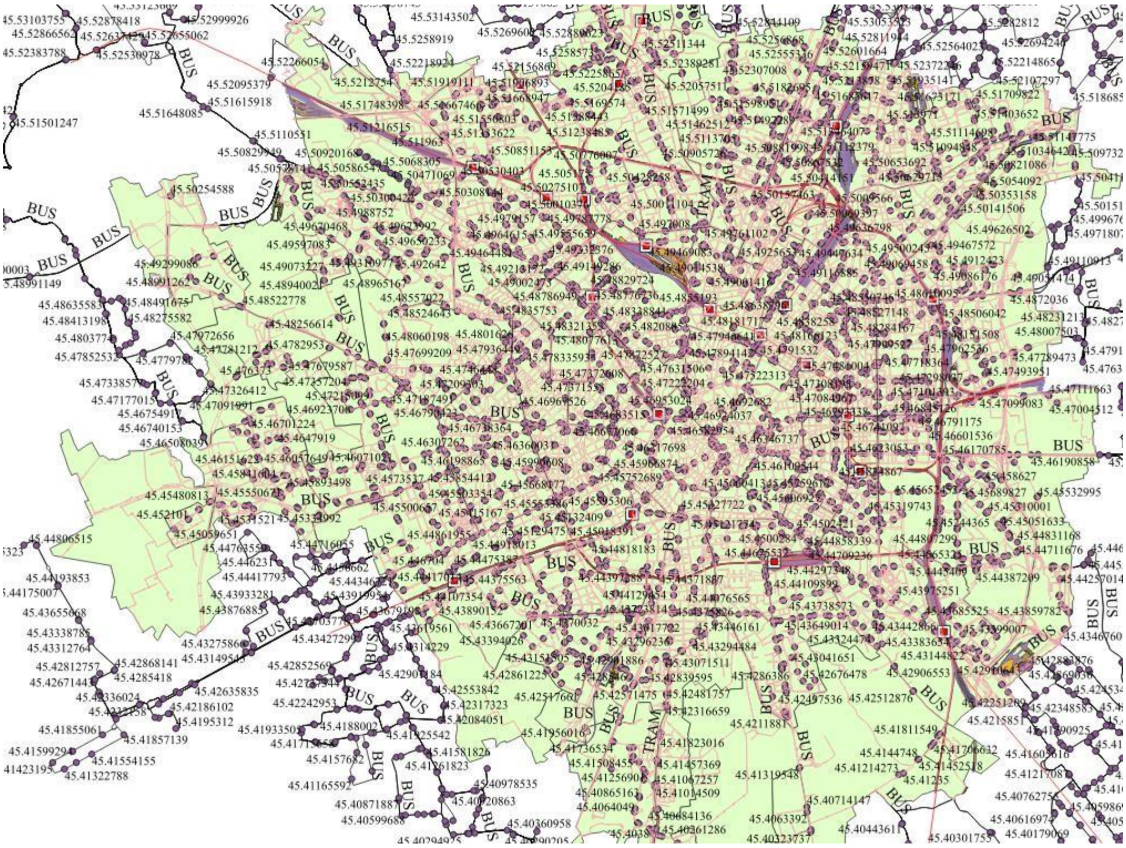


FIGURE 4-8: MAP OF PUBLIC TRANSPORT SYSTEM IN MILAN

Understanding the dynamics of the city's public transport spread, it will become easy to analyse the impact the public transport has on the grid. So that one can align the data obtained from it with the private EV adoption. This will ensure a better segregation of the load profiles.

TABLE 4: ACTIVITY TABLE FOR MILAN

S. NO.	ACTIVITIES	PLACE	LATITUDE	LONGITUDE	TIME
1	Home	Viale Argonne	45.4684	9.2265	8
2	School	Leonardo Da Vinci	45.4793	9.2267	9
3	Work	Porta Garibaldi	45.4836	9.1867	10-16
4	Supermarket	Piazza Tricolore	45.4728	9.2069	17-18
5	Home	Viale Argonne	45.4684	9.2265	20

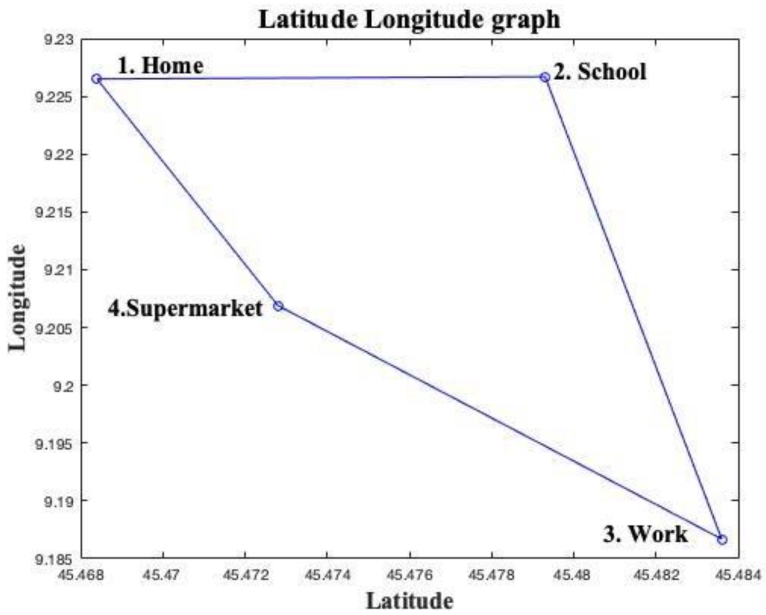


FIGURE 4-9: LATITUDE LONGITUDE GRAPH

The data about the space and time as obtained can be used to obtain the spatial-temporal graphs that help understand the journey of the vehicle throughout the day. Considering the case for instance on an individual who is a day has following activities to complete in their set duration. His activities for the day include; dropping children to school, going for work, doing grocery. It can be analysed that the fixed anchors are his home and his place of work. Based on the coordinates as per the movement of the car throughout the day, the spatial-temporal plots can be obtained.

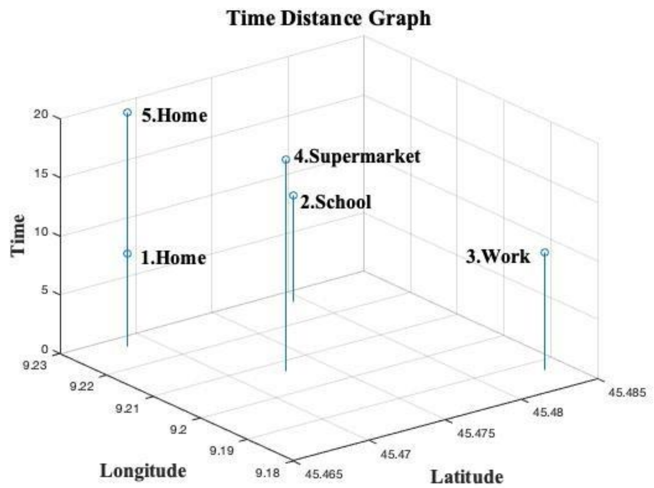


FIGURE 4-10: TEMPORAL SEQUENCE GRAPH

The Figure 4-9 shows the movement of the car in terms of the latitude and longitudes. One can clearly see that the movement of the car was as follows; Home-School-Work-Supermarket-Home. In the Figure 4-10, the spatial-temporal data has been plotted and it is evident to notice all the anchors; home, school, work and supermarket. The Figure 4-11 highlights the stationary activity time of the car.

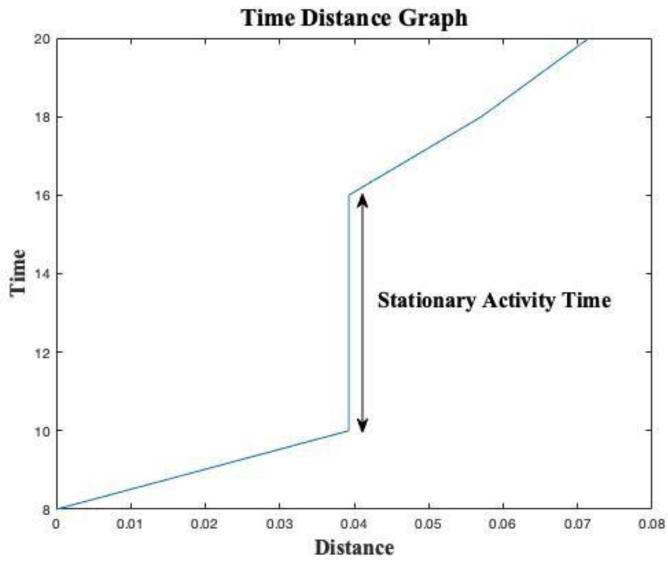


FIGURE 4-11: TIME DISTANCE GRAPH

4.5.2 SPACE TIME ACTIVITY GRAPH: SUB-URBAN AREA (AOSTA)

As it can be seen from the above case study, a typically case of a metropolitan city has been discussed. In this research a case of a small city has been discussed. Due to the unavailability of resources for the analysing the grid of Milan in detail, since the data would have been huge to process, the data of Aosta city has been analysed.

Consider a car's activity throughout the day as: Station, Ponte Romano, Castello and Hotel. Throughout the course of the day, through the location-based technologies the data of the car will be obtained. Based upon the temporal sequences obtained from the GIS software, following graphs regarding the spatial-temporal activity model have been obtained.

TABLE 5: ACTIVITY MODEL (AOSTA CITY)

S. NO.	ACTIVITIES	PLACE	LATITUDE	LONGITUDE	TIME
1	Station	Aosta Valley	45.73454567	7.322185	8
2	Sight Seeing	Castello	45.7339840	7.333060	10-12
3	Sight Seeing	Ponte Romano	45.739700	7.331040	14-20
4	Hotel	Frazione Rigollet	45.728890	7.27270	22

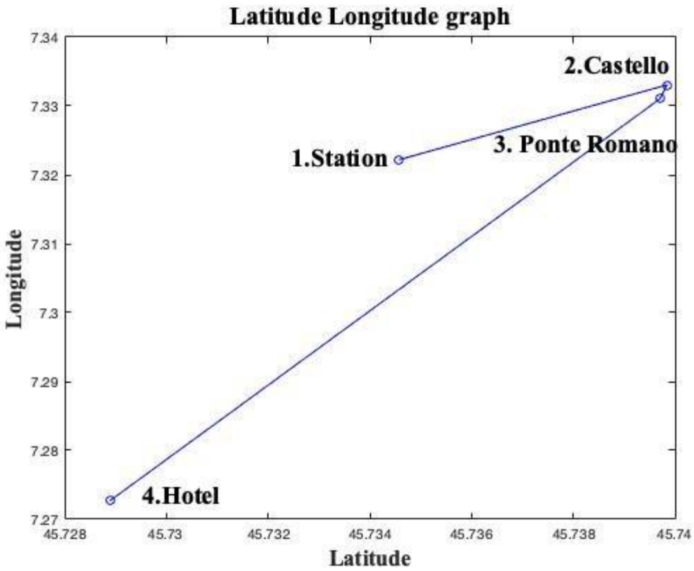


FIGURE 4-12: LONGITUDE AND LATITUDE GRAPH

The graph in the Figure 4-12 depicts the latitude longitude graph for an individual car's activity for the city of Aosta. The movement of the car throughout the day has been around the anchors; Station, Castello, Ponte Romano and Hotel.

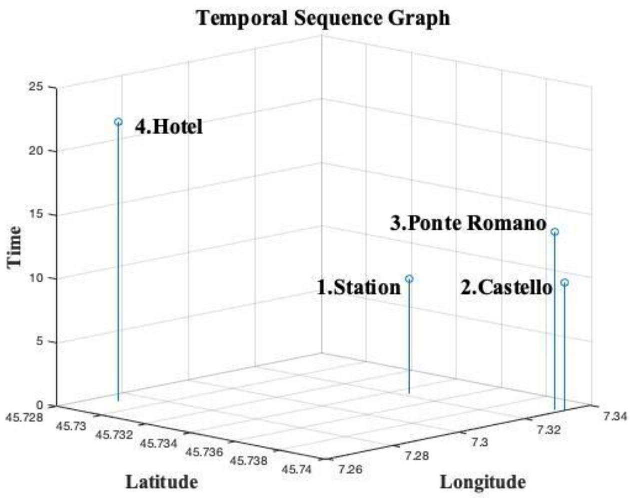


FIGURE 4-13: TEMPORAL SEQUENCE GRAPH

Figure 4-13 represents the Temporal Sequence Graph for the data obtained from the location-based technologies. It can be seen from the graphs that the anchors Station and Hotel represent the fixed anchors, as the station and hotel the person visiting the city chooses to stay remain fixed. The time of the arrival of the train is defined and so is the time of check-in for the hotel, so, this also emphasis that they are fixed anchors, as for the anchors Ponte Romano and Castello, they are the flexible anchors because the person has the flexibility to choose which place, he wants to explore first and at what time.

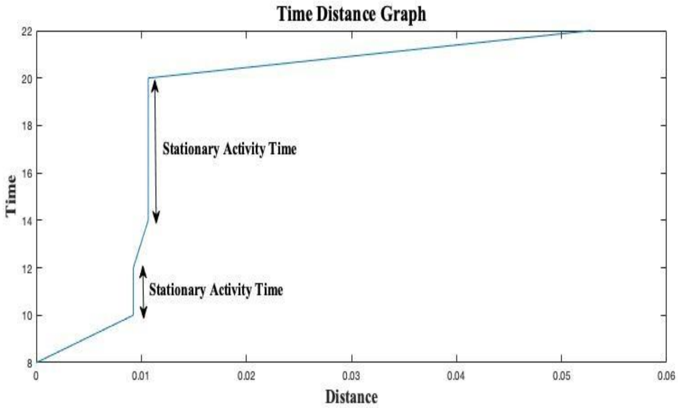


FIGURE 4-14: TIME DISTANCE GRAPH

The Figure 4-14 shows the Time distance graph for the whole Spatial-Temporal Activity model. It can be observed that the stationary activity time of the car in indicated. The location corresponding to that time can be evaluated from the temporal sequence graph.

4.5.3 Flowchart for implementation of Spatial-Temporal Activity Model

For the implementation and application of the Spatial-Temporal activity model, a flowchart has been described in Figure 4-15. The parameters necessary for the implementation and application of the Spatial-Temporal model are; Information about the activities, Spatial-Temporal Activity Model, Spatial-Temporal Graphs, Stationary Activity Time and Location, and Grid capacity.

The algorithm described it the figure contains a set of roughly 17 steps to be followed, with 4 areas that are for decision making. There are four decision making areas to check whether the EV belongs to the locality, is it in stationary state, is the data verified at the substation and is it accepted by the user and is the SoC enough for the next trip or not.

The steps of the algorithm include; location of the EV inside the area of scope, generating real-time activity graph for the area of travel inside the area of scope, obtaining and integrating the energy profile of EV including the SoC by Pull-Energy profile service, computing the stationary activity time, computing the next destination and possible time of departure from the user input/historical Spatial-Temporal graph, Estimating the required energy consumption to reach the destination, calculating the SoC and SoH of the battery at the estimated arrival time at the next destination, Estimate the duration of the travel, send the data to the destination substation/busbar, computing and updating the new composite load model, computing the load forecast considering new composite load model or the busbar/substation, computing the variance between the updated and the old load forecast, Tagging GIS position of the busbar to the updated load forecasting along with the variance, informing the user regarding the available nearest charging station before reaching the lowest battery capacity threshold.

First and foremost, it is important to locate the presence of EV in the Area of Scope. After locating the EV in the Area of the Scope, it is important to check whether the EV belongs to that locality or does id belong to another locality or city and it will be the Area od Scope for a short period of time. If the EV does not belong to that locality, it is required to generate a request to access its Energy Profile.

In the case where the EV belongs to that locality, it is required to generate a Real-Time activities graph from the temporal sequences obtained through the data stored in the EV. Then the interaction of the Energy Profile of the EV with the Real-Time Activities Graph is carried out. It is then checked whether the EV is in the stationary state at that instant or not.

If the EV is in the stationary state, the stationary activity time is calculated along with the computation of the Next Destination and possible time of departure from the user input/historical Spatial-Temporal graph. Based upon this data obtained, the required energy consumption to reach the destination is estimated.

The SoC and SoH of the battery at the estimated arrival time at the next destination is calculated and as per the calculation the estimation of the duration of the travel is carried out. The information is then sent to the destination substation/busbar.

Then the verification of the data is done. Upon the positive verification, the new composite load model is obtained. The load forecast is done for the busbar/substation keeping into account the new composite models generated. After computing the variance between the updated and the old load forecast and Tagging GIS position of the busbar to the updated load forecasting along with the variance, the data is sent to update the SCADA of the substation.

In the case where the SoC is not enough for the next trip, the user will be informed regarding the available nearest charging station before reaching the lowest battery capacity threshold. After this update the whole steps will be followed again from the decision-making block for finding whether the EV is stationary or not.

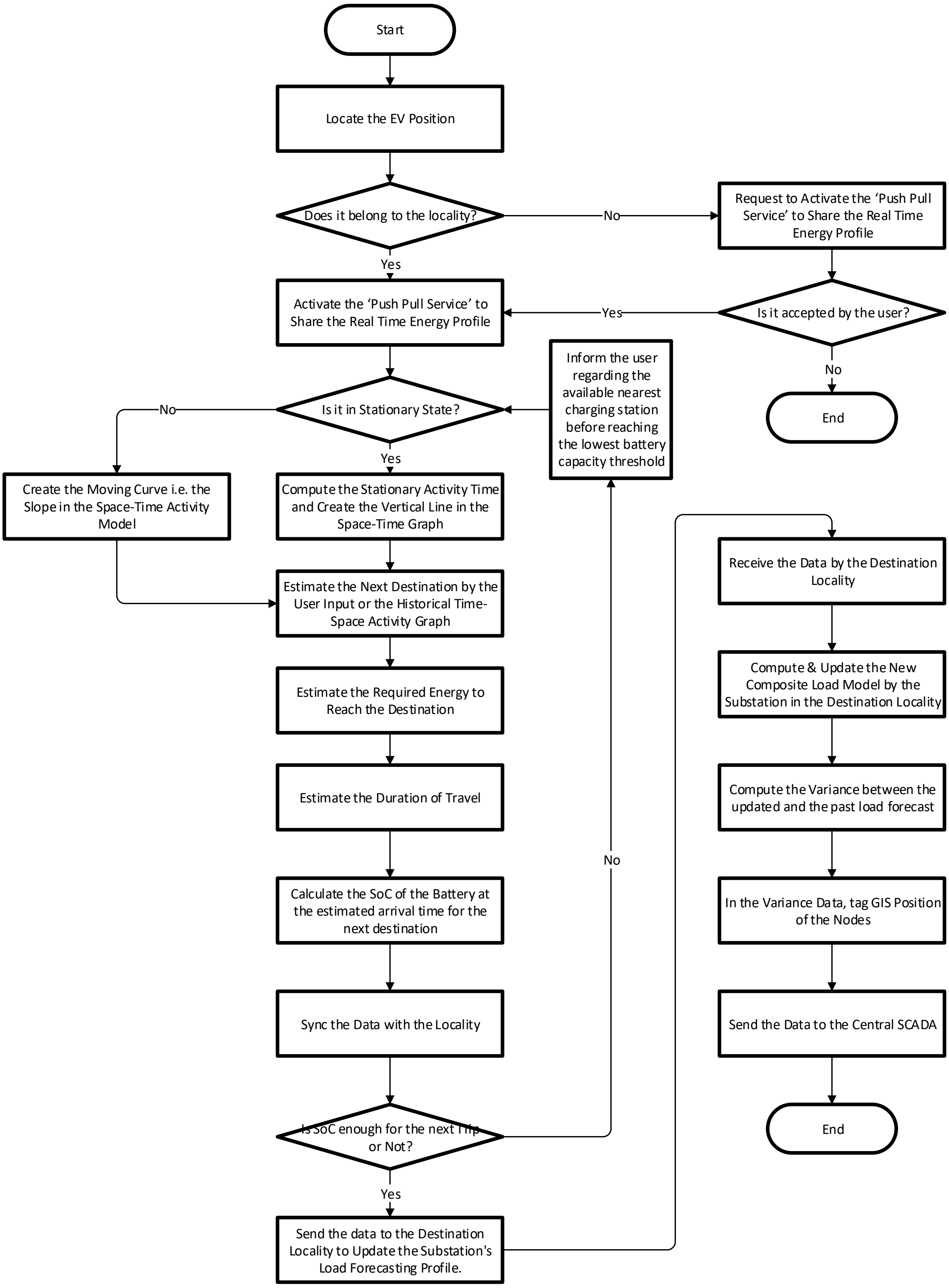


FIGURE 4-15: ***FLOWCHART FOR IMPLEMENTATION OF SPATIAL-TEMPORAL ACTIVITY MODEL***

4.5.4 Flowchart for the Selection of the Place and Capacity OF THE Charging Station

The algorithm described below focuses on exploiting the Stationary Activity Time that has been obtained from the stationary Activity model described before, in to examine whether that area has enough concentration of the EVs in the stationary state at the same time. The area can be further examined and can be proposed as a potential location for a charging station. Afterwards, the grid capacity and the nodal hosting capacity in that location has to verified. If the results come out to positive, the construction of charging station can be started.

The whole algorithm is divided into 11 steps and 2 decision areas. The steps include; collecting the Space-Time Activity Graph from the EV in the locality, storing the graphs in the Central Server, Segregating the Parking Places and Calculating the duration of stationary activity Time in the locality, merging the data further of the all the EVs in that locality, finding the lowest Average Stationary Time of the EVs in the parking places, Finding Day-wise Lowest and Highest number of EVs parked in the parking places, Finding the lowest average SoC for the EVs, proposing the parking places for the Charging Stations.

After these steps followed in a sequence, it will checked whether the Nodal Hosting Capacity of the nearest nodes is ensured or not. In the case were the above is not insure, then another location will be chosen to check its Nodal Hosting Capacity. The case for which the criteria regarding the Nodal Hosting Capacity will be satisfied, the designing of new charging station will be started to check for the feasibility. In case the new charging station being issued will prove to be economically feasible, the construction of charging station will be started, else a new location will be analysed.

