Electric vehicles and smart grids: impacts, challenges and opportunities

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Electric Vehicles and Smart Grids: Impacts, Challenges and Opportunities

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To my wife,
To my parents

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I would like to express my deepest appreciation to professors Tenconi, Bompard and Hadj-Said for guiding my research activity and study at both POLITECNICO DI TORINO and GRENOBLE ALPES universities. They have been always accessible and enthusiastic, making my research successful.

Abstract

This Doctoral thesis presents Electric Vehicles integration into the smart grid including impact study, various challenges and their capacity to improve power system security and operational indexes. In this way, the impact of EVs charging on distribution grid is investigated and a comprehensive models are proposed in order to consider various uncertainties in the power system, EVs parameters and drivers behavieurs. Proposed models in this study consists of three main subjects; In the first step, a comprehensive model is presented in order to take into account all above mentioned uncertainties. This model is based on a stochastic method and applied the Monte Carlo Simulation (MCS) in modeling uncertainties. Results of exerting this model on two dumb and smart charging scenario, shows that with control on EVs charging the power system security can be improved.

In the second step, the fast charging station for EVs planning in the urban regions is investigated. The proposed method for locating the optimal location for fast charging station is presented. This model uses the Particle Swarm Optimization (PSO) method in finding the best economic and technical location for installing fast charging stations. The third step is dedicated to the EVs capacities to increase distributed generations penetration levels in the grid. Two model are proposed in this part: a heuristic method based model and a PSO approach based model. Results of simulation of this models on a real case study demonstrates the capacity of EVs charging in increasing DGs penetration level in the grid.

In all the above mentioned models, the tools developed, tested on a case study and can be applied to the other power system cases.

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Introduction

European Union policies put a key priority to preventing dangerous climate change. EU climate and energy package, known as 2020 package is published as a guideline for energy policy makers in the EU. Europe is working hard to cut its greenhouse gas emissions substantially while encouraging other nations and regions to do likewise. Key EU targets, known as the "$20 - 20 - 20$" targets, set three key objectives for 2020 [Com];

- 20% cut in greenhouse gas emissions compared with 1990.
- 20% of total energy consumption from renewable energy.
- 20% increase in energy efficiency.

The Kyoto Protocol, another international agreement in climate change domain is linked to the United Nations Framework Convention on Climate Change, which commits its parties by setting internationally binding emission reduction targets.

Recognizing that developed countries are principally responsible for the current high levels of GHG emissions in the atmosphere as a result of more than 150 years of industrial activity, the Protocol places a heavier burden on developed nations under the principle of *"common but differentiated responsibilities."*

The Kyoto Protocol was adopted in Kyoto, Japan, on 11 December 1997 and entered into force on 16 February 2005 [Nat]. Emergency need for reducing the air pollution, especially in urban areas, have promoted the policy makers to reduce the transportation sector dependency on fossil fuels. The increase of electric vehicle (EV) in the current and next automobile generations necessitates more attention to the impact study of electric vehicles charging in large scales on power system.

Power system network components are constructed actually to supply, transmit and use electric power with the actual demands. The actual power grid can be broadly divided into the generators that supply the power, the transmission system that carries the power from the generating centers to the load centers and the distribution system that feeds the power to nearby homes and industries.

Some modifications in distribution grid and some new challenges like Distributed generation of energy (DG) and electric vehicles in power system domain leads into new definitions of power system using a “smarter” power grid called *Smart Grid*. In fact Smart Grid provides the facilities in information technology and communication to support generation and load components to control the power flow in the distribution grid.

The current thesis presents the specific perspectives in which the EVs integration into smart grids challenges are considered in various models. These models investigate EVs integration into power system challenges like high EV_{pr} fast charging stations optimization problems and increase in Distributed Generation Penetration Level (DG_{pr}) . Thus, propose a controlled charging models in order to improve power system quality indexes, EV_{pr} and DG_{pl} for each problem. These models cover all the electric vehicles in the urban area with their uncertain behaviour variants of charging including the state of charge in batteries, the charging mode (normal / fast), the charging location, time and rate. All these uncertain properties are considered in the EVs charging model through a probability density function.