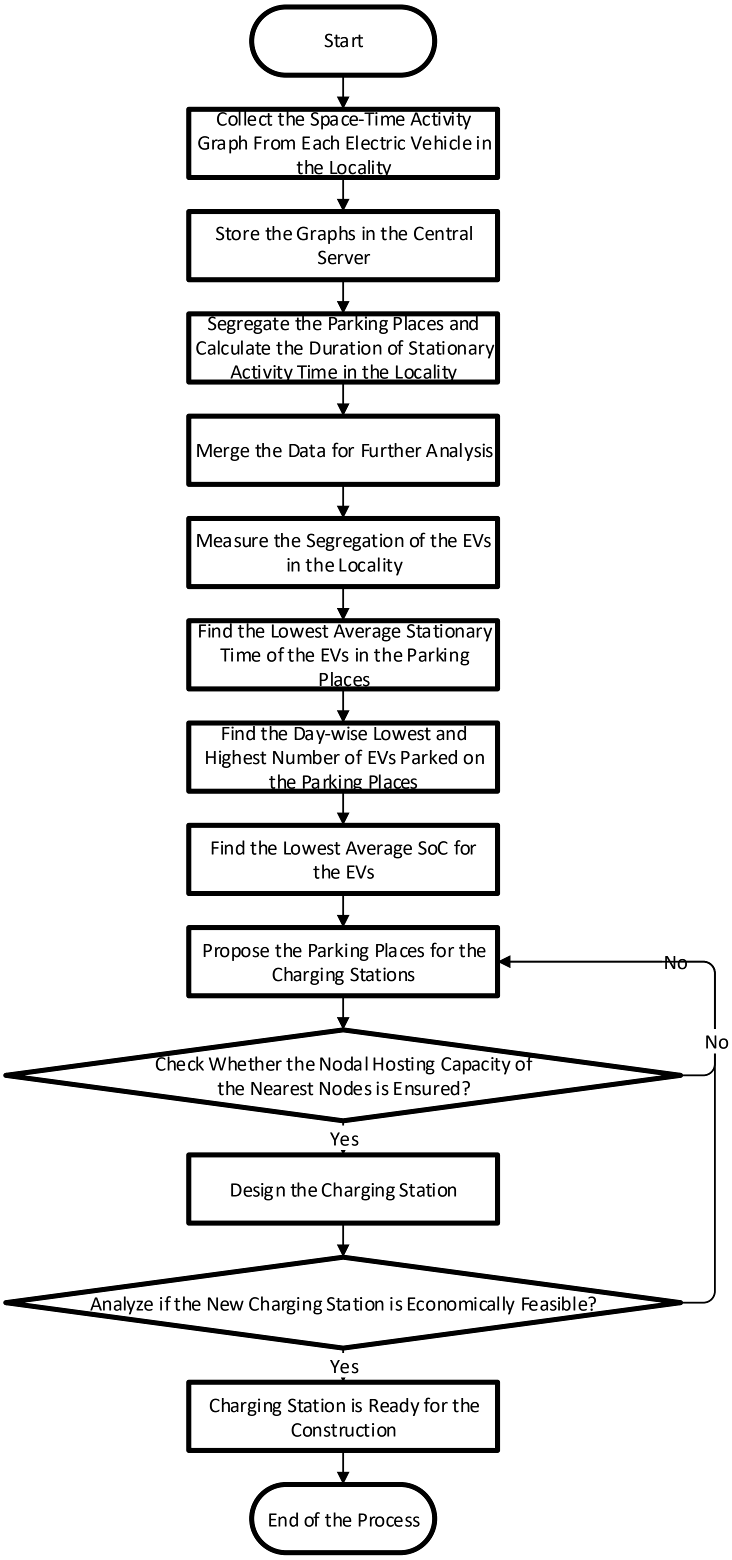


FIGURE 4-16: 4.5.4 FLOWCHART FOR THE SELECTION OF THE PLACE AND CAPACITY OF THE CHARGING STATION

So, after the formulation of the algorithms in this chapter, that will elevate the integration on EV in the grid, in the next chapter the battery management aspects of it will be discussed further.

CHAPTER FIVE

5 FABRICATION OF ESS AS A LOCALITY

5.1 OVERVIEW

A significant number of the European countries are focusing to decrease the conventional power plants by substituting them by renewable energy sources. The dependency to more renewables creates some issues to electrical networks as most of them are nonprogrammable despite those are from the green energy sources. The renewables energy drives power plants are completely dependent on the locations and the weather. So, the required amount of dispatch isn't possible always considering the power demand in the electrical network.

Moreover, the large number of small DG penetration in the low and medium voltage network make a possibility of a reverse power flow to the high voltage network which is not expected at all. Moreover, the rapid increment of non-programmable power plants creates more challenge to the ancillary services and specifically costlier. The utility service providers are needed to pay more to the power producers in unit commitment programs. So, reducing the dependency to the conventional power it's really needed to adopt the ancillary services by the renewable energy progressively. So, the first solution unveiled by integrating big battery bank to the electrical networks which is mostly known as Battery Energy Storage System i.e. BESS [46].

Most common BESS has the capability to provide the Ancillary Services within shortest notice, or we may say it has the capability to respond instantly. In addition, the surplus power of renewable energy can be stored while the renewables power productions are on the peak. The flexibility of the BESS is making it popular among the utility service provider despite the stringent parameters of the battery technologies. The battery technologies are not matured yet to handle the bigger quantity of energy. The initial investment of the BESS is also so high, and the utility service providers are considered the cost as a barrier of the technology while they're flexible and welcome to pay for the service rendered.

Finally, it is also quite difficult to attract the investors to invest their money on the BESS while it doesn't have any unit commitment yet. Even with a unit commitment it'll not serve the purpose to swap from the conventional power plants; at least in terms of the cost comparison. So, what could be the possible solution for having the BESS service without investing a huge amount as initial investment? Or, which scheme can make people more interested to invest to the BESS like the renewable energy plants? The achievable answer could be the Virtual Battery Energy System i.e, VBESS or VESS [47]

The solution of the problems was beyond the scope until the electric vehicles didn't appear in the market commercially. But the major challenges for the users of the EVs are like the utility service providers i.e. high initial investments and slow returns. The battery technologies are also improving faster which may demotivate the buyers to invest money to the Electric Vehicles. So, the EV market is not improving significantly. The issues can be solved for both stakeholders by enabling the service to provide the ancillary service as an addition option to the EV owners. Now the technical challenges will arise to manage a big number of the moving vehicles for this purpose.

5.2 Virtual Battery Energy Storage System (VBESS or VESS)

The drives of the EVs are powered by the set of the batteries and it's possible to offer an additional service to the grid to sell the energy back to the grid with a higher price for the ancillary services while it is stationary within a logical proximity of the grid. In the previous chapter we've discussed the possibility to communicate between grid and the Electric Vehicles. The Energy Profile of the EVs will provide the key indicators if it is able to provide the power back to utility grid. Also, the estimated spatial-temporal path will direct the possible duration to connect with the grid. The multiple units of such Electric Vehicle will ensure the adequacy to provide the ancillary services to the grid [47].

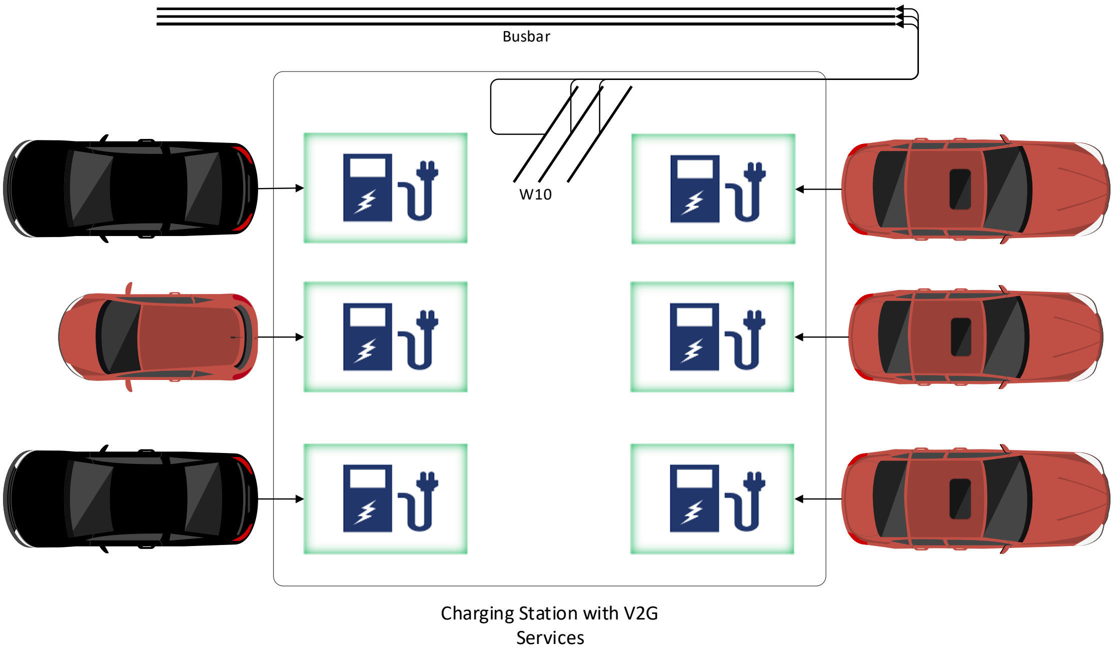


FIGURE 5-1: CREATING A VESS IN A CHARGING STATION

The numbers of the vehicles will create a big virtual energy storage where a complex algorithm will define the amount of energy withdrawn from different vehicles. The aggregate capacities of the vehicles in the parking lot and the duration of the stay are also the determinant of the services. To create a virtual energy storage system for the ancillary services is still a complex task despite the Spatial-Temporal based load forecasting and integration of GIS at the nodes are giving privilege to track the time and proximity of the Electric Vehicles. To make it easier there is a need to bring up the concept of 'the locality'.

5.2.1 THE LOCALITY

To enable the service of VESS, the electricity utility service providers needs to extend the competences more on the network handling like the telecom service providers. Specially they must need to design the territory of the VESS considering the requirements of the grid and available vehicles on the territory. As the utility service providers are already exploiting the possibility to dispatch the renewable energy generated power to the grid by the applications, it is also possible to register the Electric Vehicles in such territory. The registration of the Electric Vehicles to the utility service providers will allow the access to inject the energy back into the grid, which, will also guarantee economic benefits to the owner.

By the locality concept, the utility company will have a clear estimation of the battery capacities of the EVs which are going to enable the services, and which are not. Also, it will lead the utility to carry out the asset management of the batteries which is also necessary for the planning of the virtual energy storage system. The asset management process for the locality will lead the utility service provider and the users to operate, maintain, upgrade, and disposing the batteries in the most cost-effective manner as it will be included along with the cost, risks, performance attributes and the life cycle. To implement the locality concept, we must introduce such a model where it will not overlap with the other localities and it will be identical for the utility service provider.

5.2.1.1 THE STRUCTURE OF THE LOCALITY:

The electrical network has been spread to the areas of the developed countries. It covers the civilized area like a fish net. Now it's in our scope to add new utility in it. The GIS integration to the nodes creates the new opportunities to analysis the grid network under the exact positions on the earth plane. Now we've to find a shape of the locality to activate the VESS and other services. The shape of the locality should be such so that it covers all the areas without intersecting each other or overlapping each other.

These issues have been solved many years back in telecom industries. In telecommunication the engineers design a hexagonal shaped cell to make the coverage areas identical to each other. The hexagonal cell shapes can be laid to each other with no overlap, thus they are able to cover the entire geographic area without having any gaps between them [48]. While the circular shape cannot overcome these two issues i.e. the overlapping and non-covering areas. We may have followed the below depicted figure to understand the concept of the shapes of the locality for the Electric Vehicles.

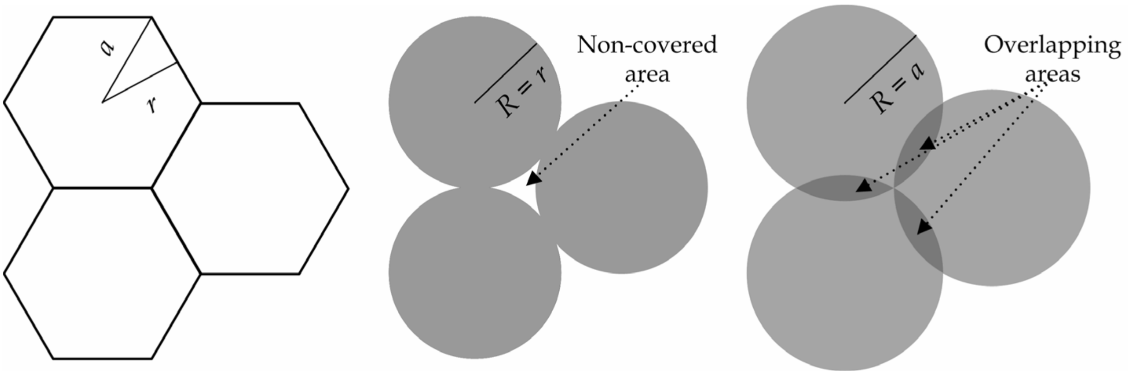


FIGURE 5-2: HEXAGONAL CELL LAYOUT; AND IDEALIZED CIRCULAR COVERAGE AREAS

Now the next challenge will be for the utility service providers to identify the locality with the unique code so that they can proceed the asset management of the locality. Of course, it will include the nodes, busbars and the substations. So, the unique codes will allow the locality to communicate and share the assets with each other and enable other services by the utility service provider in future.

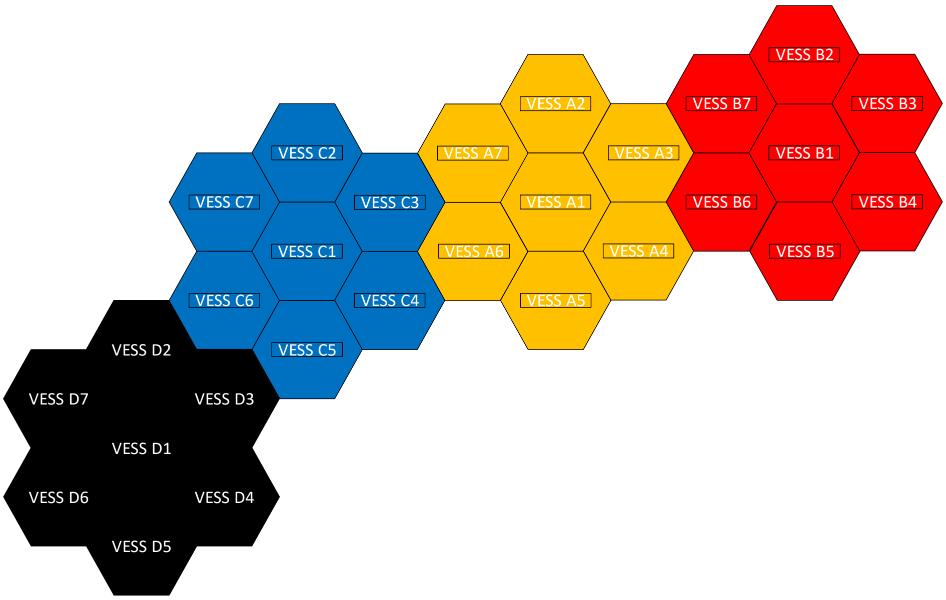


FIGURE 5-3: THE LOCALITY STRUCTURE

The Utility Service Provider may consider the above depicted hexagonal shape as a locality. Here every unit of the locality has a unique identification name and it is possible to deploy IP addressing method based on future requirements. By the deployment of it, every locality will be able to communicate with each other to update the vehicle movement. The size of the locality i.e. the hexagonal shape may vary with the area, population, numbers of the vehicles, location and of course the size and capacity of the grids.

5.2.2 Aggregate the Electric Vehicles as VESS

To aggregate the EV's battery capacity, it is needed to consider the SoC and SoH of the batteries within the locality. The utility service providers will decide the amount of the withdrawn power considering the requirements and energy profile of the EVs. To complete the process, we need to define an algorithm by which it will be more convenient to select the fleets for the ancillary services. Of course, the spatial temporal load forecasting method will give the positions and the duration of the connection to the grid.

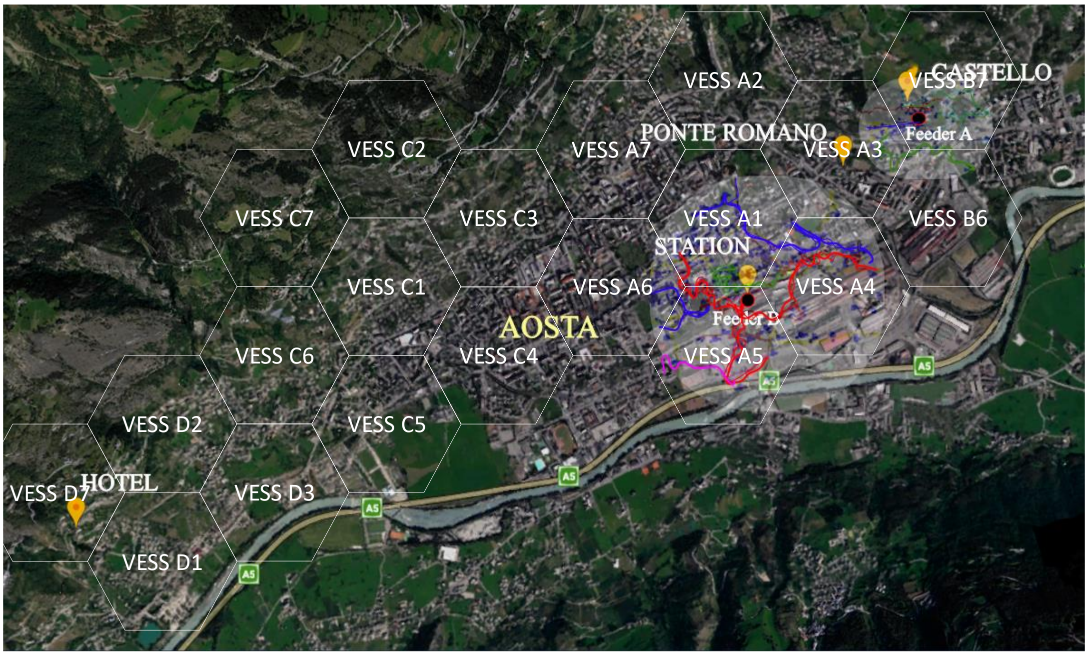


FIGURE 5-4: DEFINING THE LOCALITY FOR AOSTA CITY

To understand the scenario, we have selected the map of Aosta, Italy. In the last chapter we've portrayed the grid line in the map. The nodes are also projected considering the position into the map, which is giving the facilities to understand the real position of the grid line. We've superimposed the hexagonal shape on the map of Aosta to realize the concept of the Locality. Now, the city has defined by the locality concept to implement the VESS. By looking into the above picture, it is now clear which node is the part of which locality.

5.3 GIS integration to the Nodes

In the era of the Internet & Information it's not enough to have only the load flow models and the proposed load forecasting technique, the locality concept but the substation or the busbars, more specifically the nodes should have a proper mapping on the earth plane with the tagging of the accurate position i.e. GIS [49]. These integrations will not only give the utility a privilege to distribution but also open the new page of calculate the proximity of the Electric Vehicles of the locality. Moreover, the analysis of the nodes status will be more convenient, especially for the calculation of the Nodal Hosting Capacity and Virtual Energy Storage System through the moving battery banks i.e. the Electric Vehicles. It's also important to have the GIS positioning of each nodes for the implementation of 'the locality model' by the utility model. The concept of the locality model has elaborated already in the earlier paragraphs to create a proper Virtual Energy Storage System. In addition, the GIS information for the nodes will also support the utility service providers to open a new era of the communication through the power cables i.e. Power Line Communication despite the issues of Voltage Steps in the distribution system.

5.3.1 GIS Integration to the Nodes for Aosta City

To realize the GIS integration on the nodes we take Aosta City in our consideration. And superimposed the grid model (the model we've used later in chapter number five) in the map.

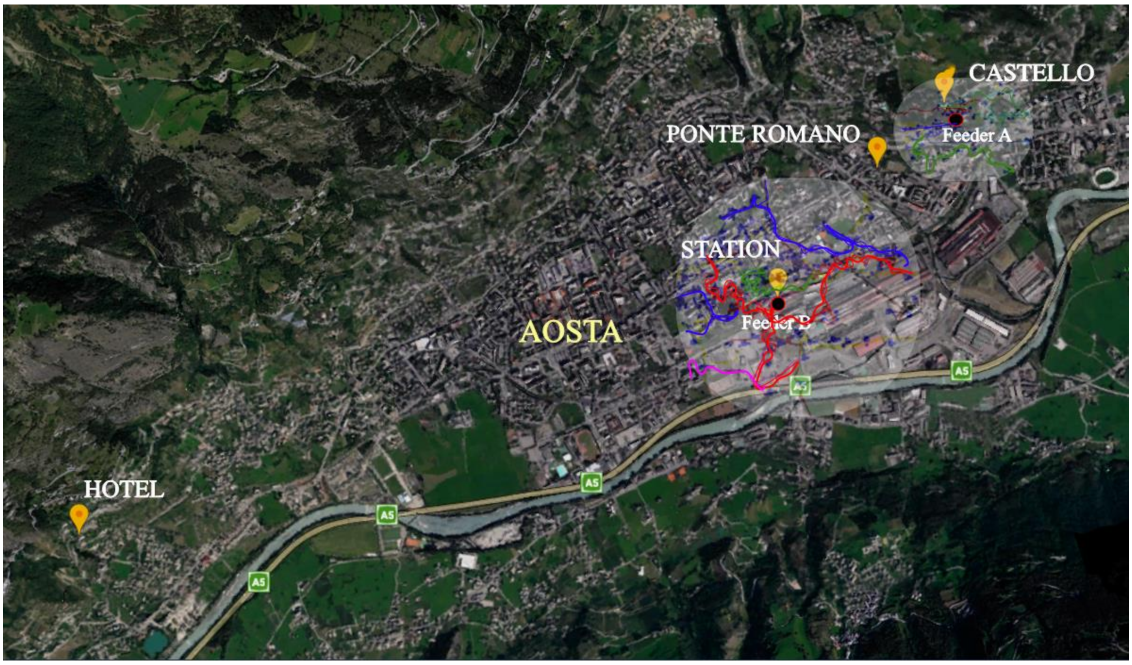


FIGURE 5-5: GIS INTEGRATION TO THE NODES FOR AOSTA CITY

After fitting the data, we are more interested to zoom in the feeder section to visualize the loads.

5.3.1.1 FEEDER A

FIGURE 5-6: GIS INTEGRATION TO FEEDER A

Now the nodes are clearer to identify from the above picture. We can complete the following table considering the locality model of Aosta and the above picture.

TABLE 6: NODES POSITION FOR FEEDER A INSIDE THE LOCALITY

S. No.	Locality Code	Feeder Name	Node Number
1.	A3	A	A1, A2
2.	B7	A	A3, A4

5.3.1.2 For Feeder B

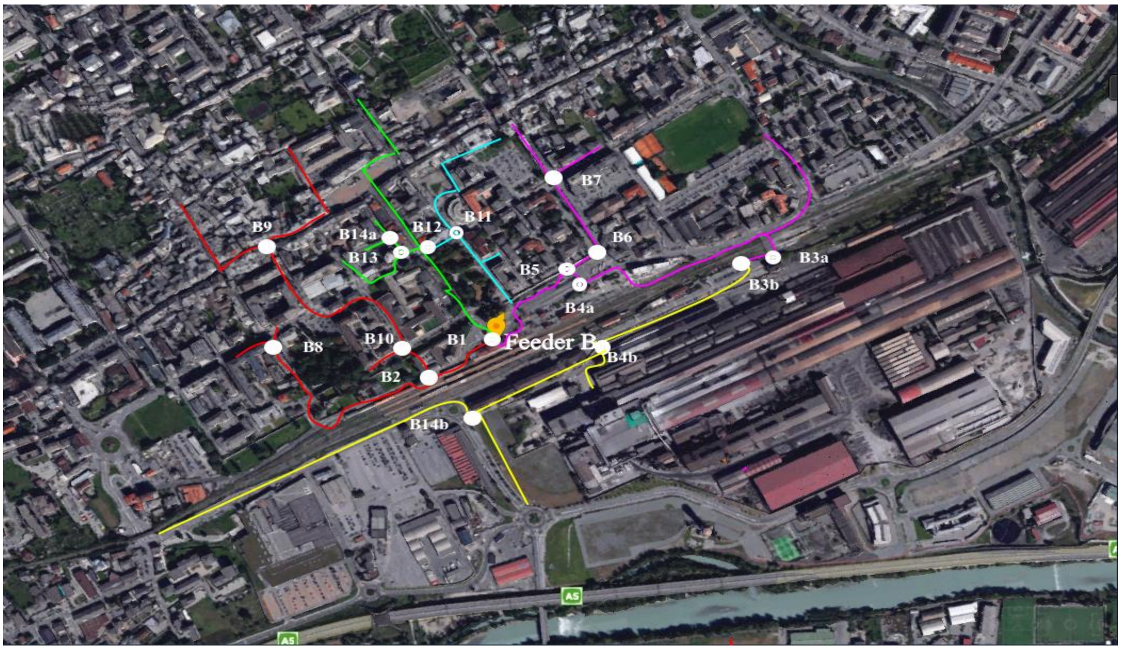


FIGURE 5-7: GIS INTEGRATION TO FEEDER B

We can complete the following table considering the locality model of Aosta and the above picture.