The previous impact studies of EVs integration into power system, used models in which considers only one or limited number of parameters. In some cases with more numbers of parameters, the uncertainties of power system or EVs variants are neglected or considered as constant. The proposed model in this chapter takes into account various parameters with their uncertainties including power system, EVs, drivers behavieurs and traffic curves parameters.As such, these classifications do not provide enough information to the distribution service providers.

Chapter 1 shows general aspects of power system, smart grid challenges, EVs charging parameters, batteries and other storage devices, EVs inside power system architectures. Chapter 2 recalls modeling the uncertainties in power system,EVs charging parameters modeling, power flow calculations and Monte Carlo Simulations (MCS) and finally presents modeling of power system and EVs parameters based on a case study. Chapter 3 is dedicated to the proposed models in EVs integration into power system impact study. A comprehensive model of uncertainties in EVs, power system and drivers behavieurs is proposed and tested on the case study from Chapter 2. In Chapter 4, fast charging stations for electric vehicles planning, is studied. A stochastic method based model for finding the optimal location for installing fast charging stations is proposed. The Conclusions are presented, highlighting the originality of the work. In Chapter 5, reciprocal impact of electric vehicles and distributed generation of energy simultaneously integration into power system is investigated. Two proposed model based on heuristic method and Particles Swarm Optimization method are presented. These models find the maximum EV_{pr} and DG_{pl} increase in the grid.

Two models are tested on the case study and results are compared.

Chapter 1

Power System, Electric Vehicles and Smart Grid General View

Emergency need for reducing the air pollution, especially in urban areas, have promoted the policy makers to reduce the transportation sector dependency on fossil fuels. The increase of electric vehicle (EV) in the current and next automobile generations necessitates more attention to the impact study of electric vehicles charging in large scales on power system.

Power system elements and structures, either transmission or distribution systems, are designed in order to support the actual power demand and loads. EVs Integration into the actual power system in large scales is a new challenge for configuration of the power demand and the generation plan. Power system constraints including voltage drops on bus voltages and power flow in branches should be taken into account to ensure energy security in the grid.

1.1 Power system and new energy paradigm general view

This power network ensures the quality and continuity of the supply. Quality factors includes respect of voltage ranges, limitation of imperfections such as harmonics, supply continuity, number and duration of power-outages.

1.1.1 Conventional power system main parts

The conventional electrical networks are consist of four levels from the structure of the global electrical system point of view [HS12]:

- *Power generation*: are generally large units installed in power plants. Depending on the source of power, power plants can provide energy to power grid with energy from nuclear fuel, carbon sources or large renewable power generation.

- *The transmission system*, is the interface between large power plants and large consumption centers or other sub-transmission and distribution systems.

- *Distribution grid*: which allows power transferred from transmission grid to be distributed between end user named sometimes the "customer". They are connected to the transmission grid through "interface buses" called "substations" via transformers. Distribution grids are generally operated in radial structures for economic reasons and simplicity of operation.

- *End users* are mostly passive customers characterized by "non-controlable" loads and do not contribute to power system management.

Figure 1.1 depicts a schematic diagram of traditional power network. Unidirectional power flow is shown in this figure.

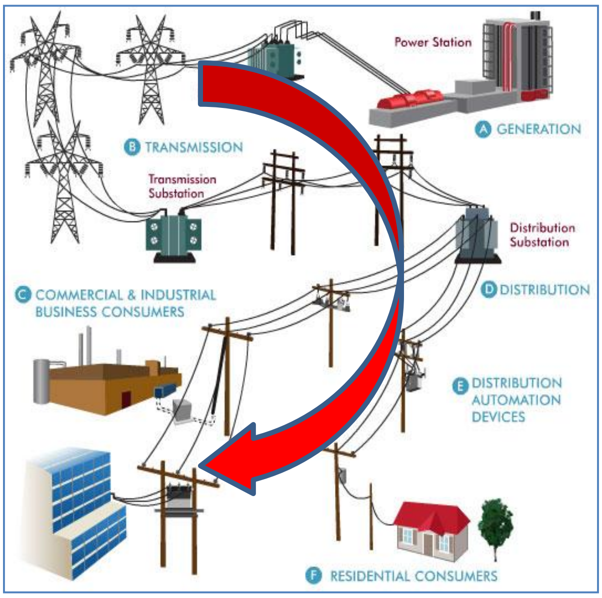

Figure 1.1: Unidirectional power flow in conventional power system.

1.1.2 Smart grid of energy and new challenges

The electrical grid is facing significant changes that will lead to a significant increase in the complexity of the system. In fact, until now electricity was very predictable, going from large power plants to large electricity transmission grids, then to the distribution grids to supply customers. The direction of the flow was predictable. With the development of distributed generation, a significant proportion of generation is connected to the distribution grid. Furthermore, the means of distributed generation are mainly wind and solar power stations, whose generation varies depending on the wind and sun. It is therefore possible, for example, to have a generation greater than the local consumption in the middle of the afternoon in a housing development where there are many solar panels, at a time when people are at work or school and when the panels produce at their maximum rate. There will therefore temporarily be an electricity flow that will return a higher voltage to the grids. At night the flow returns to its usual direction. There are therefore varying directions of flow.

1.1.2.1 The distribution system operator and smart grid

The distribution grid is at the center of the emerging smart electrical system and the role of distribution system operators (DSO) is facing a real revolution. Operators should be ready to encounter technical complexity in power grid. Furthermore they should limit the sudden rise in costs and ensure the quality of service expected by customers.

Distribution grid constitute around two third of the network costs. Beside, a third are allocated to the transmission grid . Network costs make around a half of electricity bill paid by customers.

Therefore, distribution system operators have significant challenges and it is essential to regard the distribution grid when designing the future power system. The distribution grid will move forward, as it will have significant consequences for customers.

The future power grids are affected by four main new events including distributed generation, active demand management, means of storage connected to the distribution grid and finally development of new uses, new heat pumps and electric vehicles. These four new challenges will lead to increase the complexity of the system. They will form a system whose management will require much more intelligence than in the past. The distribution system operator is at the center of the transformations[Mal12]:

- 95% of wind and solar power stations are connected to the distribution grid;
- 100% of charging stations for electric vehicles will be connected to the distribution grid; and

- The distribution system operators implement and operate the smart meters and maintain and supply the actors in the market with the messes of data obtained.

Smart grids and systems will provide customers with the development of new services. Customers will be able to receive precise information about their consumption: quantity, cost and even the carbon content of the energy consumed. Warning devices will be in place for when the agreed consumption threshold is exceeded. Customers will also be able, if they wish, to compare their consumption with customers of a similar profile.

The distribution system operator is at the heart of the emergence of these new services: they are the ones who will store and provide different actors with the data collected by the meters.

Figure 1.2

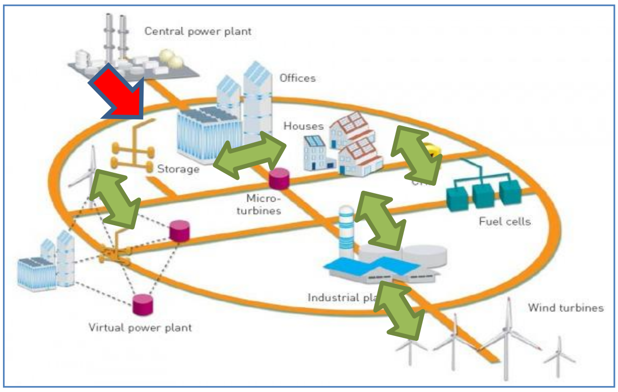

Figure 1.2: Bidirectional power flow in smart grid.