TABLE 7: NODES POSITION FOR FEEDER B INSIDE THE LOCALITY

S. No.	Locality Code	Feeder Name	Node Number
1.	A1	B	B1, B7, B9, B11, B12, B13, B14a
2.	A4	B	B3a, B3b, B4a, B4b, B5, B6
3.	A5	B	B2, B8, B10, B14b

5.4 Locality wise Activities

To complete the locality concept, now we must bring the data of the Space Time Activity of the Electric Vehicles. The following table is holding the date of Aosta City

TABLE 8: DURATION & LOCALITY WISE ACTIVITY

S. No.	Activities	Place	Time	Status	Duration of Stay	The Locality
1.	Travelling	Around the City	8-10	On Movement		A1, A4, A5, B7
2.	Sight Seeing	Castello	10-12	Stationary	120 mins	B7
3.	Travelling	Around the City	12-14	On Movement		A2, B6, B7, A3
4.	Sight Seeing	Ponte Romano	14-20	Stationary	120 mins	A3
5.	Travelling	Around the City	20-22	On Movement		A3, A4, A1, A5, A6, C4, C5, D3, D1, D7
6.	Stay in the Hotel	Frazione Rigollet	22-8	Stationary	600 mins	D7

If we follow the data, we can notice the type of the stay i.e. if it's stationary or not. Moreover, we can visualize the movement across the localities. So, it's possible to understand the movement of the Electric Vehicle doesn't allow us to think a static VESS for one locality, rather we've to consider the dynamic VESS which is needed to update by time from the data of the individual electric vehicle's Space-Time Activity Graph.

5.5 Hand off Processes of the EVs between the Localities

As the movement of the vehicle is based upon the behaviour and purposes of the users; certainly, it is not possible to bound them to stay inside the area of one locality for the VESS service. Thus, it is needed to define the handover process to the neighbour locality and so on while moving for some purposes of the users. Or as discussed in the earlier paragraph most probable case may occur that the user may stay in different localities in different times, thus the VESS capacity may vary on time.

So how to manage the handover process between the localities? To find the answer we've to create an algorithm. The algorithm of aggregate the fleets as a VESS as well as handoff [50] the EV to the adjacent locality is mentioned below.

5.5.1 Workflow of Handoff Processes for VESS

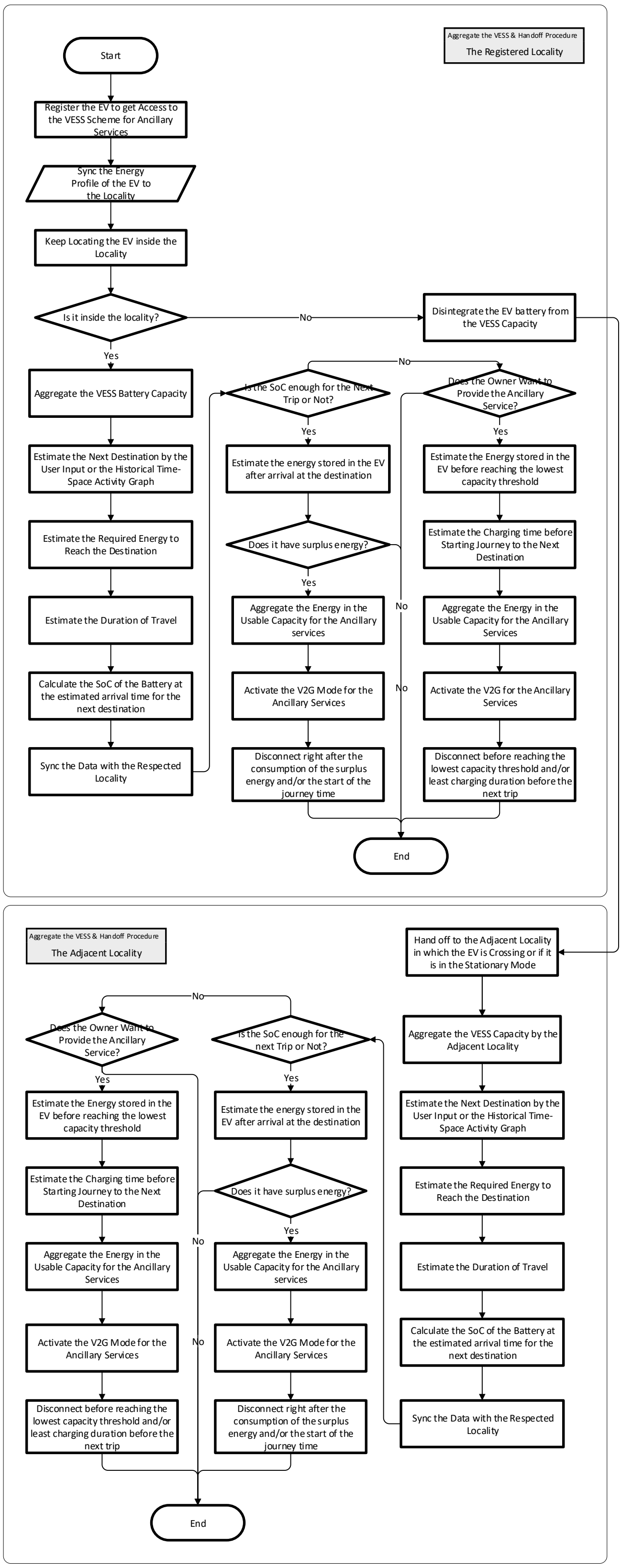


FIGURE 5-8: HANDOFF PROCESSES FOR VESS AMONG LOCALITIES

As it can be seen from the Figure 5-8, the whole algorithm has two separate block sets that have been linked together. The first block set focuses on the case of The Registered Locality and the second one focuses on the case of the adjacent locality.

The Registered Locality block set has 18 steps. The first set of steps are; registering the EV by the car owner to get access to VESS Scheme for Ancillary Services, Syncing the Energy profile of the EV to the locality data, the locality will then keep on locating/monitoring the EV, throughout this monitoring process it has be checked whether the EV is still inside the locality or not. In the case where the EV is still inside the registered locality, the steps related to the registered locality will be followed further. Whereas if the EV leaves that locality than it in that case the EV will be now belonging to the adjacent locality. Thus, the EV will be disintegrated from the VESS Capacity.

The further steps for the registered locality are; Aggregating the VESS Battery Capacity, Estimating the next destination by the user input or the historical Time-Space Activity Graph, Estimating the required Energy to reach the destination, estimating the duration of travel, Calculating the SoC of the battery at the estimated arrival time of the next destination, Syncing the data with the respected locality. After these steps it is to be checked if the SoC is enough for the next trip or not.

In the case where the SoC is enough for the next destination, the steps will be carried out further as; estimating the energy stored in the EV after arrival at the destination. It to checked now that whether the energy estimated is in surplus or not. If not, then the process will be over else the process will proceed further. Now the steps further will as; aggregation of the Energy in the usable Capacity for the Ancillary Services, Activating the V2G Mode for the Ancillary Services, disconnecting after the injection of surplus energy and/or the start of the journey time and the process will be complete.

Now we also must consider if the SoC calculated was not enough for the next trip. The steps will be followed further; it will be first checked if the owner is willing to provide the Ancillary Service. If yes then steps will be followed as; estimating the energy stored in the EV before reaching the lowest capacity threshold, estimating the charging time before starting the journey towards the next destination, aggregating the energy in the usable capacity for the ancillary services, activating the V2G Mode for the ancillary services, disconnecting before reaching the lowest capacity threshold and/or least charging duration before the next trip. The process ends here.

As it has been already stated above that the process has two block sets, lets discuss about the second one. In the case where the EV is no longer in the adjacent locality, the hand-off of the data related to it to the adjacent locality in which the EV will be located next will take place or in the case if EV is in the stationary state. The whole process described in the first block set will be performed again.

5.6 Simulation of ESS with Different Capacities for the Ancillary Services

After forming the VESS by the concept of the locality, we may use the VESS or the BESS as integrated as ESS for the ancillary services. Now, we've to estimate the required battery capacity for the ancillary services. As different type of the batteries behaves in different ways, the efficiency also varied considering the charging and discharging cycles.

In this section, we have simulated the electrical model [51] [52] of the batteries in Simulink and observed the response of the batteries as ESS against frequency regulation.

5.6.1 Battery Parameters

Before starting the estimation and the simulation we must define some important parameters of the batteries.

5.6.1.1 C-Rate

C-Rate is normally used to define the magnitude of current-based charge/discharge responses. It's the ratio between the current and the nominal cell's capacity [53].

$$C - rate = \frac{I_{ch/disch}[A]}{C_{nom}[Ah]}$$

5.6.1.2 State of Charge (SoC)

State of Charge i.e. SoC is useful indicator that defines the ration between the available capacity and the nominal capacity of the cell [53].

$$SoC[\%] = \frac{C_{actual}[Ah]}{C_{nom}[Ah]}$$

5.6.1.3 State of Health (SoH)

State of Health i.e. SoH is useful indicator that defines the ration between the battery capacity at time (t) and the nominal capacity (at the beginning of life) of the cell [54].

$$SoH[\%] = \frac{C(t)[Ah]}{C_{nom}[Ah]}$$

5.6.1.4 OPEN CIRCUIT VOLTAGE (OCV)

The potential difference mentioned for batteries and cells is usually the open-circuit voltage. The open-circuit voltage is also known as the electromotive force (emf), which is the maximum potential difference when there is no current and the circuit is not closed [55].

5.6.1.5 VARIABLE EFFICIENCY

As efficiency of ESS decreases with the increase of C-Rate (Charge/Discharge Current) i.e. the rate at which a battery is discharged relative to its maximum capacity. To make the model more realistic it is important to adopt this fact. It is given by non-relation plotted following figure:

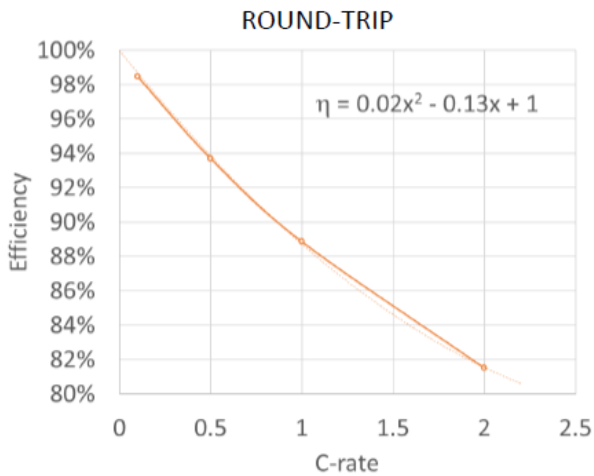


FIGURE 5-9: VARIABLE EFFICIENCY AS FUNCTION OF C-RATE

5.6.1.6 SIMULINK MODEL OF ESS WITH VARIABLE EFFICIENCY

The said effect is considered by using following model and set of equations.

- $\boldsymbol{\eta}_{CH} = \boldsymbol{\eta}_{DISCH} = (\boldsymbol{\eta}_{RT})^{1/2}$
- $\mathbf{E}_n = 5$ MWh ()
- $\mathbf{SOC}_{start} = 50\%$

And we'll assume that; C-rate = E-rate

The sub-block of BESS with variable efficiency is modelled with the square root of the round-trip variable efficiency function given in the sample data. The charging and discharging efficiencies are assumed to be equal to the square root of the variable efficiency function. The sub-block of the BESS with variable efficiency is shown below.

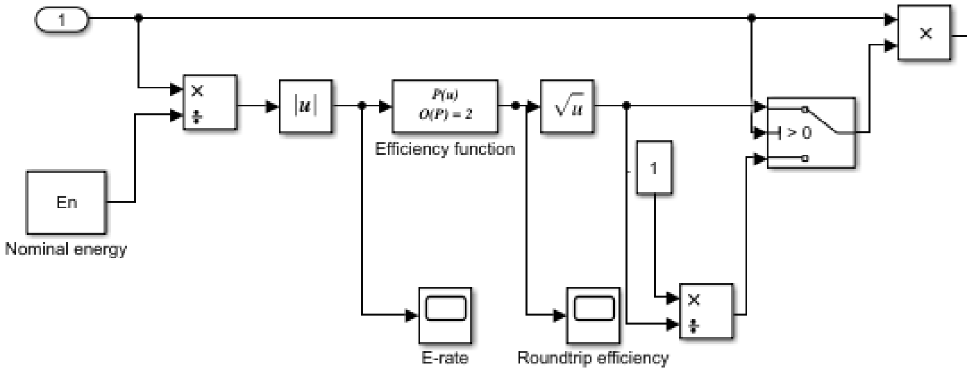


FIGURE 5-10: ESS MODELLING WITH VARIABLE EFFICIENCY

5.6.2 BATTERY MODELLING:

To estimate the battery capacity, we're more interested to the simulate the electrical model of the batteries.

To achieve it, we've to focus on the OCV curve of the battery. Two main families depending on the representation of OCV curve.

5.6.2.1 ACTIVE MODELS:

OCV is modelled by an ideal source that is typically a voltage generator, with voltage varying according to SoC. In this case the battery is seen as DC electric generators driven by chemical DC electric generators driven by chemical DC electric generators driven by chemical DC electric generators driven by chemical DC electric generators driven by chemical reactions [51].

5.6.2.2 PASSIVE MODELS:

OCV is modelled as the voltage drop across a capacitor of big variable capacitance (called incremental, differential or intercalation capacitance). Such passive element represents the charge stored in the cell in chemical way rather than electric way. Capacitance and voltage drop across the capacitor vary with the SoC.

Variations of Electrical models of the battery are shown in bellow mentioned figure in their passive formation [51].

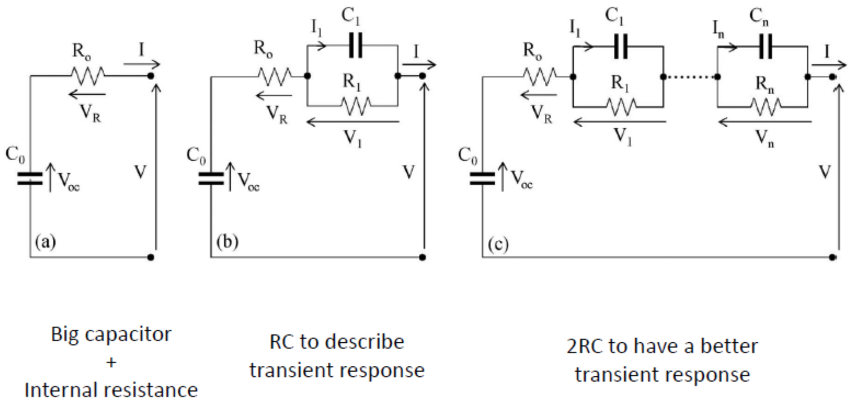


FIGURE 5-11: ESS WITH ELECTRICAL MODEL

Open circuit voltage (OCV) is modelled as a voltage drop across the capacitor. It is modelled to behave as a chemical charge storing device i.e. battery. The above figure ie a, is the model of the battery used for given simulation study.

5.6.3 SIMULINK MODEL OF THE ESS

The mathematical model for frequency regulation of BESS with electrical model of battery is shown below:

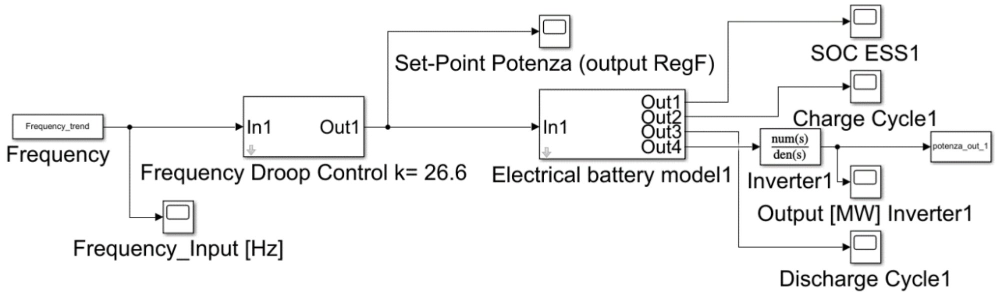


FIGURE 5-12: SIMULINK MODEL OF THE ESS

Assume, the sub-blocks of the electrical battery model have the nominal capacity of 5 MWh. The Nominal voltage of cell has been defined as 3.65 V and Nominal Capacity to be 5.3 Ah. The minimum voltage to be considered for cell is 2.75 V and maximum voltage to be considered for the cell is 4.2 V. The sub-block first changes the parameters to cell level from system level.

5.6.3.1 *SIMULINK MODEL OF THE ELECTRICAL BATTERY*

The sub-block of electrical battery model is shown below:

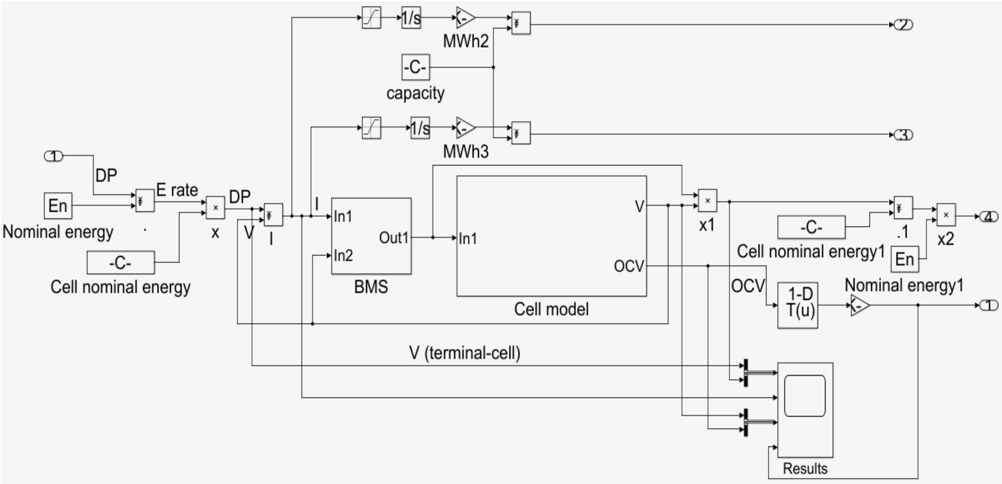


FIGURE 5-13: ELECTRICAL BATTERY MODEL

5.6.3.2 Simulink Model of the BMS

The BMS model is shown below:

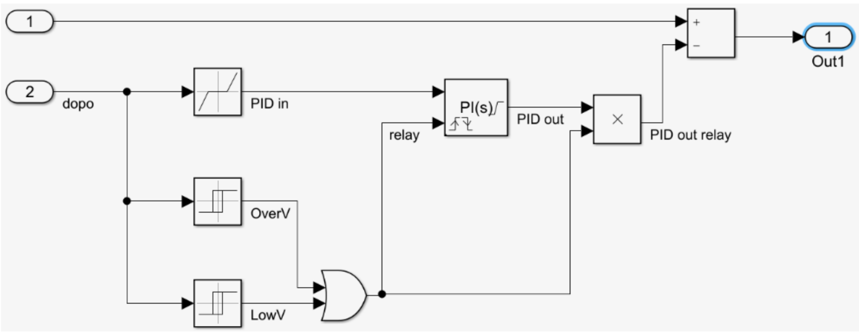


FIGURE 5-14: BMS MODEL

The Battery Management System (BMS) is used as deputy to regulate the current when the voltage is not in the defined limits.

5.6.3.3 Simulink Model of the Cell

The cell model is shown below:

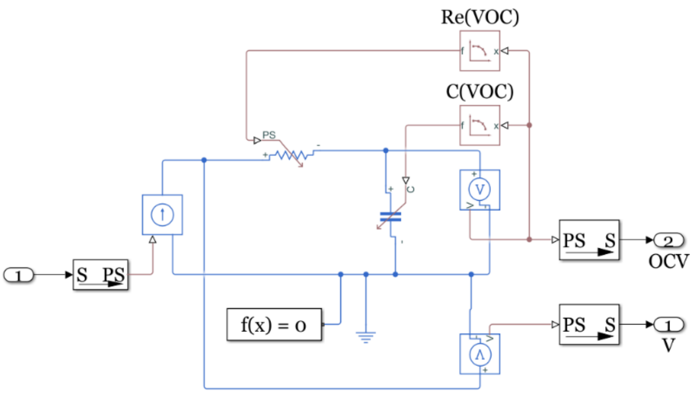


FIGURE 5-15: CELL MODEL

The electrical parameters of battery model are defined in the cell model. SOC is calculated by lookup table which gets the value of OCV generated by cell model and gives the corresponding SOC value from the input data stored in it. The power computation is then converted from the cell level to system level.

The trends of resistance with OCV and capacitance w.r.t. OCV are given in Figure 5-16 Figure 5-17 and respectively.

Capacitance can be related to OCV by given equation. Which shows change in charge stored on capacitor with respect to change of voltage.

Figure 5-16 shows trend of R with OCV, it can be observed that the lowest value of R occurs around 3.7 V. At this point the losses will be lowest and hence there will be high efficiency.

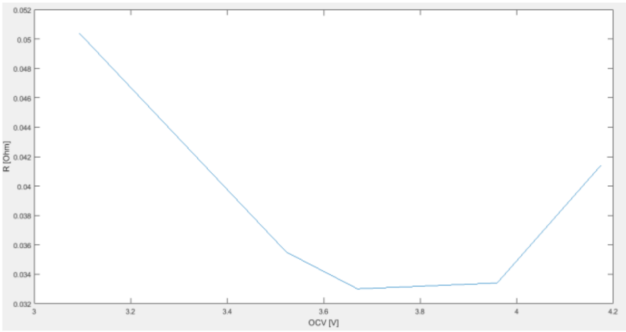


FIGURE 5-16: R_OCV

Further, Figure 5-17 shows relation of C with OCV, its highest value also occurs around 3.7 V which shows that at this point change in high amount of charge can be obtained with little change in OCV and hence can be discharged considerably with lower effect on voltage.

$$C(OCV) = \frac{dQ}{dV} = \frac{Idt}{dV}$$

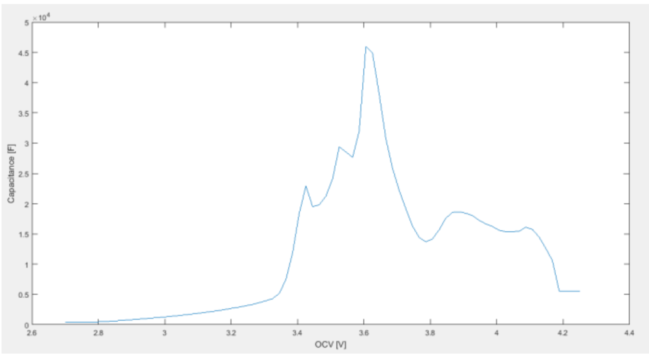


FIGURE 5-17: C_OCV

Figure 5-18shows the essence of electrical modelling of battery where OCV is related to SoC via look-up tables as charge stored in varying capacitance resembles charge stored in electrochemical batteries. OCV shows direct relation with SoC and at its highest value implies 100% SoC.

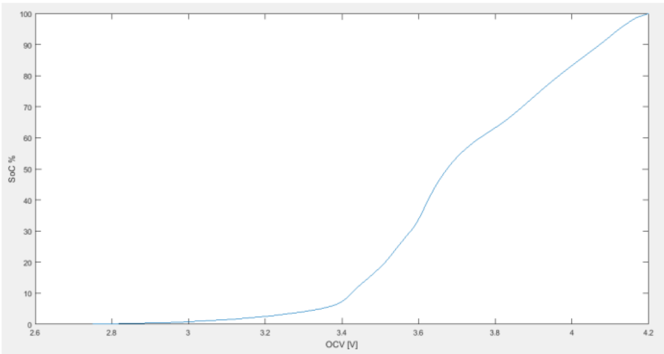


FIGURE 5-18: SOC% CORRESPONDING TO OCV

5.6.3.4 ESS POWER RESPONSE

Figure 5-19 shows comprehensive results and important conclusions can be made on their behalf. Adopting a frequency profile as a reference, when the frequency goes below the specified value it implies higher load than available power on the grid and hence the power is needed to be supplied for the frequency regulation. This provision of power is made by the ESS and hence considered negative on the battery's point of view. The dotted line shows requested power and dashed line shows power delivered by the cell. At some instances requested power is not fulfilled due to the saturation of the ESS. The relation of the OCV and V can be understood by our model given in Figure 5-16. While discharging the OCV will be higher than V because of the drop on internal resister and will be opposite in case of charging. This behaviour is an evident in the results.