1.1.2.2 Distributed storage

The possible appearance of distributed means of storage is another evolution of the electrical system. In fact, the need for flexibility to compensate for the intermittent nature of wind and photovoltaic energy could lead to the installation of such means of storage. Today this evolution is limited by the price of these devices, which are much more expensive than the simple reinforcement of the MV or LV grid. But their price could drop, especially considering the magnitude of research made worldwide on the subject. In fact, the means of storage connected to the distribution grid are likely to add value to the off-grid demand and supply balance as well as for the resolution of congestion on distribution and transmission grids. The definition of the business model allowing a actor to construct and use these installations by integrating all these sources of value remains to be established[Mal12].

1.1.2.3 Active demand management

Development of active demand management is another significant evolution of the electrical system. Smart Grids actually make it possible for customers to act on their power consumption in their home. This can either lead to deferring consumption to peak hours, when the carbon content per kWh is less, or to reduce energy consumption.

For residential customers, it is possible to act, for example, on water heaters, radiators or air conditioning, household appliances, etc. these efforts can be made on the customers initiative or be implemented by their supplier within the bounds of their contract, or can even be controlled by a grid operator. New actors (aggregators, various providers of service or advice, etc.) are likely to emerge.

1.1.2.4 Smart grid and Electric Vehicles

1.1.2.5 Smart grid advantages; operation, services and metering

The use of sensors, communication networks and software for processing data that have been collected can allow for the replacement of regular preventive maintenance with targeted maintenance before the equipment fails. The maintenance and renewal policies will thus be defined according to the history of each component. In the event of a generic fault, it will be possible to efficiently locate and replace the components concerned.

Advances in information and telecommunication systems have enabled the conduct and operation of the system to be more responsive and for instance: to implement incident analysis and automatic service recovery functions. To accurately locate the faults so the teams can be sent directly to the place where they need to operate. To communicate with the teams on site and optimize their organization, particularly by integrating optimized route planning.

Smart meters, whose implementation has been promoted, are a central element in Smart Grids. “Linky smart meters in France [ERD], is an example of the national projects in smart meters and communication infrastructure in distribution network. In Linky meters, The chosen technical solutions in terms of telecommunication are the power line communication (PLC) on the LV network and GPRS (wireless) for connections between MV/LV substations and the central data-processing agency for meter data. Concentrators will be installed in MV/LV substations. It must first be emphasized that smart meters provide the customers with new services. First, meter reading without inconvenience. With smart meters, it will no longer be necessary to go to the customers home, which will make customers lives much simpler. Then, all bills will be created on the basis of actual consumption.

With Linky it is possible:

- To more finely target investment: by knowing the consumption precisely, it is possible to determine which structures to strengthen;
- To follow the quality of service provided to customers and identify the customers who are poorly supplied;
- To locate faults on high voltage (HV) lines and therefore send teams there more quickly, where they can intervene. This will reduce the duration of power-cuts;
- To observe the LV network and in the case of an incident know where customers have been cut off;
- To know whether it is the grid or the installation in the customers home that has broken down when a customer calls us to say that they have no power.

1.1.3 Power system and distributed generation of energy

The development of distributed generation is certainly the first means of change. By 2020 the targets within the French energy policy expect to activate up to 19 GW of (on-shore) wind power and 5.4 GW of photovoltaic power. The wind and photovoltaic generation installations are currently, in the overall majority of cases, connected to the public distribution network. Most of the planned developments should also be connected to this grid, at least for photovoltaic power. The development of renewable power generation facilities is significantly modifying how the electrical system operates.

Three main factors influence the occurrence and intensity of constraints [Mal12]:

- The impact on the grid is stronger when the generation is not correlated with consumption (which is often the case for photovoltaic power);
- The need for investment is greater when development occurs in low density areas where the transmission and distribution grids are of limited capacities (this situation is often encountered in wind farms that are located where the population density is smaller); and
- The extent of the grid adaptations required for the insertion of small LV facilities is highly dependent on their level of concentration.