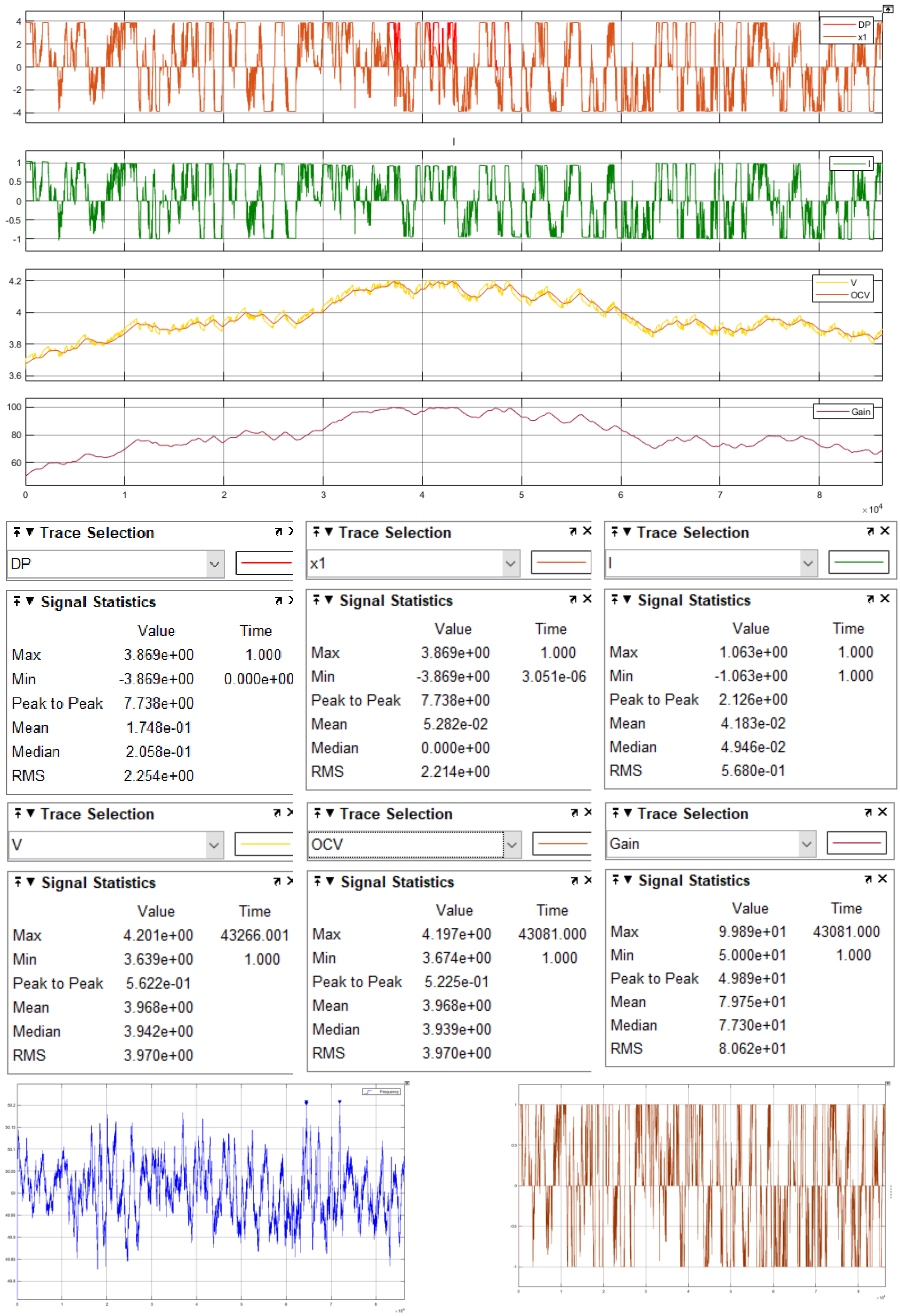


FIGURE 5-19: ESS POWER RESPONSE WITH NOMINAL CAPACITY OF 5MWH

5.6.3.5 Charging and Discharging Cycle

Figure 5-20 shows charging cycles performed in a day with considered settings. It shows charging cycle of almost 0.7. Value of Discharging cycles is giving in figure 13 which attains value of around 0.55.

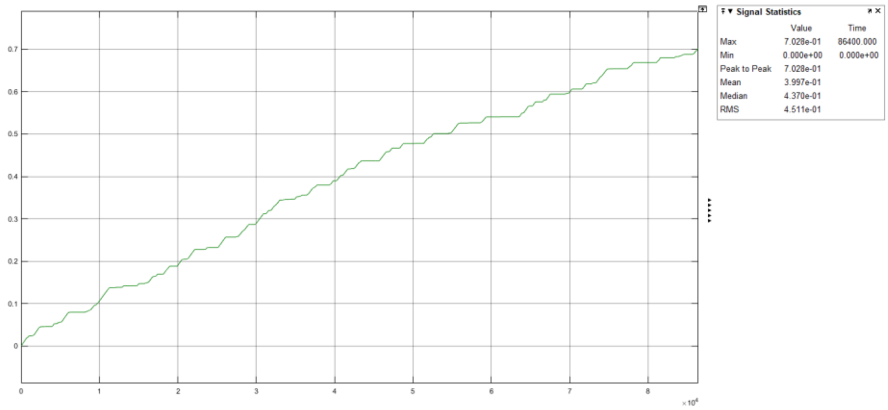


Figure 5-20: Charging Cycle

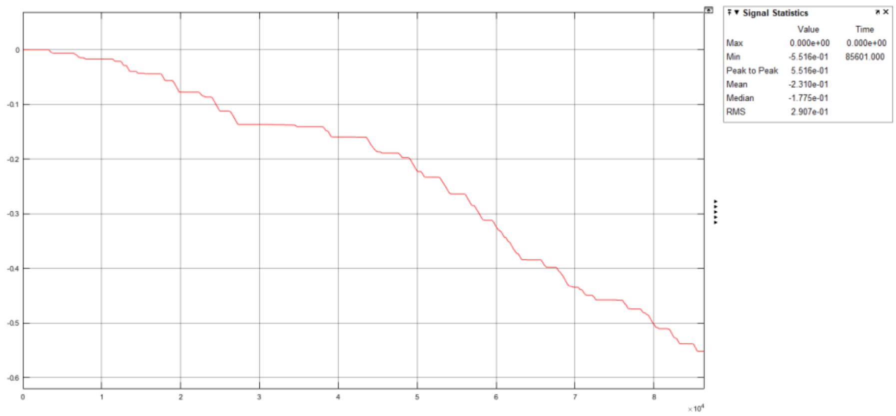


Figure 5-21: Discharge Cycle

5.6.3.6 What if we increase the Capacity of the ESS?

Further similar analysis is performed by increasing the capacity of ESS from 5 MWh to 10 MWh. Most prominent ESS's are not saturated in this case and SoC remained below 100%, which was the case previously. Similarly, power delivered is same as requested because of non-saturation. Obvious conclusion of voltage parameters is from their implication to SoC. So, Voltage and OCV will be lower at max compared to earlier case.

FIGURE 5-22: RESULTS WITH NOMINAL ENERGY AS 10 MWH

5.6.3.6.1 CHARGING AND DISCHARGING CYCLE

Further it can be seen from charge and dis-charge cycles in Figure 5-23 and Figure 5-24 that they show lower values and hence ESS is less stressed due to higher capacity. This will involve higher investment at start but in long term with decrease of C-rate the life time of battery will increase. But decision should base on analysis of longer period to assess its utilization for avoiding any over dimensioning.

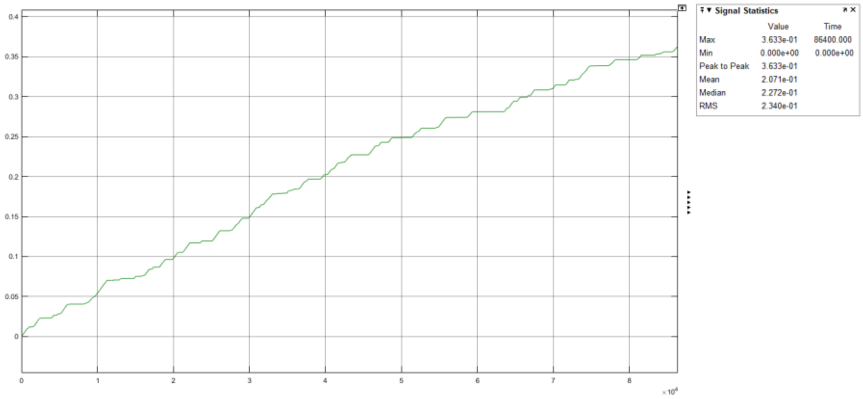


FIGURE 5-23: CHARGE CYCLE FOR ESS WITH NOMINAL ENERGY AS 10MWH

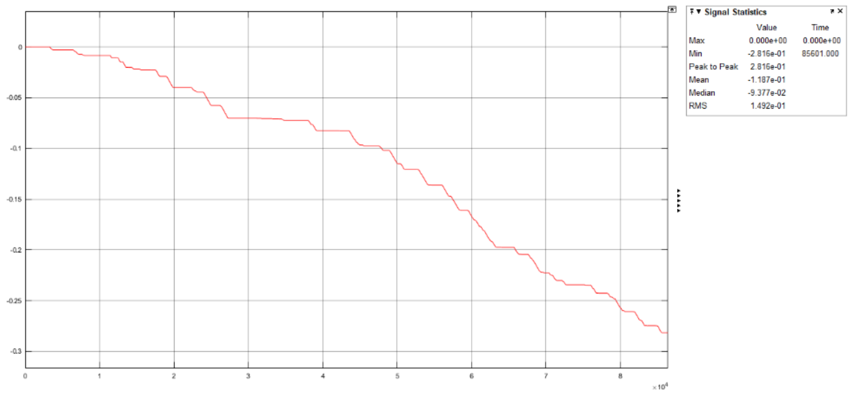


FIGURE 5-24: DIS-CHARGE CYCLE FOR ESS WITH NOMINAL ENERGY AS 10MWH

5.6.3.7 Analysis of the Simulation

Following to the result of the simulation, a combine Energy Storage System may consider. Which will form by BESS and VESS. In this case the initial investment will be reduced for the BESS. The size of the BESS should be the least capacity to handle the worst situation. So that the size of the VESS will be more flexible for both the users and the utility service providers. The aggregation of such capacity will lead the BESS and units if the VESS i.e. EV Batteries a higher C-rate and longer life. By this way it'll be possible to increase the SoH for both energy storage system.

5.7 Aggregate all kind of Batteries for ESS Service

After such combination the new question arise, is it possible extend the use of the BESS to make it a lucrative investment? The answer of this question can be analysing in the following way.

The BESS is designed to handle the ancillary services from a definite node. The insertion of bulk DG in the grid has a huge effect on the Nodal Hosting Capacity. It also depends on the type of the power injection, if it's reactive or not. But for the non-programmable

DG is fully depended on the weather despite the needs of the power dispatch control. We've discussed the about it in the next chapter.

On the other hand, the composite load model may also change for the increment of the numbers of EV. The effect of large deployment of the EV has a huge effect of the grid. So, measurement of possible services for every node should be taken in the account. As the non-programmable DG can't handle the issues though out all day long (especially at night) we may consider the ESS with travelling capacity. Thus, we're proposing an ESS in a Cargo Truck with the facilities to dispatch the facilities at LV/MV busbar at the end of this chapter. The size of the vehicle may be decided by the composition of the need and the traffic rule of the related cities.

5.7.1 Mobile Energy Storage System (MESS)

The Mobile Energy Storage System (MESS) can be deployed with the complete package of the stationary ESS (SESS). It must have the convenient and adoptable evacuation system. We may mix the concept of Pantograph from the Electric Transportation to connect the MESS in the usual grid. The Pantograph has good isolation and other relative protection equipment to complete the safe evacuation of the power in MV grid. Moreover, it takes less time to go on the operation. To connect the MESS in the grid for definite time range the utility service providers may needs to analyse the nodes further and construct the facilities to evacuate the power from the MESS.

Beyond the Ancillary services we may also provide the Vehicle to Vehicle Charging by MESS in the places where the charging station is not available or critical to build, but the presences of Electric Vehicles are there.

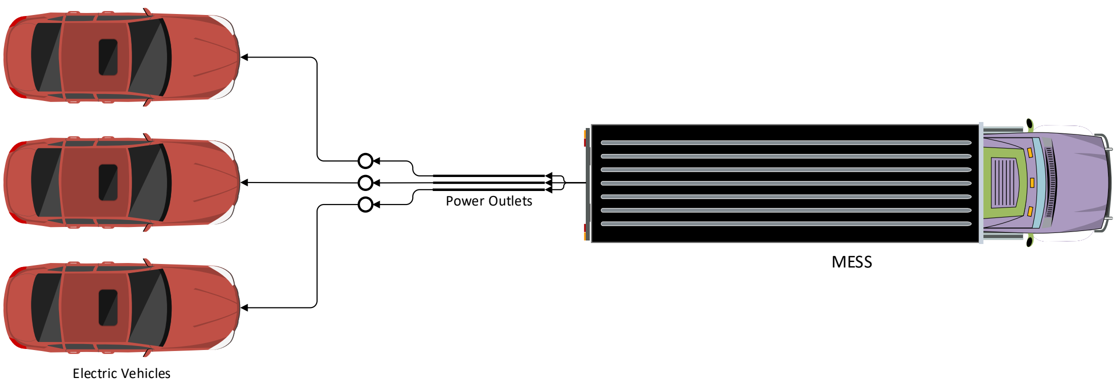


FIGURE 5-25: MESS TO VEHICLE CHARGING STATION

5.7.2 Classification of the ESS based on the Applications

In the end of the Chapter we have got different categories of ESS and to get a better presentation of the classification of the ESS, we would like to mention the following figure.

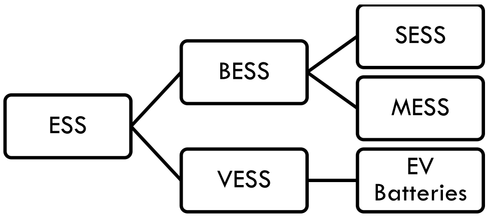


FIGURE 5-26: ESS CLASSIFICATION BASED ON THE APPLICATIONS

Considering the application point of view of the above proposed concept, there can be varying scenarios. Across the globe the cities follow different layouts for the movement of transportation. These layouts depend on many factors such as the geographical location, the size of the area, the regulations for the city. Depending upon these factors the above described proposal can be customized to fulfil the criteria. Considering the example of a city in which the cars are not inside the city or the main city centre. In this case all the cars for instance are parked in the bulk parking areas in the outskirts. These parking areas can serve a dual purpose, they can be used as a charging station. Since, throughout the day when the owners of the vehicles parked will be out for work, there vehicles will be parked there, the batteries of these vehicles together of will act as a bulk EESS. There will be a possibility of as activating a V2G mode. The Cargo truck thus can be coupled with the charging station where there is a peak demand and simultaneous the areas having peak demands. The above discussed options will make the ESS service more convenient for the ancillary services. Now, it is needed to analyse further for the C-Rate of the different type of the batteries.

CHAPTER SIX

6 THE IMPACT OF MASS EV ON THE GRID

6.1 OVERVIEW

The diffusion of mass Electric Vehicles will be on the rise as it has been already discussed in the previous chapters. The increasing demand for electricity is the result of this mass EV adoption. In order to cater to these requirements, for instance combining electric vehicles with solar panels, energy storage and dynamic pricing is one of the solutions to serve the need of the hour today. This results in the need for the system to operate based on the availability of energy in the real time when there is a surplus of solar or wind, the system sets lower charging rates, signalling every Electric Vehicle owner to charge up. Providing the owners of the Electric Vehicles with the provision so that they can select the cheapest and most convenient times to charge via a mobile app or let the system do it automatically. If no one is ready to charge, batteries will store the excess energy until it is needed.

The bottom line is that the electric utility industry needs the electrification of the transportation sector to remain viable and sustainable in the long term along with keeping into to account that in coming future the EV diffusion will be quite abrupt. Taking all this into consideration, it is important understanding how the shift from electric vehicles will impact the grid. There are some prime areas of focus, as follows:

- Last Mile: Electric distribution in the neighbourhood
- Peak Demand: Spikes in electric use from simultaneous charging
- Managed Charging: Controlling EV charging to mitigate strain to the grid
- Stabilizing the grid: Using EV batteries to powerhouse
- Congestion and generation Planning: Understanding congestion and generation planning for long-term energy use

There are some major questions that are to be kept in mind such as; can utility companies accommodate the extra load from EV charging? How will EV charge impact peak demand? Can the grid benefit from EV deployment?

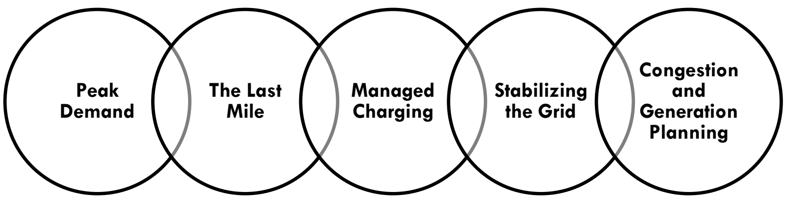


FIGURE 6-1: PRIME AREAS OF FOCUS

6.1.1 Peak Demand

Like how existing household electric consumption happens at the same time in neighbourhoods, residential charging of EVs follows similar trends. It is easy to imagine, in the early evening, homeowners returned from work, prepared dinner, turned on washers, dryers, televisions and air-conditioning. Peak demand of households alone has been enough cause for many utilities to introduce demand response and time use programs. Now add EV charging, something that could equate for additional household use of electricity per vehicle. It will become a real problem, the extent of damages to the grid from peak overloading could lead to diminishes the quality of services, brownout or even blackens.

Figure 6-2 shows the ENTSO-E (European Network of Transmission System Operators for Electricity) maximum peak load across Europe in the year 2016. It can be seen that there has been an increment after 2013 onwards. There was about a 4.4% increment in the year 2015. As per the Bloomberg report, there has been a prediction of a tremendous increase in the adoption of Electric vehicles in the years to come. Figure 3. clearly depicts that how the estimated increment would be till the year 2040. It estimates that the electric vehicles will account for approximately 35% of the new vehicle sales by 2040. Another reason to support this estimate is that, that there is greater possibility that by 2022 the electric vehicles will cost the same as there internal combustion counterparts.

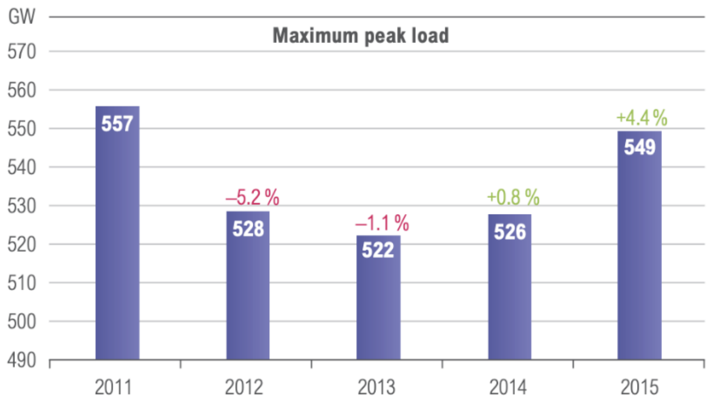


FIGURE 6-2: ENTSO-E MAXIMUM PEAK LOAD IN 2016

So, what can be done is that the utilities have looked at a number of options to provide for added demands. One approach is just to Build more infrastructure, although technically feasible, this approach could be costly and time-consuming. Another approach is to introduce a time of use rate structure for EVs (EV TOU rate structures (Static)). Now, this requires the installation of a smart meter and would manage every charging load in the same way, that household is currently managed. Although this approach works to shift load by charging customers more for electricity at peak times. It simply moves the problem to later in the day. Customers would schedule every charging to begin immediately after the peak time window. Utilities will experience a sudden spike when all EVs in a neighbourhood begin charging minutes. A third option is active load management (Active Load Management (Blind)).

This approach requires the installation of the network charging station and more importantly, it requires the permission of every owner from the utility to turn off charging when charging when there is a risk of grid overloading. So typically, customers are hesitant to handover this level of control. A fear of not having enough charge to use their vehicle is the primary concern. An alternative to the methods already mentioned is dynamic rate structure and paired load management. These methods use positive incentives to encourage every customer to charge during opportune times and the management of EV load can be curtailed with inputs from the customers. This approach spreads EV judging across a time period to fill and shape the demand load curve will have to wait and see which solution and which technologies will prevail.

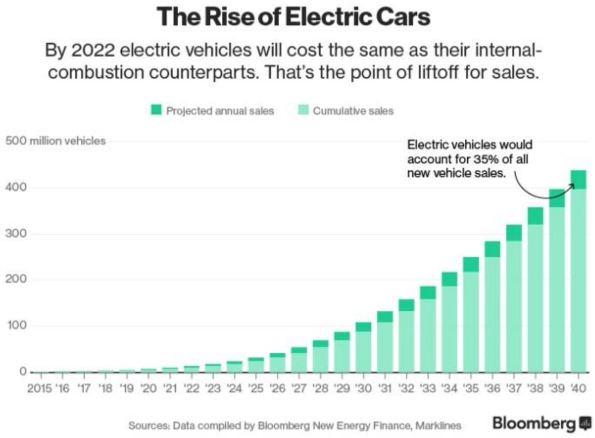


FIGURE 6-3: AN INCREMENT IN THE SALE OF ELECTRIC VEHICLES

6.1.2 THE LAST MILE

In the countries that are leading in Electric Vehicle adoption, capacity or electric generation is not the obstacle, instead, it is at the local level, the last mile, where the problem occurs. With accelerating, EV adoption in the introduction of longer range allow electric vehicles demand will not only continue but expand drastically, for e.g. charging a Tesla Model S or X from empty or full could use as much as 100 kWh. Compare this to average electrical consumption of average home which is 25 kWh/day. In homes in warmer climates consumes less energy than this. In other words, each electric vehicle in a neighbourhood equates to an additional four houses. In many neighbourhoods, load distribution grids are simply not built to accommodate increases in power demand. Power transformer, the street side metal boxes hung from. Electrical poles are the most vulnerable part of the system. Most residential transformers are designed to handle between 10-50 kVA of load and a single plug-in electric vehicle charging at home will consume 7 kW. If multiple EV owners' homes are connected to the same transformer, simultaneous vehicle charging plus normal household load from appliances may cause overloading which damages transformer equipment. A single overload transformer can have a chain effect spreading to nearby feeders, degrading service quality and reliability. Studies have suggested that higher penetration rates of EV could increase the loss of life factor for transformers by up to 10,000 times and simultaneous residential charging of electric vehicles, most commonly referred to as clustering will occur in the neighbourhood with higher than average EV adoption first.

As EV adoption becomes more common, clustering and subsequent overloading of transformers will spread. To make things even worse, transformers are not capable of signalling when overloading is occurring. At the location and the time at which EVs are becoming more common and have larger capacity batteries, meaning the day will require the solution to the load change clustering is approaching. Several technologies provide are testing to mitigate the risk to the grid from EV charging.

6.1.3 Managed Charging

Utilities are looking for a way to mitigate the risk of clustering EV charging. Spreading charging across off-peak times should solve the problem. In theory, it is a great idea, but the question is how it can be achieved. EV smart charging could be the answer. Smart Charging refers to monitoring grid for energy use, automatically scheduling EV charging. These programs (like a thermostat) do direct load controls charging by turning off EV charging at the request of EV manager. The method is often described as blind because there is no way for the network charging station to know the state of charge (SOC) of each vehicle that plugs in. The system would treat a battery with a 10% charge the same as the battery with a 90% charge, because of this there is a risk that charging will just be turned off for vehicles with an already low state of charge and drivers would be left without enough charge to get to their next destination.

Another method can be the Dynamic Reward Structure. This method is the opposite of static rate structure, which charges customers more for charging during peak hours. Positive incentives are used to encourage good charging habits among drivers. A dynamic reward structure encourages charging off-peak hours with rewards and discounts. But without a direct load control, utilities will be dependent upon their customers to reliably shift their charging times across the off-peak hours.

Another solution is a smart charge system which uses positive incentives and direct load control based on the vehicle state of charge is somehow the best solution possible, embodying the qualities of them all. By considering battery state of charge, charging can be modified on a case by case basis. Electric vehicles with low batteries could continue to charge while others simply slow the charging process. Those with an adequate Ste of charge could shift charging until later on low, slow and shift requires knowing the battery State of charge.

This system would guarantee the ability to respond to utility calls to slow down energy use. It would reward good charging and it would ensure that nobody wakes up to an empty battery. The day in which electric vehicle charging becomes the problem for electric utilities is quickly approaching. A number of companies are facilitating smart charging for electric vehicle owners in any utility territory.

6.1.4 Stabilizing the grid

Electric Vehicles are associated with taking energy from the grid. But in the future, it will also be possible for electric cars to operate in discharge mode and supply power back to the grid, essentially acting like a big giant battery pack for reserved energy. This ability is known as V2G and it may be the most promising aspect of mass EV adoption. So, outside of normal commutes to and from work, most drivers' car stays in a parking space for most of their lifespan and studies have shown that, that the downtime could be as much as 95%. With battery electric vehicles that time can be put to good use and the operating opportunities are numerous.

By this, the benefits for EV owners, consumers and utility operators are significant. Vehicle to the grid can help amplify the benefits of the renewable energy sources as distributed energy storage units. This implies that each EV will act as a storage unit for clean energy. Electric vehicles would store excess energy generated by wind, solar or geothermal and use that same energy later instead of generating energy from non-renewable sources.

Electric vehicles can also act as a source of power back. The loss of electricity as a result of extreme weather is a primary reason why consumers invest in backup generators and larger commercial and residential buildings require backup generators for safety and to keep essential systems online during the case of blackout and brownout. Electric vehicles could replace or complement those backup generators if the power was to go out that's a meaningful extra layer of security.

By charging when the demand is low and supply back to the grid when the demand peaks. This could happen each day when residents return home and operate household appliances and would otherwise charge Electric vehicles or it can during each stream like heat waves when air-conditioning is running at full blast and consuming a large amount of energy.

A study national grid an engineering firm Riccardo indicates that vehicle to the grid could provide 600 to 8000 pounds of income in a year for Electric vehicle owners in Britain.

Finally, electric vehicles could operate like smart homes thermostat programs and they can help iron out network load curves by reducing load and shifting load to off-peak times. However Electric vehicles use much more energy than air conditioning and they do it all year round so, the potential impact is much more significant.

Additionally, feeding energy back to the grid from Electric vehicles on mass could replace standby energy generation altogether, a process called valley filling. The overall benefit to all energy consumers from large-scale Electric vehicle adoption and vehicle to grid technology is enormous. Homeowners will benefit from an additional backup power energy source and generate income from participating in energy markets.

The impact of renewable energy sources could be amplified by storing and prioritizing the consumption of clean energy over non-renewables and the stability of the energy grid could be reinforced from using Electric vehicles as distributed storage units. With the quickening adoption of electric vehicles, advances in load management technology and the requirements for electric utilities to manage network load, the vehicle to grid maybe a load closer than anticipated

6.1.5 Congestion and generation Planning

For the long-term grid use, it is extremely important to keep into consideration the factors such as congestion and generation planning. Since it has been forecasted that there will a diffusion of electric vehicles at a fast pace which in turn will result in an abrupt demand to serve the charging requirements of this vast deployment of Electric Vehicles. It is always utmost importance for the utilities to ensure uninterruptible power supply. But at the same time, this mass diffusion might also result in congestion at certain points of connection on the grid. This will tend to make the grid overloaded. In order to ensure the proper operation of the grid, the critical situations should be dealt with in time to avoid the problems of congestion at various points of connection on the grid. Due to the same reasons, the grid planning for future energy needs it to be carried out

6.2 Impact of penetration of RES for supporting mass EV adoption

It is evident that the mass diffusion of Electric vehicles will elevate the demand for electricity and at the same time predicting the real-time instance of this demand is posing a challenge. As the demand for electricity is on a rise because of the mass EV diffusion, it poses a challenge for the grid manager to maintain a balance between the generation and demand. The dire necessity to meet the on growing demand for powering the Electric Vehicle charging load is of utmost importance. The situation becomes even more critical in cases of vehicles that are on a long-distance travel, as they have to be charged as per the requirement during the whole course of travel.

Since the agenda of the majority of countries across the globe is to move towards a clean energy environment, then this Electric Vehicle charging load proves to a big chunk of demand that has to be fulfilled. In order to satisfy the increasing demand for electricity, the utilities and policymakers have to incorporate an even greater diffusion of Renewable Energy Sources and coupling them to the grid. This coupling of a large amount of Renewable Energy Sources also create obstacles in the path of the grid manager, as they already they are greatly affecting the demand profiles.

The effects of Renewable Energy Penetration are a cause of concern for the grid managers. The main effects of it have been discussed below, with major emphasis on the developed countries.

6.2.1 Duck Curve

The power companies supply the least amount of power overnight. Then it ramps up in the morning. Then at sunset energy demand peaks. Utility companies try to update the demand curve to operate as efficiently as possible. But the introduction of renewable energy, especially solar energy has started causing problems in the demand curve.
As per the California ISO report, “The electric grid and the requirements to manage it are changing. Renewable resources increasingly satisfy the state's electricity demand. Existing and emerging technology enables consumer control of electricity consumption. These factors lead to different operating conditions that require flexible resource capabilities to ensure green grid reliability. The ISO created future scenarios of net load curves to illustrate these changing conditions. Netload is the difference between forecasted load and expected electricity production from variable generation resources. In certain times of the year, these curves produce a “belly” appearance in the mid-afternoon that quickly ramps up to produce an “arch” like the neck of a duck—hence the industry moniker of “The Duck Chart”.”

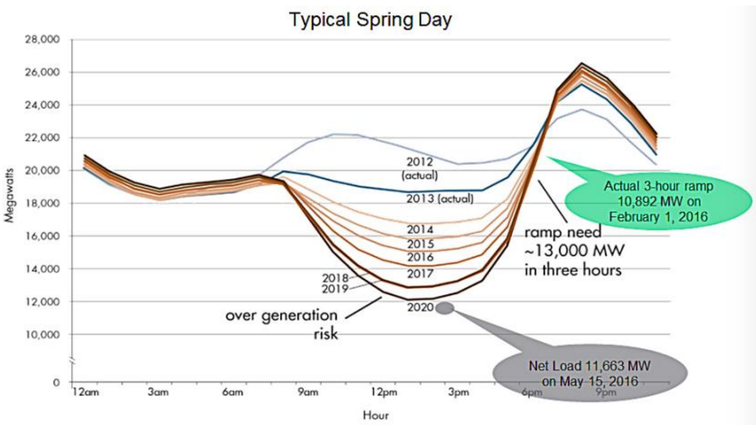


FIGURE 6-4: THE DUCK CURVE SHOWS STEEP RAMPING NEEDS AND OVERGENERATION RISK IN CALIFORNIA

The sun produces the maximum energy in mid-day and when the grid manager factor in the new mid-day production, the demand curve changes. Every year means new-solar capacity which makes mid-day demand dip lower and lower. In Figure 6-4 This duck curve has been shown from the California ISO.

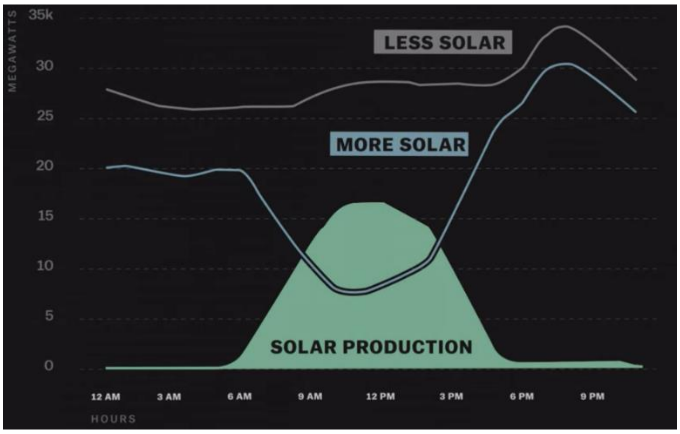


FIGURE 6-5: THE CURVE DEPICTING THE EFFECTS OF SOLAR

From the grid manager's perspective, whose job is to constantly balance generation and demand, this looks like a drop in the demand. This drop-in demand creates two major problems:

- Grid Flexibility
- Overgeneration

6.2.1.1 GRID FLEXIBILITY

The first problem is due to the intense ramps in the new chart. As the sun sets, solar energy production ends. Ironically, at that instance the demand for energy typically peaks. Power plants then have to rapidly ramp up production to compensate for that. This seems difficult to carry out with the current fleet of power infrastructure.

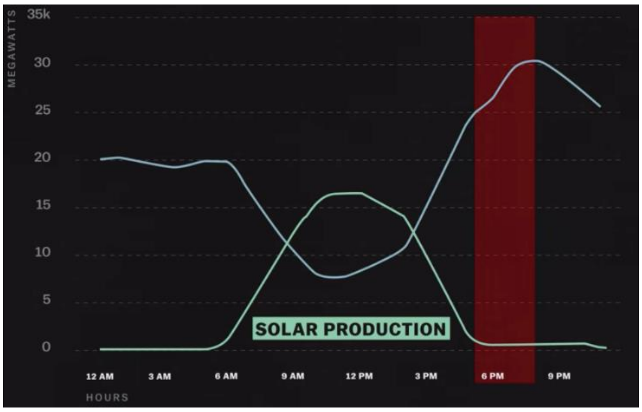


FIGURE 6-6: CURVE SHOWING IN THE INTENSE RAMPS POST SUNSET

6.2.1.2 OVERGENERATION

There is also an economic problem associated with the duck-curve. In the case of thermal and nuclear power plants, these plants are yielding economic benefits only when they are running all the time. And if they have to turned-off at mid-day, it will have adverse effects on the economics and moreover, most of the times utilities have contracts with those power plants to keep them running all the time. This situation creates an artificial floor. If solar generates too much power and there is no consumption of it then, in that case, the grid managers have to turn some solar panels off. If this does not happen then it will cause risk of overloading the grid and damaging it. As a result of this, solar power is being wasted.

6.2.2 SHARK CURVE

The demand curve across Europe, the US and most of the developed countries look like the one that is shown in the figure. There is a morning ramp and then again, the demands peaks near sunset. For instance, you can see from the figure, the demand forecast curve of Italy. In Figure 6-7., the curve as taken from the website of the Italian Transmission System Operator Terna tends to depict both the forecasted demand as well the real-time demand curve.

As we have discussed above that the demand curve affected due to the large penetration of the renewable energy sources, especially the solar. Hence, this results in the duck curve as we discussed before.

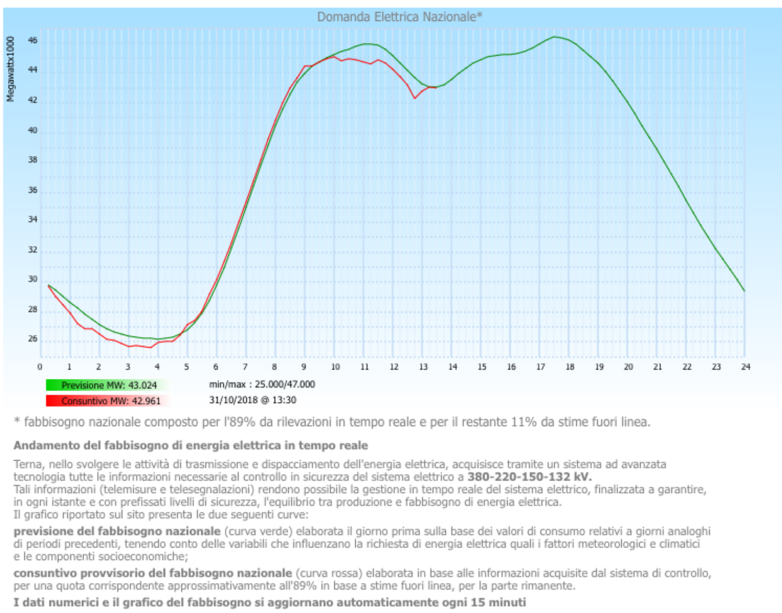


FIGURE 6-7: REAL-TIME AND FORECASTED DEMAND CURVE BY TERNA

But this is only the scenario for the developed countries. When it comes to the developing countries the scene is completely different. As per the report by Toby D. couture based in Berlin, “As pointed out above, load shedding is greatest during the early evening hours; however, this unmet electricity demand is often unrepresented in charts of daily load curves, partly because utilities don’t like emphasizing how much latent power demand, they are actually unable to serve.”

When this unmet demand is incorporated into the demand curve, the curve takes the form of a shark, thus getting the "Shark Curve". Toby D. Couture further states that ‘The shark curve is the reality in most developing countries around the world. The duck comes later. In the absence of concerted efforts at peak shaving, including the adoption of more energy-efficient appliances, demand-side management, demand response, and greater use of both battery and thermal storage, the challenges associated with the shark curve are likely to get worse before they get better.’

As per the Nepal Electricity Authority, Figure 6-8 shows the daily load curve of Nepal. The curve clearly takes the form of the shark.

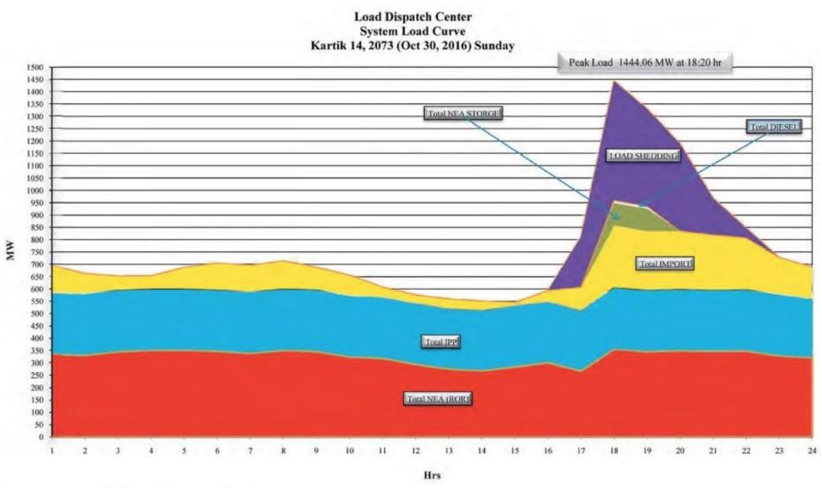


FIGURE 6-8: DAILY LOAD CURVE OF NEPAL

6.3 How the Grid Response on Real and Reactive Power

In the previous chapter we’ve simulated the Power Response of the ESS with different capacities, which discussed mostly about the penetration of electricity from the focus point of ESS. Additionally, we’re interested to study the behaviour of the grid in terms of Voltage Regulation and Nodal Hosting Capacity by the change of real power and reactive power. By these ways, it’ll be easier to understand the response of the grid by the charging of the ESS as real power consumer. On the other hand, in the study Photovoltaic Power Plants will represent the DG to depict the penetration of large number of DGs in the grid.

6.3.1 VOLTAGE REGULATION

The variation of Voltage amplitude is one of the elements characterizing the quality of service. Consumers operate at best in terms of performance & continuity when they are supplied at the nominal voltage. Any variation in the voltage deteriorates the performance. This voltage variation is caused by the disturbances and control actions of reactive power sources in the grid. The disturbances may be a variation of load specially for emerging electric vehicles and variation of the system structure. So, to respond to these variations, voltage regulation is done which voltage is controlled in the grid.

The voltage controls the set of actions carried out to keep the voltage in all busses of the grid within values that do not deviate significantly from nominal ones and that ensures the good operation of the loads. CEI-EN 30160 defines voltage characteristics of electricity supplied by the public distribution network.

Under normal conditions, excluding the periods with interruptions, supply voltage variations should not exceed ±10% of the rated voltage of the system. For networks that are not interconnected with transmission systems or special remote grids, the supply voltage variations should not exceed +10% to -15% of the rated voltage of the system.

The means of controlling the voltages on distribution grid networks mainly consist of:

- HV/MV Transformer with On Load Tap Changer (OLTC)
- MV/LV Transformer merely with No Load Tap Changer

OLTCs in HV/MV transformer can regulate the voltage in the busses downstream of the Primary Substation (PS) within the variation range of the turn ratio of the transformer. Unlike HV/MV transformers, MV/LV transformers do not automatically regulate the voltages, but they only offset the voltage drops in the distribution network.

The voltage regulation service must be approached by looking to the regulation bounds overall electric system

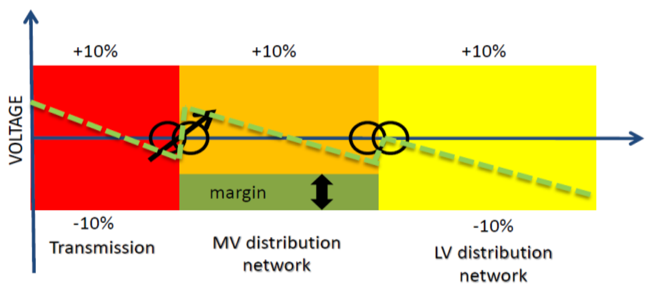


FIGURE 6-9: THE VOLTAGE REGULATION

6.3.2 Nodal Hosting Capacity

MV grids are also equipped with Distributed Generation (DG) units which can cause a deterioration in the working condition of the distribution grid. It is more important to manage the distribution grid in the presence of DG units because DG units' impact on the voltage profile of feeders and increase the voltage at the Point of Common Coupling (PCC).

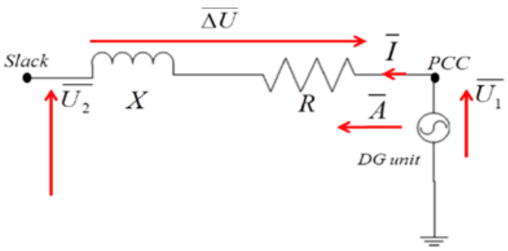


FIGURE 6-10: THE POINT OF COMMON COUPLING (PCC).

It is necessary to identify the maximum penetration of DG units compliant with gird constraints and the metric used to determine the maximum penetration of DG unit without deteriorating the performance of the grid is known as Hosting Capacity. The hosting capacity is defined as the amount of new production or consumption that can be connected to the grid without endangering the reliability or voltage quality for other customers

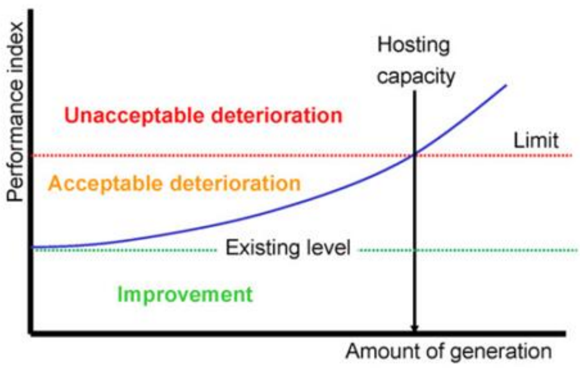


FIGURE 6-11: HOSTING CAPACITY GRAPHICAL REPRESENTATION

It is possible to regulate the voltage in a grid equipped with DG units by properly regulating the (P, Q) injections. To limit the overvoltage due to DG units (i.e. to increase the hosting capacity) it can be possible to:

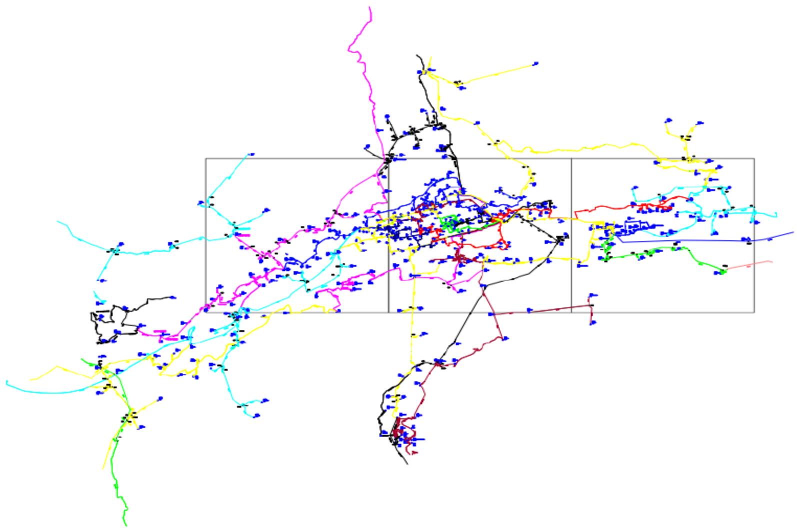
- Decrease real power injections
- Increase reactive power injections (absorb reactive power)
- Change both P and Q injections

The most sensible option is to manage the reactive power injections to control the voltage i.e. in order to avoid the costs for real power reductions. On the other hand, the connecting Electric Vehicle increase the consumption of the real power which can make the grid more stabilized on the case of overvoltage due to the DG units. In the following paragraphs we're going to simulate the behaves of the grid in terms voltage regulation and nodal hosting capacity by balancing the real and reactive loads which was nearly impossible before the emerge of ESS.

6.4 A Case Study for Aosta City

As in the previous chapter based upon the proposed methodology, the focus of the work has been on primarily two cites in Italy. The first one being a metropolitan city, Milan, and other being a small city Aosta. The methodologies have been proposed keeping into mind the Spatial-Temporal Activity Model and the battery analysis in that area in order to integrate the EVs into the grid with more precision. For the GIS technique all with Space-Time graphs has been implemented. Furthermore, the algorithms regarding the grid integration of EV and battery related data have been developed. Since Milan is a big a city and the data can be huge to handle, hence, the case of Aosta has been carried forward. The case study for the goals of this work is the MV Distribution Grid of Aosta city of Italy. We have considered the composite load model in following studies as the integration of Active Load and Reactive Load in each single substation.