For wind farms, whose development has occurred gradually over the past five years, we now have proven solutions. For photovoltaic power plants, however, the development is much more recent, and poses significant challenges, particularly for the management of the voltage plan. In fact, the LV grid was not designed to accommodate the generation and we lack sensors and the means to control this grid. Solutions exist and are used, but we still have more work to do to improve the insertion of power plants.

1.2 Electric vehicles different types according to internal architectures, energy, charging and batteries

1.2.1 Electric, Hybrid, Plug-in Hybrid vehicle

Different types of small Electric Vehicles (EVs) could be summarized in these categories; battery electric, fuel cell, standard hybrid and plug-in hybrid. These categories include only small vehicles while some public vehicles like buses and service vehicles are not included in these categories.

- Battery Electric Vehicles (BEVs), run exclusively on electricity via on-board batteries that are charged by plugging into an outlet or charging station.
- Fuel Cell Electric Vehicles (FCEVs) use an electric-only motor like a BEV, but stores energy quite a bit differently. Instead of recharging a battery, FCEVs store hydrogen gas in a tank.
- Conventional Hybrids Electric Vehicles (CHEVs) combine both a gasoline engine with an electric motor. While these vehicles have an electric motor and battery, they cant be plugged in and recharged. Instead their batteries are charged from capturing energy when braking.
- Plug-In Hybrid Electric Vehicles (PHEVs) are similar to conventional hybrids in that they have both an electric motor and internal combustion engine, except PHEV batteries can be charged by plugging into an outlet [Bur07],[Pil13].

Both battery electric vehicles and plug-in hybrid electric vehicles are hereafter referred to as electric vehicles, or EVs. [EEM04]

1.2.2 Electric vehicles and different architectures inside

1.2.2.1 Distribution system architecture of EVs

The conventional electrical system in an automobile can be divided into the architectural elements of energy storage, generation, starting, and distribution. Electrical distribution systems provide electrical power to connected consumers including ignition, interior and exterior lighting, electric motor driven fans pumps and compressors, and instrumentation subsystems. In order for the power available at the sources to be made available at the terminals of the loads, some organized form of distribution throughout an automobile is essential. At present, most automobiles use a 14V DC electrical system. Figure 1.3 shows the conventional electrical distribution system for automobiles. This has a single voltage level, i.e., 14V DC, with the loads being controlled by manual switches and relays [MERE99] [Kas96]. Because of the point-to-point wiring, the wiring harness is heavy and complex.

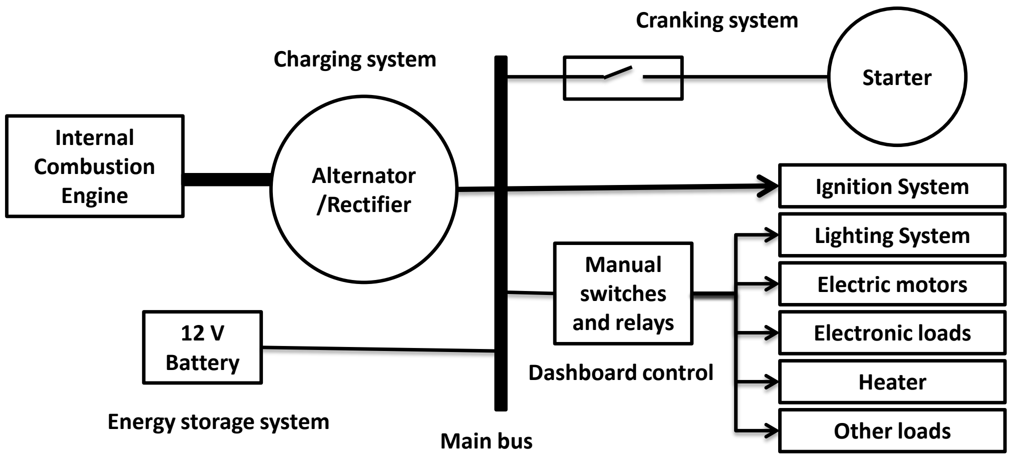

Figure 1.3: Conventional 14 V DC distribution system architecture.[EEM04]