The structure of the grid is shown below:



HV Level=132 KV
MV Level = 15 KV
2 Transformers (25 MVA)
17 Feeders
486 Nodes

FIGURE 6-12: MV DISTRIBUTION GRID OF AOSTA CITY OF ITALY

6.4.1 Model of the Grid in DIgSILENT Power Factory

DIgSILENT Power Factory software has been used to perform simulations on the MV Distribution Grid of Aosta. The Model used for the grid Simulation has been shown below:

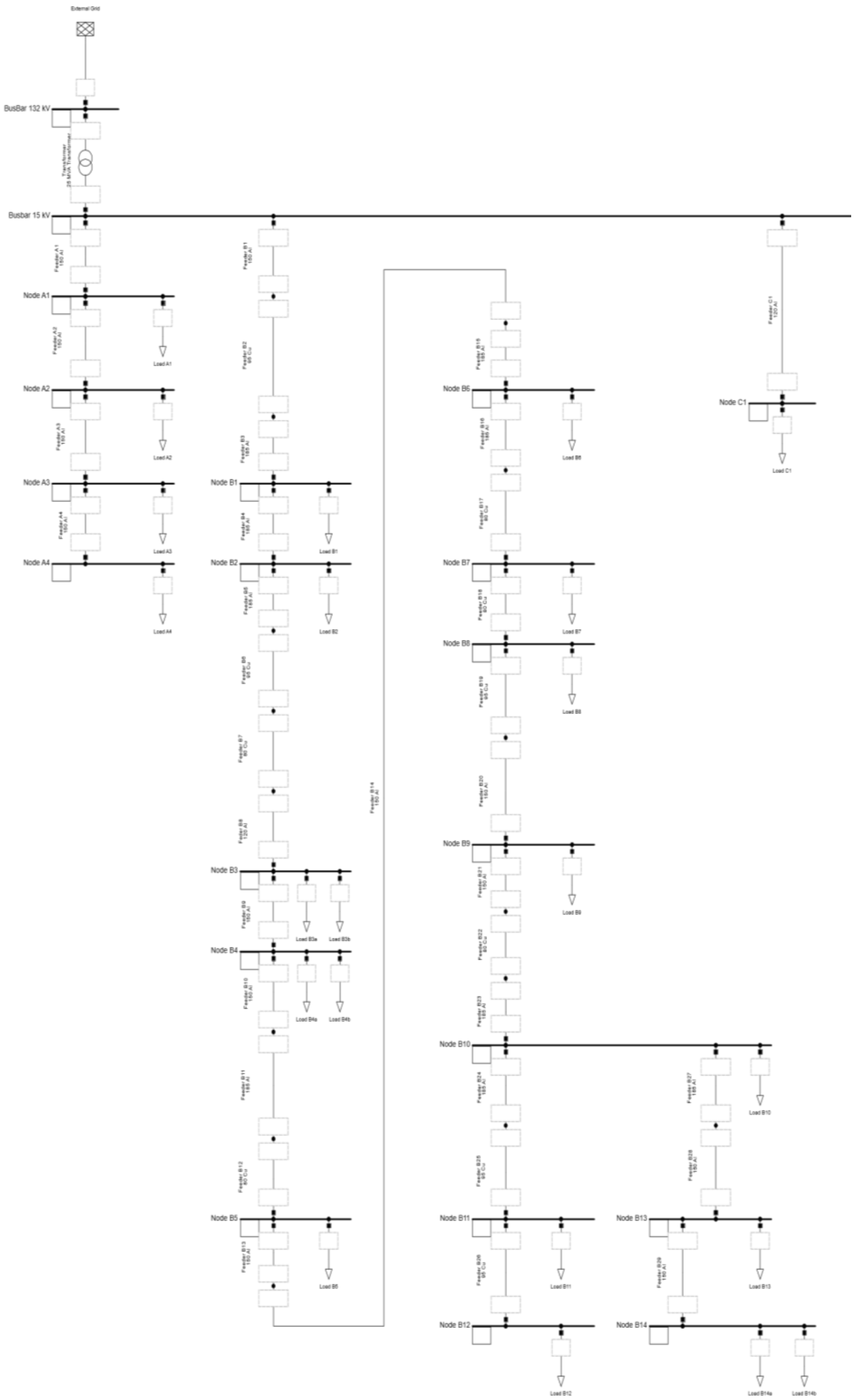
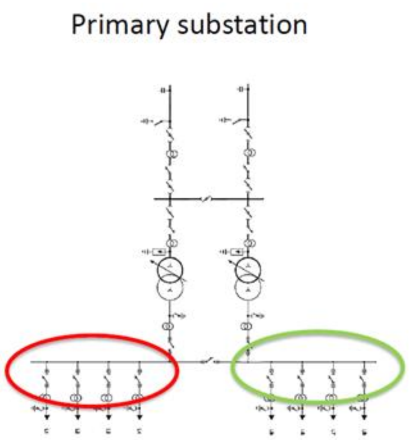


FIGURE 6-13: THE COMPLETE GRID MODEL FOR AOSTA (TWO FEEDERS ONLY)

The primary substation structure with its parameters is shown below:

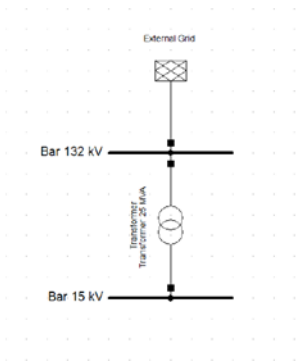


Parameters of the PS

HV Level=132 KV
MV Level = 15 KV
2 Transformers (25 MVA)
7 Feeders on Green Busbar
10 Feeders on Red Busbar

FIGURE 6-14: THE PRIMARY SUBSTATION STRUCTURE WITH ITS PARAMETERS

The model is simplified to the following structure and parameters:



HV Level=132 KV
MV Level = 15 KV
1 Transformers (25 MVA)
2 Feeders on a Single Busbar
Automatic Tap Changer (±12×1.5%)

FIGURE 6-15: SIMPLIFIED MODEL

6.4.1.1 CABLES PARAMETERS

The parameters of cables are considered according to the following data:

TABLE 9: CABLES PARAMETERS

Nominal Voltage U_0/U [kV]	Maximum Voltage U_m [kV]	Current Thermal Limit 1 [A]	Current Thermal Limit 2 [A]	Resistance [Ω/km]	Reactance [Ω/km]	Capacity [nf/km]	Resistance Zero Seq. [Ω/km]	Reactance Zero Seq. [Ω/km]	Capacity Zero Seq. [Ω/km]	Type	Material	Section [mm^2]	Max SC Current [kA]
8.5/15	17.5	260	260	0.206	0.118	420	1.5	0.84	420	3	AL	150	18
8.5/15	17.5	240	240	0.253	0.12	400	1.317	1.107	400	3	AL	120	14.4
8.5/15	17.5	320	320	0.164	0.115	450	1.281	0.83	450	3	AL	185	22.2
8.5/15	17.5	280	280	0.23	0.13	330	1.4	0.986	330	3	CU	80	15.3
8.5/15	17.5	300	300	0.193	0.125	350	1.3	0.95	350	3	CU	95	18.1

6.4.1.2 FEEDER A MODEL

Loads on Feeder A are considered according to the following:

TABLE 10: LOADS ON FEEDER A

Load	Type	Nominal Power [kW]	Number of Users	Active Power [kW]	Cos phi
Load A1	Secondary Substation	350	145	210	0.95
Load A2	Secondary Substation	250	234	150	0.95
Load A3	Secondary Substation	100	82	60	0.95
Load A4	Secondary Substation	250	302	150	0.95

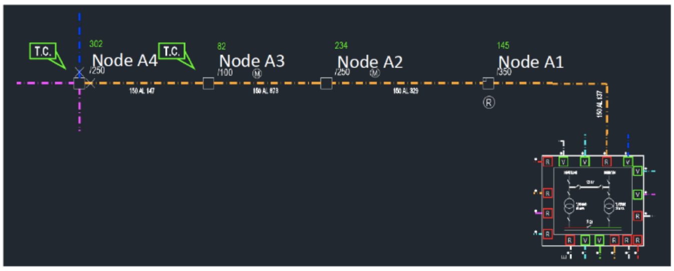


FIGURE 6-16: FEEDER A

6.4.1.3 FEEDER B MODELS

Loads on Feeder B are considered according to the following:

TABLE 11: LOADS ON FEEDER B

Load	Type	Nominal Power [kW]	Number of Users	Active Power [kW]	Cos phi
Load B1	Secondary Substation	400	245	240	0.95
Load B2	Secondary Substation	250	53	150	0.95
Load B3a	Secondary Substation	400	444	240	0.95
Load B3b	MV User	507	-	-	0.95
Load B4a	Secondary Substation	160	50	96	0.95
Load B4b	MV User	1660	-	-	0.95
Load B5	Secondary Substation	160	119	96	0.95
Load B6	Secondary Substation	320	186	192	0.95
Load B7	Secondary Substation	320	271	192	0.95
Load B8	Secondary Substation	260	199	156	0.95
Load B9	Secondary Substation	400	103	240	0.95
Load B10	Secondary Substation	250	289	150	0.95
Load B11	Secondary Substation	350	127	210	0.95
Load B12	Secondary Substation	250	146	150	0.95
Load B13	Secondary Substation	320	93	192	0.95
Load B14a	Secondary Substation	400	13	240	0.95
Load B14b	MV User	650	-	-	0.95

FIGURE 6-17: FEEDER B

6.4.2 Simulation Voltage Profile for Peak Load Condition

For the peak load condition, the active power rating of the loads is taken as 60% of the nominal power.

6.4.2.1 Feeder A

The voltage profile on Feeder A in the peak load condition is given below:

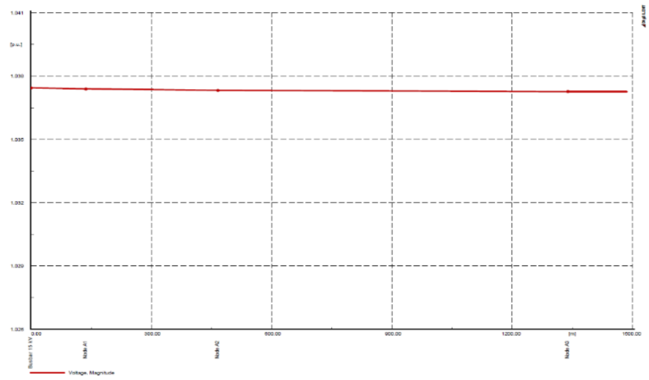


FIGURE 6-18: THE VOLTAGE PROFILE ON FEEDER A IN PEAK LOAD CONDITIONS

The voltage profile on Feeder A is almost constant because there is a negligible voltage drop on the lines.

6.4.2.2 Feeder B

The voltage profile on Feeder B in the peak load condition is given below:

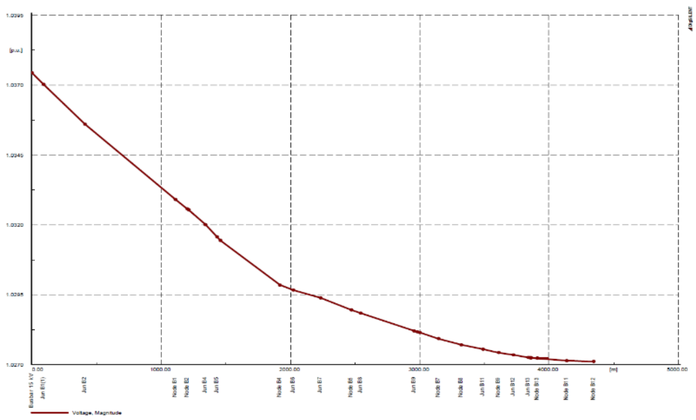


FIGURE 6-19: THE VOLTAGE PROFILE ON FEEDER B IN PEAK LOAD CONDITIONS

The voltage profile of Feeder B is not constant because of the voltage drop on the lines along the feeder.

6.4.3 Simulation Voltage Profile for Low Load Condition

For the low load condition, the active power rating of the loads is taken as 20% of the nominal power.

6.4.3.1 Feeder A

The voltage profile on Feeder A in the low load conditions is given below:

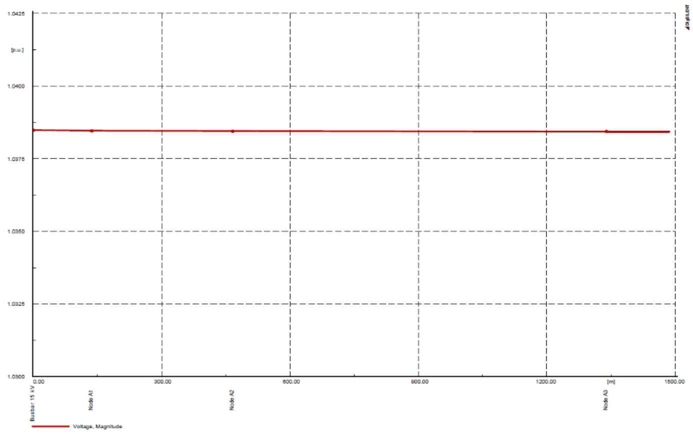


FIGURE 6-20: THE VOLTAGE PROFILE ON FEEDER A IN LOW LOAD CONDITIONS

The voltage profile on Feeder A is almost constant because there is a negligible voltage drop on the lines but is better than the peak loading conditions.

6.4.3.2 Feeder B

The voltage profile on Feeder B in the low load conditions is given below:

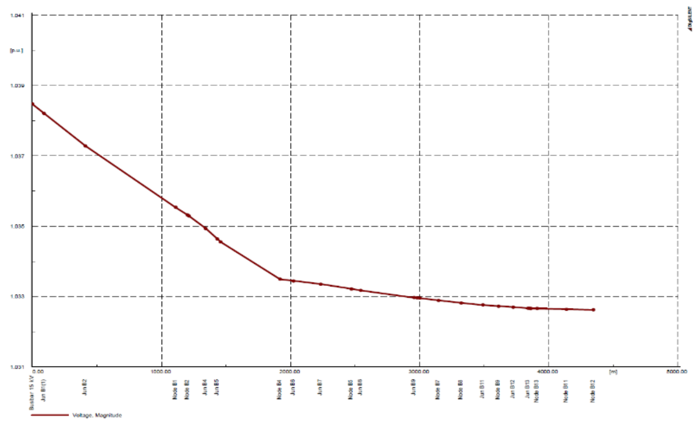


FIGURE 6-21: THE VOLTAGE PROFILE ON FEEDER B IN LOW LOAD CONDITIONS

The voltage profile of Feeder B is not constant because of the voltage drop on the lines along the feeder but is better than peak loading conditions.

6.4.4 Current Flow on Each Line and Quantify the Margin w.r.t I_{MAX}

The current flowing in each line was computed during the load flow and the loading of lines was analysed to get the margins w.r.t to the maximum current. The following figure shows one of the illustrations of the current flowing on a line showing the loading of the line.

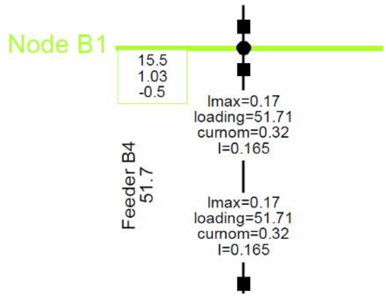


FIGURE 6-22: CURRENT FLOW ON FEEDER B

The nominal current of the line is 0.32 A and the current flowing through that line is represented by both I and I_{max}. As this load flow is run for only single time I_{max} and I are same. By comparing with the nominal current of the line, the loading of the line is computed as in this case the loading is 51.71% which means that the margin w.r.t to the maximum current that can flow from this line is 48.29%.

6.4.5 A Quasi-Dynamic Load Flow

In this part of the lab, the quasi-dynamic load flow simulation has been run by associating all the loads with the load profiles for 24-hour time. Three different load profiles are associated according to the following:

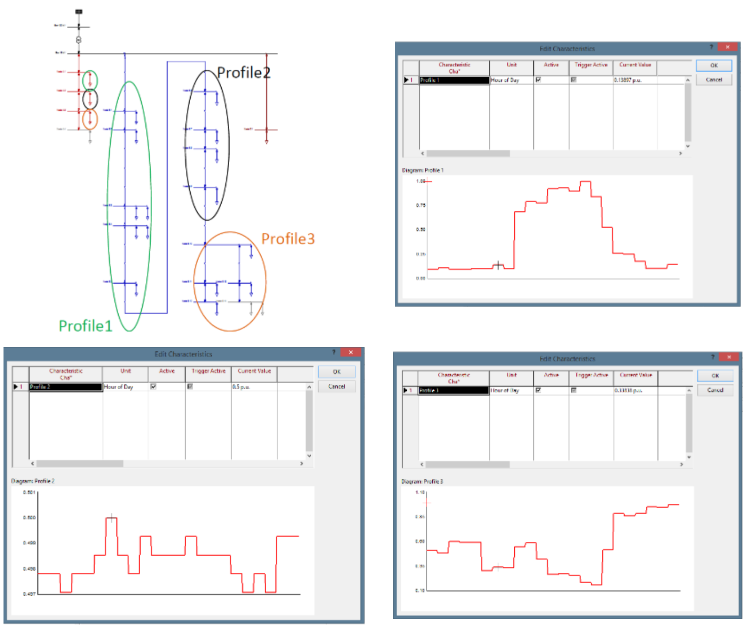


FIGURE 6-23: GRID MODEL, THE LOAD PROFILE 1, THE LOAD PROFILE 3, THE LOAD PROFILE 2 (CLOCKWISE)

6.4.5.1 Voltage Profile on Feeder B

The voltage profile of the final busbar of the feeder B i.e. Node B12 is shown below:

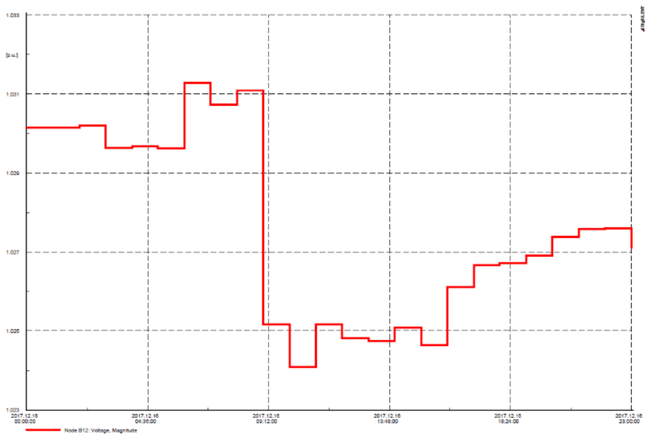
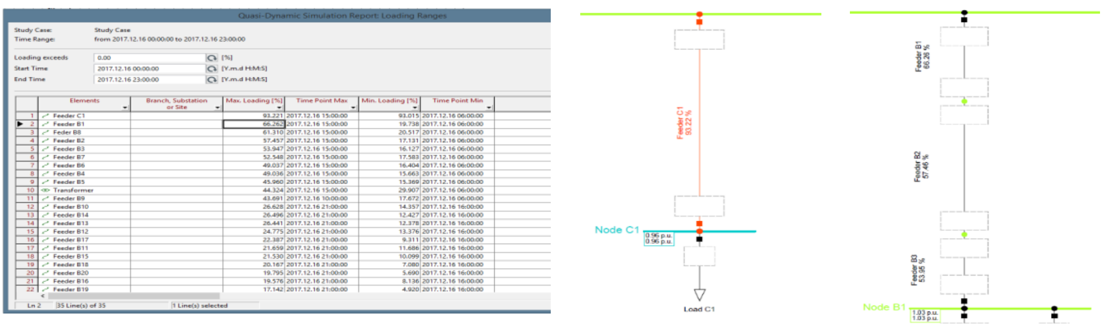


FIGURE 6-24: THE VOLTAGE PROFILE OF THE FINAL BUSBAR OF THE FEEDER B I.E. NODE B12

The voltage profile shows that when the loading is low as it can be seen in the first portion of time, the voltage magnitude profile is higher and when the loading is increased then the voltage magnitude decreases which is visible during the peak hours of the daily profile and in the last portion of the time, the loading decreases and consequently the voltage magnitude increases.

6.4.5.2 Percentage Loading of Each Line

The percentage loading of each line was checked, and the most loaded line was observed to be Feeder C1 (93.22%) and after this feeder C1, the most loaded line was observed to be Feeder B1 (66.26%). The results are shown below:



Quasi-Dynamic Simulation Report: Loading Ranges

Study Case: Study Case
Time Range: from 2017.12.16 00:00:00 to 2017.12.16 23:00:00

Loading exceeds 0.00 [%]
Start Time 2017.12.16 00:00:00 [Y.m.d H:M:S]
End Time 2017.12.16 23:00:00 [Y.m.d H:M:S]

	Elements	Branch, Substation or Site	Max. Loading [%]	Time Point Max	Min. Loading [%]	Time Point Min
1	Feeder C1		93.221	2017.12.16 15:00:00	93.015	2017.12.16 06:00:00
2	Feeder B1		66.262	2017.12.16 15:00:00	19.738	2017.12.16 06:00:00
3	Feder B8		61.310	2017.12.16 15:00:00	20.517	2017.12.16 06:00:00
4	Feeder B2		57.457	2017.12.16 15:00:00	17.131	2017.12.16 06:00:00
5	Feeder B3		53.947	2017.12.16 15:00:00	16.127	2017.12.16 06:00:00
6	Feeder B7		52.548	2017.12.16 15:00:00	17.583	2017.12.16 06:00:00
7	Feeder B6		49.037	2017.12.16 15:00:00	16.404	2017.12.16 06:00:00
8	Feeder B4		49.036	2017.12.16 15:00:00	15.663	2017.12.16 06:00:00
9	Feeder B5		45.960	2017.12.16 15:00:00	15.369	2017.12.16 06:00:00
10	Transformer		44.324	2017.12.16 15:00:00	29.907	2017.12.16 06:00:00
11	Feeder B9		43.691	2017.12.16 10:00:00	17.672	2017.12.16 06:00:00
12	Feeder B10		26.628	2017.12.16 21:00:00	14.357	2017.12.16 16:00:00
13	Feeder B14		26.496	2017.12.16 21:00:00	12.427	2017.12.16 16:00:00
14	Feeder B13		26.441	2017.12.16 21:00:00	12.378	2017.12.16 16:00:00
15	Feeder B12		24.775	2017.12.16 21:00:00	13.376	2017.12.16 16:00:00
16	Feeder B17		22.387	2017.12.16 21:00:00	9.311	2017.12.16 16:00:00
17	Feeder B11		21.659	2017.12.16 21:00:00	11.686	2017.12.16 16:00:00
18	Feeder B15		21.530	2017.12.16 21:00:00	10.099	2017.12.16 16:00:00
19	Feeder B18		20.167	2017.12.16 21:00:00	7.080	2017.12.16 16:00:00
20	Feeder B20		19.795	2017.12.16 21:00:00	5.690	2017.12.16 16:00:00
21	Feeder B16		19.576	2017.12.16 21:00:00	8.136	2017.12.16 16:00:00
22	Feeder B19		17.142	2017.12.16 21:00:00	4.920	2017.12.16 16:00:00

Ln 2 | 35 Line(s) of 35 | 1 Line(s) selected

FIGURE 6-25: FEEDER C1 & B1

6.4.6 Nodal Hosting Capacity

To check the Nodal Hosting Capacity, it’s required to increase the DG penetration by iterative increment procedure. The main technical constraints of the grids are

Steady-State Voltage variation

$$V_{min,k} \leq V_{DG,k} \leq V_{max,k}$$

Transformer and Lines Thermal Limits

$$I_{DG,kj} \leq I_{Max,kj}$$

Rapid Voltage Change

$$\left|V_{DG,k} - V_k\right| \leq 4\% \div 6\%$$

6.4.6.1 FEEDER A

To evaluate the grid constraints in feeder A, we have added a duplicate generator to get a better comparison between the presence and absence of the generator. Despite activate of one of the generators in each time, we added generator at Node A1 & Node A2 and then added the generator profile (Active Power=0.5 MW, PF=1 & Active Power=7MW, PF=1). Then, we have evaluated the grid technical constraints. If it satisfied the condition, we increase the capacity of the generator and evaluate the data again. In case of reaching the thermal limit of the grid line (i.e. negative), we have found the nodal hosting capacity. Finally, we look after the possibility to achieve the Nodal Hosting Capacity at unity power factor by controlling reactive power. The taken work steps are mentioned below in the figure.

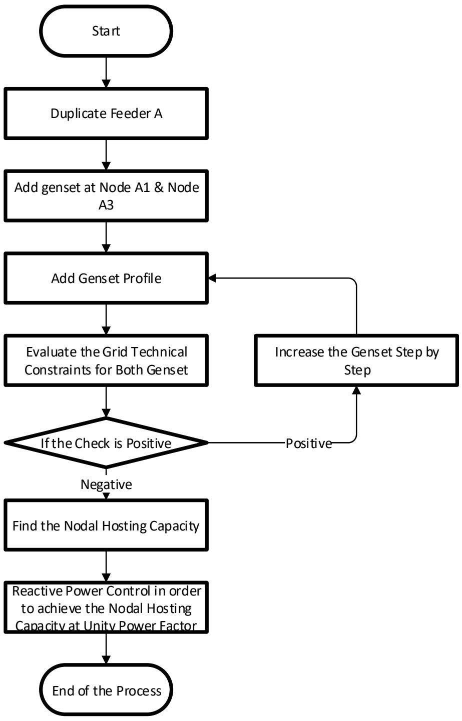


FIGURE 6-26: FLOWCHART TO FIND THE NODAL HOSTING CAPACITY ON FEEDER A

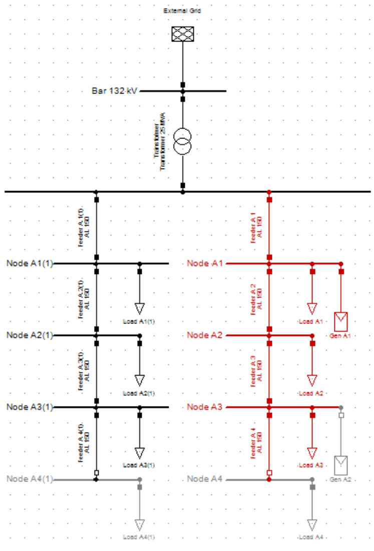


FIGURE 6-27: FEEDER A

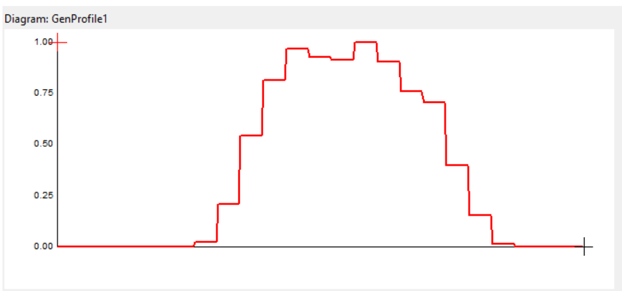


FIGURE 6-28: PV GENERATOR PROFILE

6.4.6.2 Grid Constraints Evaluation (Active Power=0.5 MW, PF=1)

Node A1 (Active Power=0.5 MW, PF=1)

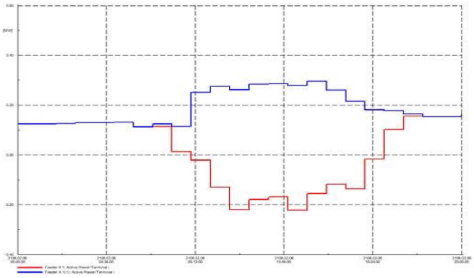


FIGURE 6-29: ACTIVE POWER AT BRACH A1

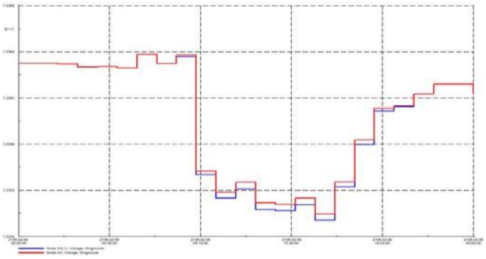


FIGURE 6-31: VOLTAGE AT NODE A3

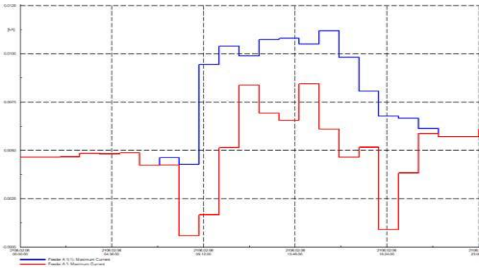


FIGURE 6-33: CURRENT AT BRANCH A1

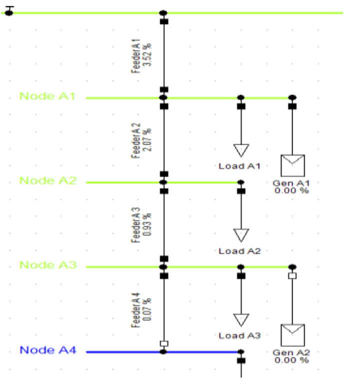


FIGURE 6-35: NODE A1

Node A3 (Active Power=0.5 MW, PF=1)

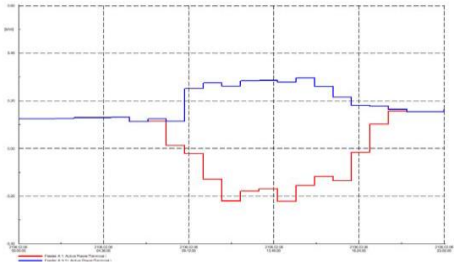


FIGURE 6-30: ACTIVE POWER AT BRANCH A1

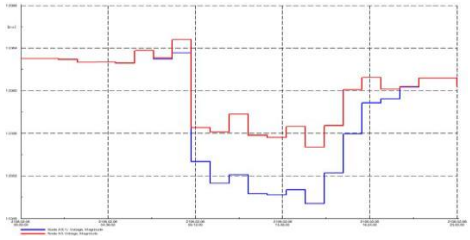


FIGURE 6-32: VOLTAGE AT NODE A3

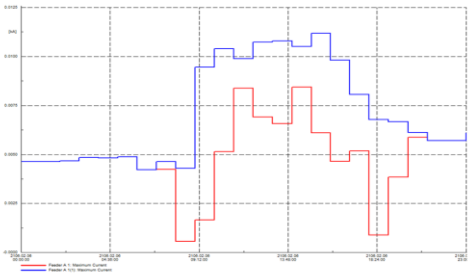


FIGURE 6-34: CURRENT AT BRANCH A1

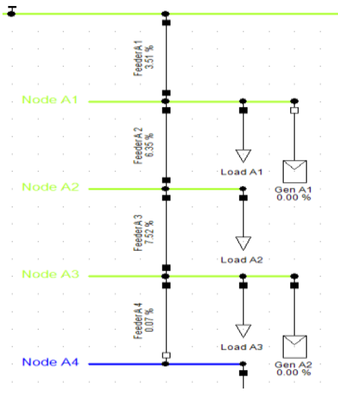


FIGURE 6-36: NODE A3

The check is positive in terms of grid's constraints for the injection equal to 0.5 MW. The following figures are the evaluation after increasing the injection equal to 7 MW till it reached its Nodal Hosting Capacity at PF equal to 1 and then simulate again with equal injection but with a different PF equal to 0.9.

Node A3 (Active Power=7 MW, PF=1)

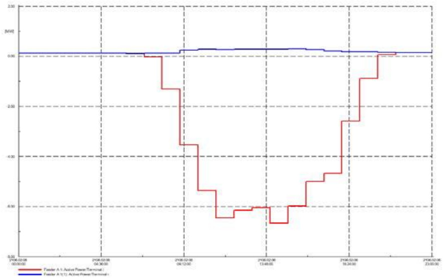


FIGURE 6-37: ACTIVE POWER AT BRANCH A1

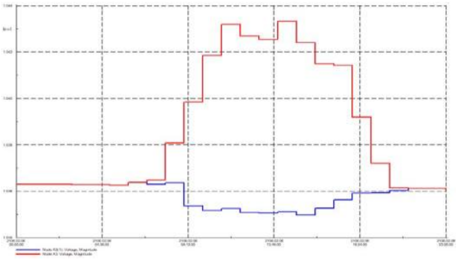


FIGURE 6-39: VOLTAGE AT NODE A3

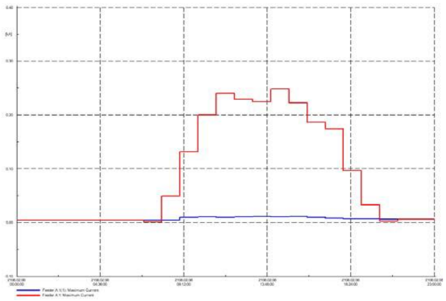


FIGURE 6-41: CURRENT AT BRANCH A1

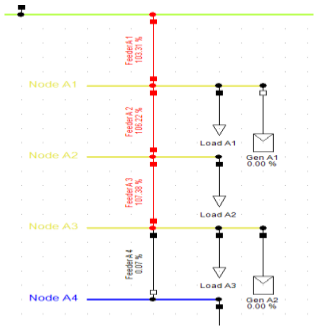


FIGURE 6-43: NODE A3

Node A3 (Active Power=7 MW, PF=0.9)

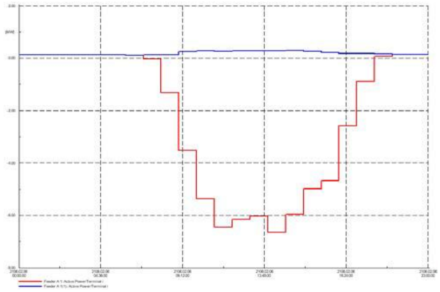


FIGURE 6-38: ACTIVE POWER AT BRANCH A1

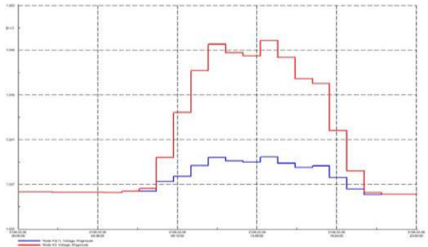


FIGURE 6-40: VOLTAGE AT NODE A3

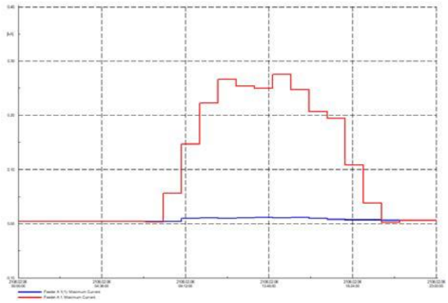


FIGURE 6-42: CURRENT AT BRANCH A1

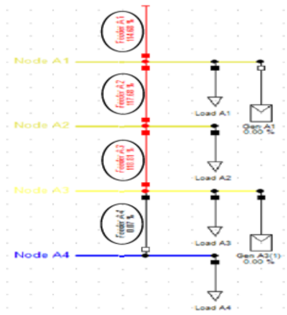


FIGURE 6-44: NODE A3

6.4.6.3 *FEEDER B*

After having the simulation for Feeder A we increased step by step the active power of generator in following nodes of Feeder B to hit the grid constraints for PF=1 and PF=0.9, found the hosting capacity and the effect of reactive power control on hosting capacity.

- Node B2
- Node B6
- Node B10

Three PV Systems are installed on three different nodes i.e. Node B2, Node B6 and Node B10 for determining the hosting capacity on these nodes for power factor=1 and power factor=0.9. The PV generation profile is added for each PV generating unit according to the following profile:

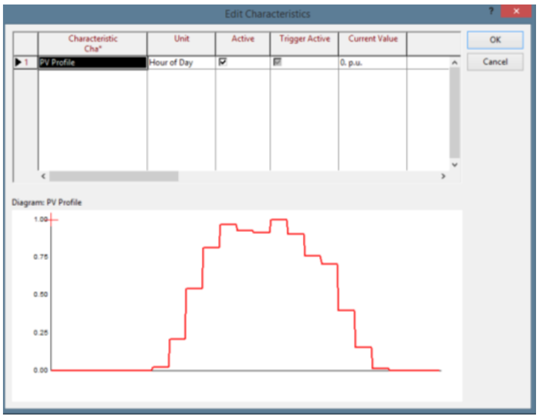


FIGURE 6-45: THE PV GENERATION PROFILE

The grid constraints are evaluated for each node equipped with the DG unit and the following results are obtained.

6.4.6.3.1 Node B2, PF=1:

The active power has been increased to the values of 0.5 MW, 5 MW, 10 MW and finally to 11.2 MW where the loading of the line Feeder B1 approached its limit (99.27%) so the hosting capacity for node B2 with PF=1 has been defined as 11.2 MW. The voltage profile on node closest to the busbar i.e. node B1 and farthest node i.e. node B14 has been recorded which are given below:

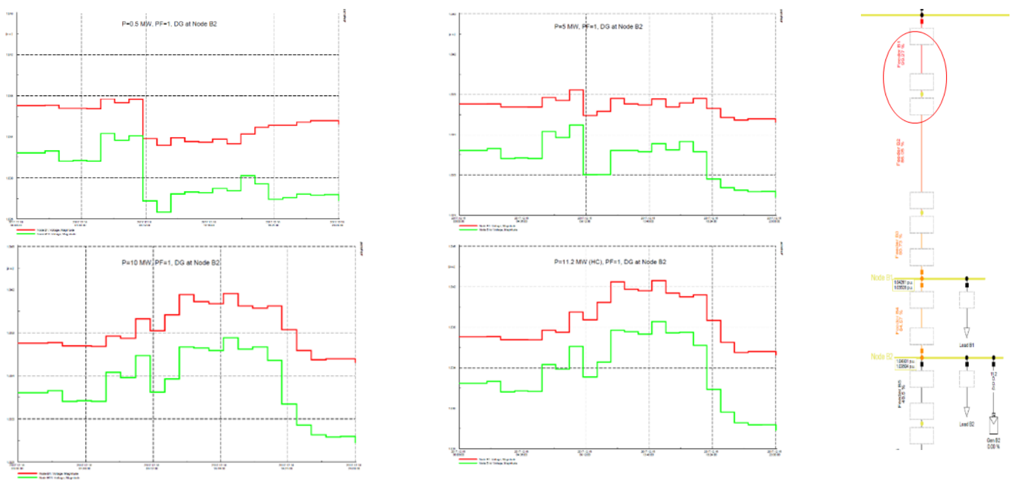


FIGURE 6-46: VOLTAGE PROFILES OF NODE B2 AT P.F 1

The voltage on both nodes B1 and B14 are increasing by increasing the active power injection of the PV at node B2 until the loading of the line Feeder B1 approaches its limit and sets the hosting capacity to 11.2 MW.

6.4.6.3.2 Node B2, PF=0.9:

The active power has been increased to the values of 0.5 MW, 5 MW, 7 MW and finally to 8.625 MW where the loading of the line Feeder B1 approached its limit (99.9%) so the hosting capacity for node B2 with PF=0.9 has been defined as 8.625 MW. The voltage profile on node closest to the busbar i.e. node B1 and farthest node i.e. node B14 has been recorded which are given below:

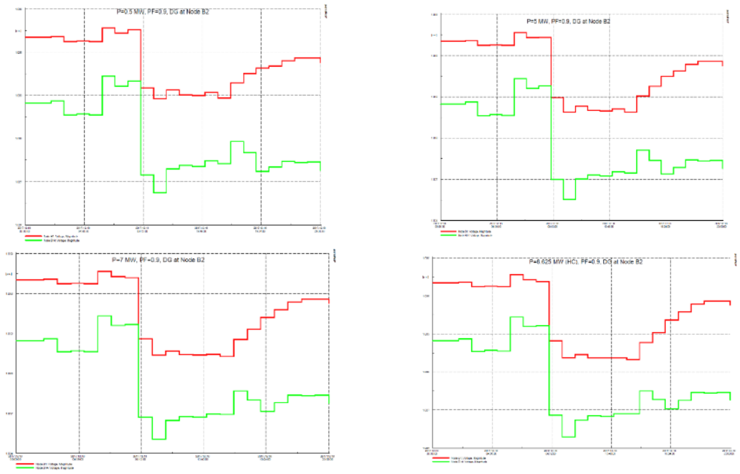


FIGURE 6-47: VOLTAGE PROFILES OF NODE B2 AT P.F 0.9

The voltage of nodes B1 and B14 are decreasing by increasing the power injecting of DG which is now accompanied by reactive power injection as the PF has been set to 0.9. As the loads are constants so the decreasing of voltage by increasing the power injections increase the current passing through the lines and hence the loading of Feeder B1 is violated at 8.625 MW i.e. much earlier as compared to the hosting capacity of same node B2 when the PF was set to 1.

6.4.6.3.3 Node B6, PF=1:

The active power has been increased to the values of 0.5 MW, 4.5 MW, 7.5 MW and finally to 8.21 MW where the loading of the line Feeder B14 approached its limit (99.8%) so the hosting capacity for node B6 with PF=1 has been defined as 8.21 MW. The voltage profile on node closest to the busbar i.e. node B1 and farthest node i.e. node B14 has been recorded which are given below:

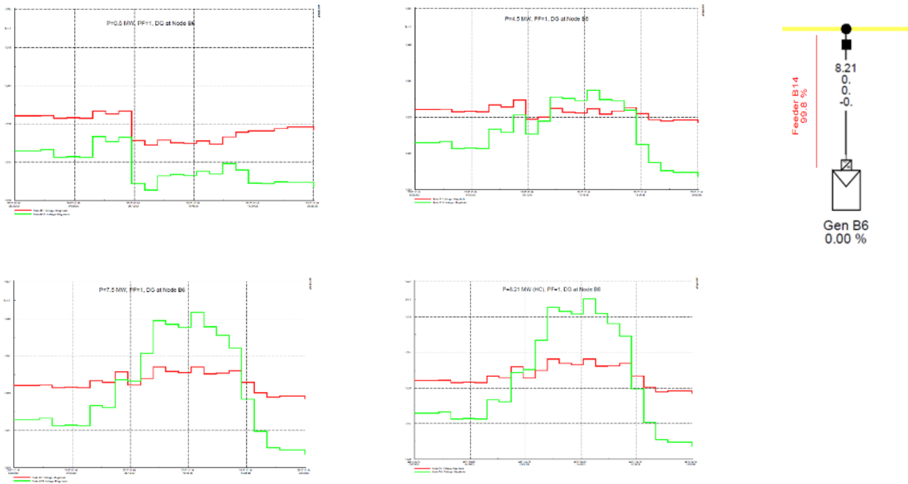


FIGURE 6-48: VOLTAGE PROFILES OF NODE B6 AT P.F 1

The voltage on both nodes B1 and B14 are increasing by increasing the active power injection of the PV at node B6 until the loading of the line Feeder B14 approaches its limit and sets the hosting capacity to 8.21 MW.

6.4.6.3.4 Node B6, PF=0.9:

The active power has been increased to the values of 0.5 MW, 4.5 MW, 6.5 MW and finally to 7.025 MW where the loading of the line Feeder B14 approached its limit (99.61%) so the hosting capacity for node B6 with PF=0.9 has been defined as 7.025 MW. The voltage profile on node closest to the busbar i.e. node B1 and farthest node i.e. node B14 has been recorded which are given below:

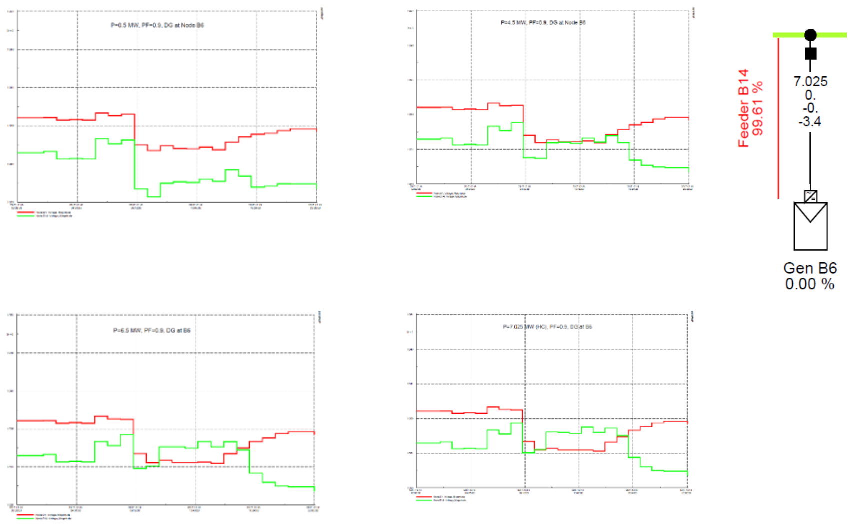


FIGURE 6-49: VOLTAGE PROFILES OF NODE B6 AT P.F 0.9

The voltage on node B1 is decreasing and node B14 increasing by increasing the power injections at node B6 with PF=0.9 until the loading of line Feeder B14 is approaches its limit and sets the hosting capacity to 7.025 MW at node B6.

6.4.6.3.5 Node B10, PF=1:

The active power has been increased to the values of 0.5 MW, 4.5 MW, 6.5 MW and finally to 7.60 MW where the loading of the line Feeder B21 approached its limit (99.91%) so the hosting capacity for node B10 with PF=1 has been defined as 7.60 MW. The voltage profile on node closest to the busbar i.e. node B1 and farthest node i.e. node B14 has been recorded which are given below:

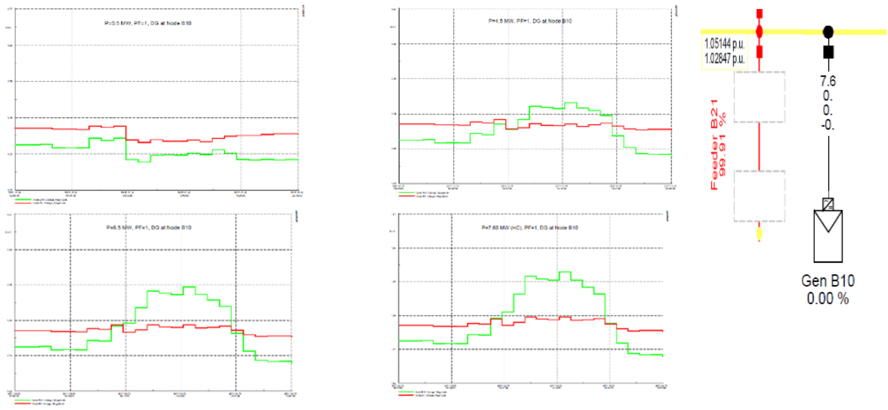


FIGURE 6-50: VOLTAGE PROFILES OF NODE B10 AT P.F 1

The voltage on node B1 and node B14 is increased by increasing the power injections at node B10 with PF=1. The voltage of the farthest node i.e. node B14 is increasing rapidly as compared to the voltage on node B1 because the power injection on node B10 is near proximity of node B14 than node B1.

6.4.6.3.6 Node B10, PF=0.9:

The active power has been increased to the values of 0.5 MW, 3.5 MW, 5.5 MW and finally to 6.645 MW where the loading of the line Feeder B21 approached its limit (99.94%) so the hosting capacity for node B10 with PF=0.9 has been defined as 6.645 MW. The voltage profile on node closest to the busbar i.e. node B1 and farthest node i.e. node B14 has recorded which are given below:

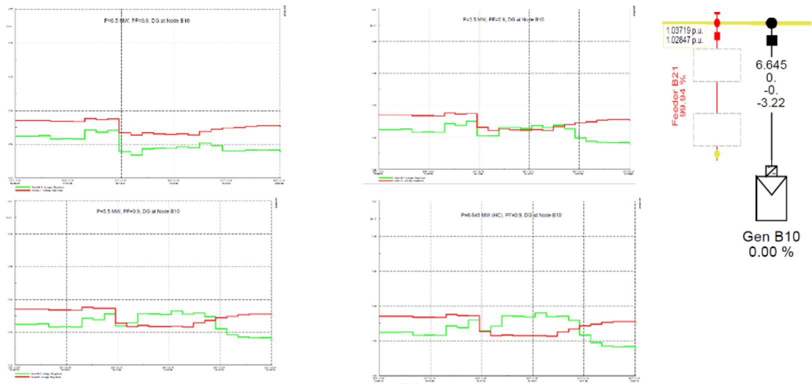


FIGURE 6-51: VOLTAGE PROFILES OF NODE B10 AT P.F 0.9

The voltage on node B1 is decreasing and the voltage on node B14 is increased by increasing the power injection at node B10 with Pf=0.9 until the loading of line 21 approaches it limits and sets the hosting capacity to 6.645 MW at node B10.

The hosting capacity is highest at Node B2 when simulated at PF=1 and the value of that hosting capacity is 11.2 MW.

The reactive power injection decreases the voltage of the nodes of the grid and in our simulation the loads are constant, so the voltage decreasing on the nodes increases the current flowing through the lines and the loading is violated before the voltage limits are violated so overall hosting capacity is decreased by injection of reactive power. If the voltage limits are close to its maximum limits and reactive power is injected through DG then the hosting capacity increases but this is not in our case as the loading approaches to its limit before the voltage limits.

6.4.6.4 RVC in terms of the Proximity from the PS:

The rapid voltage change is caused by the unexpected disconnection of a generator from a MV bus. The reference values of voltages change according to EN 50160 are 4%-6% of the nominal voltage of the MV bus. In the presence of DG at a MV node, the voltage of the MV bus increases and the consequently the current flowing decreases which ultimately decreases the voltage drop and the voltage profile of last node becomes better so if the DG is disconnected unexpectedly then the probability of RVC on the where DG is connected is less than that of last node hence the last node is affected more with respect to RVC. So, in these cases ESS may support to maintain a constant injection for certain time.

The mass EV adaptation will have a great impact on the composite load models for the substation (the portion of active load will be increased in the time of charging) depending on the time. So, the load will vary by the time thus the composite load. On the other hand, it is also possible to increase the injection reactive power by the ESS to handle the non-operating schedule of the DGs (as most of them depends on the weather and time, specifically Photovoltaic Power). Also, the possibility to maintain the RVC for the nodes increase the technical viability of the VESS or MESS further if the utility service provider extends the facilities to connect the VESS or MESS at different nodes. Also, the simulation may extend further in the near future to see the behaviour of the grid after adding more dynamic composite load profile (considering the space-time activity graph-based load forecast) and adding VESS or MESS as DGs in the nodes despite the cost involvement of those items.

CHAPTER SEVEN

7 FEASIBILITY: EV FOR SINGLE USER

7.1 OUTLINE

So far, in the thesis report the it has been seen that the future will see a mass EV adoption. In order to have better integration of the EVs into the grid, an innovative has been proposed. Along with the focus has been on the battery management as well. It has been proposed how to model ESS as a locality. A case a city in Italy, Aosta has been analysed at every step of the development and the grid simulation has been carried out for the grid of Aosta.

In order to carry out the feasibility study on the same case of Aosta has been considered further. On a micro scale, a single EV user has been considered. For the purpose of carrying out the feasibility study the PV*SOL software has been used. PV system has been coupled in order to charger the EV. The EV considered is a tesla model S which has around 70% derating after driving 160.934,40 km.

In the simulation a commercial office has been considered along with a grid-tied photovoltaic system as the financial scheme for the electric vehicle is not realized till now. The Electric Vehicle itself has a huge advantage despite the less opportunities of generating cash due to the lack of the incentives like the clean energy sources. This is the reason; the model has been combined with PV and EV together to observe the financial outcome as a business model.

After carrying out the feasibility study the Mileage per year has been noted as 18.250 km, out which 18.247 km has been served by the PV module itself.

7.2 PROJECT OVERVIEW

The details related to the EV and PV Module has been described below in depth. The whole report is as follows:

7.2.1 PV SYSTEM

Grid-connected PV system with Electrical Appliances and Electric Vehicle

Climate Data	Aosta (UNI 10349), ITA (1986 - 2005)	
PV Generator Output	50,4	kWp
PV Generator Surface	282,2	m²
Number of PV Modules	168	
Number of Inverters	2	
No. of vehicles	1	

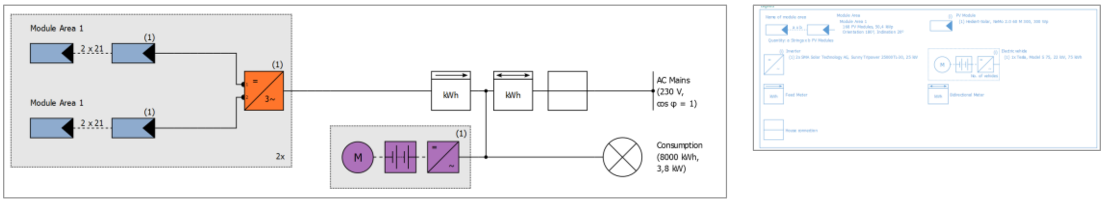


FIGURE 7-1: PV SYSTEM

7.2.2 The Yield

The yield		
PV Generator Energy (AC grid)	62.844	kWh
Direct Own Use	6.310	kWh
Charge of the electric vehicle	5.201	kWh
Grid Feed-in	51.334	kWh
Down-regulation at Feed-in Point	0	kWh
Own Power Consumption	18,3	%
Solar Fraction	87,2	%
Spec. Annual Yield	1.246,91	kWh/kWp
Performance Ratio (PR)	86,5	%
CO_2 Emissions avoided	37.707	kg / year

7.2.3 Financial Analysis

User's Gain		
Total investment costs	153.785,00	€
Return on Assets	7,10	%
Amortization Period	10,9	Years
Electricity Production Costs	0,13	€/kWh
Energy Balance/Feed-in Concept	Surplus Feed-in	

7.3 Set-up of the System

7.3.1 Overview

System Data	
Type of System	Grid-connected PV system with Electrical Appliances and Electric Vehicle
Start of Operation	29.11.2018

Climate Data	
Location	Aosta (UNI 10349), ITA (1986 - 2005)
Resolution of the data	1 h
Simulation model used:	
- Diffuse Irradiation onto Horizontal Plane	Hofmann
- Irradiance onto tilted surface	Hay & Davies

Consumption		
Total Consumption	8000	kWh
BDEW commercial load profile (G1)	8000	kWh
Load Peak	3,8	kW

7.4 Module Areas

7.4.1 1. Module Area - Module Area 1

PV Generator, 1. Module Area - Module Area 1

Name	Module Area 1
PV Modules	168 x NeMo 2.0 60 M 300
Manufacturer	Heckert-Solar
Inclination	20 °
Orientation	South 180 °
Installation Type	Mounted - Roof
PV Generator Surface	282,2 m²

Shading, 1. Module Area - Module Area 1

Shading	0 %

Degradation of Module, 1. Module Area - Module Area 1

Remaining power (power output) after 25 years	80 %

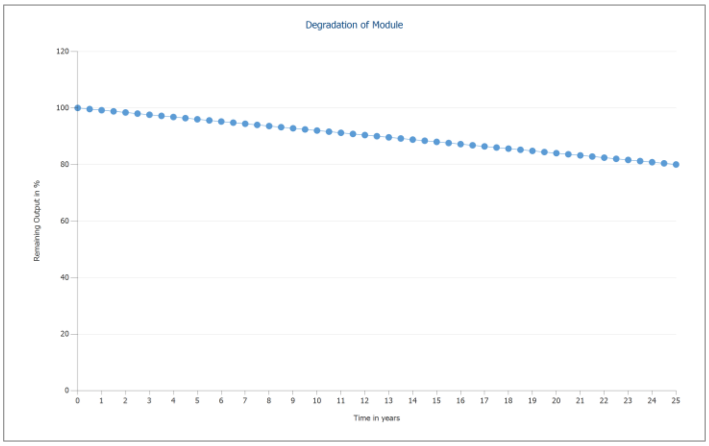


FIGURE 7-2: DEGRADATION OF MODULE, 1. MODULE AREA - MODULE AREA 1

7.4.2 Inverter configuration

Configuration 1

Module Area	Module Area 1
Inverter 1	
Manufacturer	SMA Solar Technology AG
Model	Sunny Tripower 25000TL-30
Quantity	2
Sizing Factor	100,8 %
Configuration	MPP 1: 2 x 21
	MPP 2: 2 x 21

7.4.3 AC Mains

AC Mains	
Number of Phases	3
Mains Voltage (1-phase)	230 V
Displacement Power Factor (cos phi)	+/- 1

7.4.4 Electric vehicles

Electric vehicle - Group 1	
Electric vehicle	
Manufacturer	Tesla
Model	Model S 75
No. of vehicles	1
Range in accordance with NEDC	480 km
Battery Capacity	75 kWh
Consumption	22 kWh / 100km
Charging station	
Charging Power	22 kW
Charging technology	AC Typ 2
Discharge for covering consumption	No
Use	
Desired range per week	350 km
Mileage per year	18250 km

7.5 Simulation Results

7.5.1 Results Total System

PV System	
PV Generator Output	50,4 kWp
Spec. Annual Yield	1.246,91 kWh/kWp
Performance Ratio (PR)	86,5 %
PV Generator Energy (AC grid)	62.844 kWh/year
Direct Own Use	6.310 kWh/year
Grid Feed-in	51.334 kWh/year
Down-regulation at Feed-in Point	0 kWh/year
Charge of the electric vehicle	5.201 kWh/year
Own Power Consumption	18,3 %
CO_2 Emissions avoided	37.707 kg / year

Appliances	
Appliances	8.000 kWh/year
Standby Consumption (Inverter)	30 kWh/year
Charge of the electric vehicle	5.202 kWh/year
Total Consumption	13.232 kWh/year
covered by PV power	11.510 kWh/year
covered by grid	1.693 kWh/year
covered by electric vehicle	0 kWh/year

Electric vehicle	
Charge at beginning	75 kWh
Charge of the electric vehicle (Total)	5.202 kWh/year
Charge of the electric vehicle (PV System)	5.201 kWh/year
Charge of the electric vehicle (Grid)	1 kWh/year
Discharging the electric vehicle for consumption	0 kWh/year
Losses due to charging/discharging	229 kWh/year
Losses in Battery	1.033 kWh/year

Consumption due to kilometres driven	4015 kWh
Mileage per year	18250 km
of which is solar	18247 km

Level of Self-sufficiency	
Total Consumption	13.232 kWh/year
covered by grid	1.693 kWh/year
Level of Self-sufficiency	87,2 %

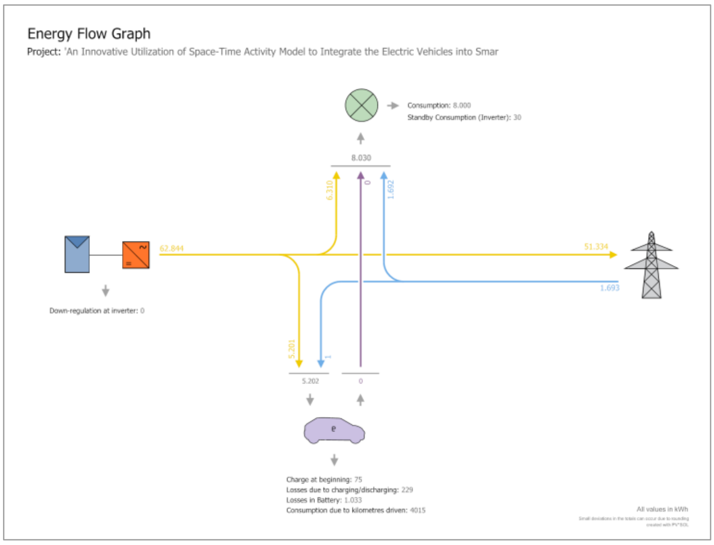


FIGURE 7-3: ENERGY FLOW GRAPH

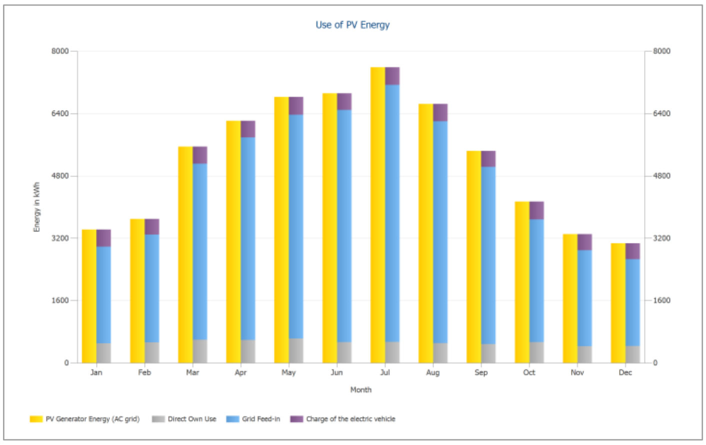


FIGURE 7-4: USE OF PV ENERGY

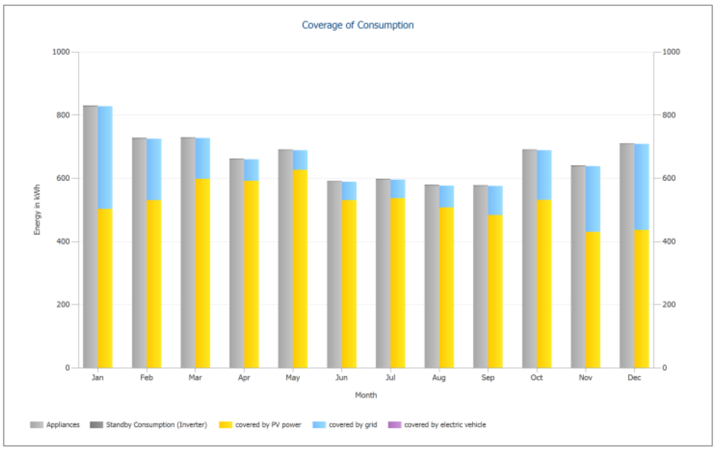


FIGURE 7-5: COVERAGE OF CONSUMPTION

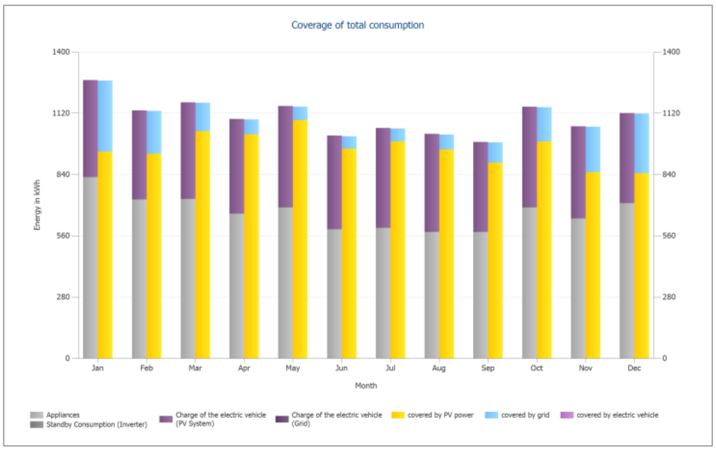


FIGURE 7-6: COVERAGE OF TOTAL CONSUMPTION

7.6 PV System Energy Balance

PV System Energy Balance

Global radiation - horizontal	**1.273,23**	**kWh/m²**	
Deviation from standard spectrum	-12,73	kWh/m²	-1,00 %
Ground Reflection (Albedo)	7,60	kWh/m²	0,60 %
Orientation and inclination of the module surface	169,24	kWh/m²	13,35 %
Shading	0,00	kWh/m²	0,00 %
Reflection on the Module Interface	-41,78	kWh/m²	-2,91 %
Global Radiation at the Module	**1.395,56**	**kWh/m²**	
	1.395,56	kWh/m²	
	x 282,24	m²	
	= 393.887,82	kWh	
Global PV Radiation	**393.887,82**	**kWh**	
Soiling	0,00	kWh	0,00 %
STC Conversion (Rated Efficiency of Module 17,91 %)	-323.333,08	kWh	-82,09 %
Rated PV Energy	**70.554,74**	**kWh**	
Low-light performance	-2.014,93	kWh	-2,86 %
Deviation from the nominal module temperature	-1.596,29	kWh	-2,33 %
Diodes	-334,72	kWh	-0,50 %
Mismatch (Manufacturer Information)	-1.332,18	kWh	-2,00 %
Mismatch (Configuration/Shading)	0,00	kWh	0,00 %
PV Energy (DC) without inverter down-regulation	**65.276,62**	**kWh**	
Failing to reach the DC start output	-17,64	kWh	-0,03 %
Down-regulation on account of the MPP Voltage Range	0,00	kWh	0,00 %
Down-regulation on account of the max. DC Current	0,00	kWh	0,00 %
Down-regulation on account of the max. DC Power	0,00	kWh	0,00 %
Down-regulation on account of the max. AC Power/cos phi	-0,08	kWh	0,00 %
MPP Matching	-165,58	kWh	-0,25 %
PV energy (DC)	**65.093,32**	**kWh**	
Energy at the Inverter Input	**65.093,32**	**kWh**	
Input voltage deviates from rated voltage	-120,36	kWh	-0,18 %
DC/AC Conversion	-1.493,90	kWh	-2,30 %
Standby Consumption (Inverter)	-30,31	kWh	-0,05 %
Total Cable Losses	-635,10	kWh	-1,00 %
PV energy (AC) minus standby use	**62.813,65**	**kWh**	
PV Generator Energy (AC grid)	**62.844,26**	**kWh**	

7.7 Financial Analysis

7.7.1 Overview

System Data	
Grid Feed-in in the first year (incl. module degradation)	51.086 kWh/year
PV Generator Output	50,4 kWp
Start of Operation of the System	29.11.2018
Assessment Period	20 Years
Interest on Capital	1 %

Economic Parameters	
Return on Assets	7,10 %
Accrued Cash Flow (Cash Balance)	110.537,64 €
Amortization Period	10,9 Years
Electricity Production Costs	0,13 €/kWh
Travel cost without PV	4,06 €/100 km
Travel cost with PV	3,7 €/100 km

Payment Overview	
Specific Investment Costs	3.051,29 €/kWp
Investment Costs	153.785,00 €
One-off Payments	0,00 €
Incoming Subsidies	0,00 €
Annual Costs	0,00 €/year
Other Revenue or Savings	0,00 €/year

Remuneration and Savings	
Total Payment from Utility in First Year	13.800,62 €/year
First year savings	1.634,21 €/year

Conto Energia IV S2 2012 - Impianti su edifici	
Validity	29.11.2018 - 28.11.2038
Specific generation remuneration	0,2206 €/kWh
Generation Tariff	13.800,62 €/year

Tariffa standard (Example)	
Energy Price	0,14 €/kWh
Base Price	0,50 €/Month
Inflation Rate for Energy Price	2 %/year

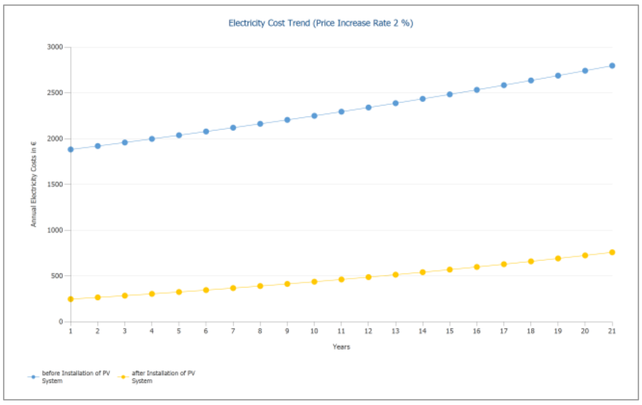


FIGURE 7-7: ELECTRICITY COST TREND (PRICE INCREASE RATE 2 %)

7.7.2 Cash flow

Cashflow Table

	year 1	year 2	year 3	year 4	year 5
Investments	-153.785,00 €	0,00 €	0,00 €	0,00 €	0,00 €
Feed-in / Export Tariff	12.989,70 €	13.419,94 €	13.179,40 €	12.942,31 €	12.708,62 €
Electricity Savings	1.493,78 €	1.620,93 €	1.623,72 €	1.626,40 €	1.628,98 €
Annual Cash Flow	**-139.301,52 €**	**15.040,87 €**	**14.803,12 €**	**14.568,72 €**	**14.337,61 €**
Accrued Cash Flow (Cash Balance)	-139.301,52 €	-124.260,65 €	-109.457,53 €	-94.888,81 €	-80.551,20 €

	year 6	year 7	year 8	year 9	year 10
Investments	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €
Feed-in / Export Tariff	12.478,29 €	12.251,28 €	12.027,54 €	11.807,02 €	11.589,70 €
Electricity Savings	1.631,46 €	1.633,82 €	1.636,07 €	1.638,20 €	1.640,22 €
Annual Cash Flow	**14.109,75 €**	**13.885,10 €**	**13.663,60 €**	**13.445,22 €**	**13.229,91 €**
Accrued Cash Flow (Cash Balance)	-66.441,45 €	-52.556,36 €	-38.892,75 €	-25.447,53 €	-12.217,61 €

	year 11	year 12	year 13	year 14	year 15
Investments	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €
Feed-in / Export Tariff	11.375,52 €	11.164,44 €	10.956,43 €	10.751,45 €	10.549,45 €
Electricity Savings	1.642,11 €	1.643,88 €	1.645,53 €	1.647,04 €	1.648,43 €
Annual Cash Flow	**13.017,63 €**	**12.808,32 €**	**12.601,96 €**	**12.398,49 €**	**12.197,88 €**
Accrued Cash Flow (Cash Balance)	800,02 €	13.608,34 €	26.210,30 €	38.608,79 €	50.806,67 €

	year 16	year 17	year 18	year 19	year 20
Investments	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €
Feed-in / Export Tariff	10.350,39 €	10.154,25 €	9.960,97 €	9.770,52 €	9.582,87 €
Electricity Savings	1.649,68 €	1.650,80 €	1.651,77 €	1.652,60 €	1.653,29 €
Annual Cash Flow	**12.000,07 €**	**11.805,04 €**	**11.612,74 €**	**11.423,13 €**	**11.236,16 €**
Accrued Cash Flow (Cash Balance)	62.806,74 €	74.611,78 €	86.224,52 €	97.647,65 €	108.883,81 €

	year 21
Investments	0,00 €
Feed-in / Export Tariff	0,00 €
Electricity Savings	1.653,83 €
Annual Cash Flow	**1.653,83 €**
Accrued Cash Flow (Cash Balance)	110.537,64 €

Degradation and inflation rates are applied on a monthly basis over the entire observation period. This is done in the first year.

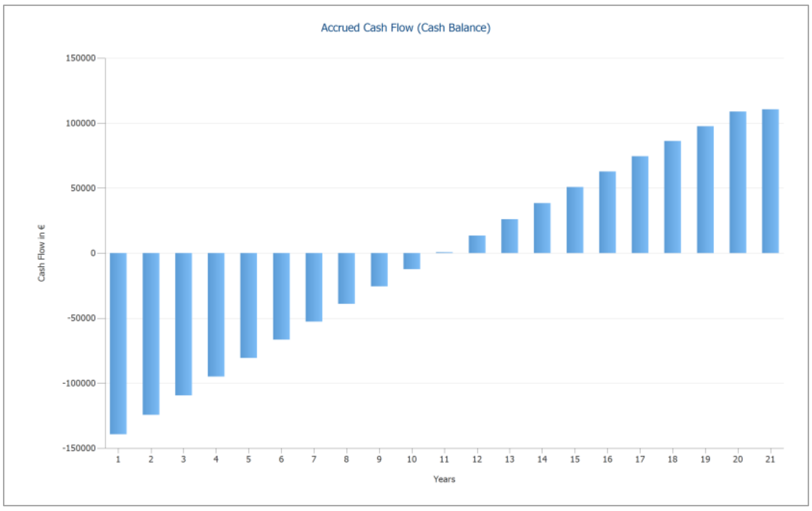


FIGURE 7-8: ACCRUED CASH FLOW (CASH BALANCE)

7.8 CONCLUSION

Throughout the report case study of Aosta has been considered. A feasibility study (technical and financial) has been carried out for a single user. The EV has been coupled along with the PV system. Also, a commercial office load profile has been considered as most of the offices usually have the vehicles in their parking lot. The load profile and the nature of the parking justified the use of the solar energy at day time.

The simulation of 50.4 kWp PV system shows the charging of the EV has been done almost fully all around the year. The clean energy may help the environment more by reducing the carbon footprints by the wheels. Also, the financial profitability will inspire the people to invest more money on the future electric vehicles.

It has been observed that the single user setup delivered some promising results. This shows that the proposed model has an immense potential to be replicated as a large-scale project with decentralized renewable energy mixes. Hence, this paves the way for greater humanitarian future works.

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