In more electric cars (MEC), there is a trend towards expanding electrical loads and replacement of more engine driven mechanical and hydraulic systems with electrical systems. These loads include the well-known lights, pumps, fans, and electric motors for various functions.

Figure 1.4 shows electrical loads in MEC power systems. As is described in [MN98] [MERE99], most of the future electric loads require power electronic controls. In future automobiles, power electronics will be used to perform three different tasks. First task is simple on/off switching of loads, which is performed by mechanical switches and relays in conventional cars. Second task is the control of electric machines. Third one is not only changing the system voltage to a higher or lower level, but also converting electrical power from one form to another using DC/DC, DC/AC and AC/DC converters [EEM04].

Due to the increasing electrical loads, automotive systems are becoming more electric. Therefore, MEC will need highly reliable, fault-tolerant, autonomous controlled electrical power systems to deliver high quality power from the sources

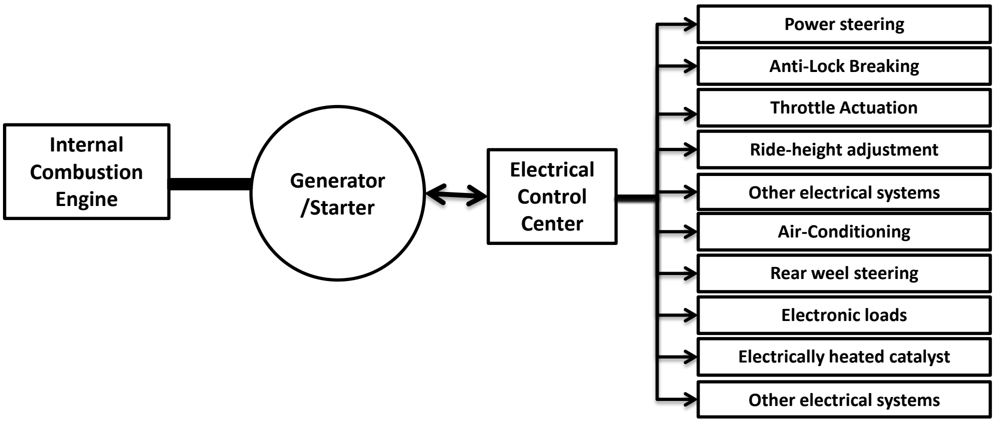

Figure 1.4: Electrical loads in in the MEC power system.[EEM04]

to the loads. The voltage level and form in which power is distributed are important. A higher voltage, such as 42V, will reduce the weight and volume of the wiring harness, among several other advantages [JMMJ98], [MN98]. In fact, increasing the voltage of the system, which is 14V in the conventional cars, is necessary to cope with the greater loads associated with the more electric environments in future cars. The near-future average power demand is anticipated to be 3KW and higher. Figure 1.5 shows the concept of a dual-voltage automotive power system architecture of the future MEC. Indeed, it is a transitional two-voltage system, which can be introduced until all automotive components evolve to 42V. Finally, the future MEC power system will most likely be a single voltage bus (42V DC) with a provision for hybrid (DC and AC), multi-voltage level distribution and intelligent energy and load management.

1.2.2.2 Architectures of Hybrid Electric Drivetrains

Due to the environmental concerns, there is a definite development towards new propulsion systems for future cars in the form of electric and hybrid electric vehicles (EV and HEV). Electric vehicles are known as zero emission vehicles. They use batteries as electrical energy storage devices and electric motors to propel the automobile. Hybrid vehicles combine more than one energy source for propulsion. In heat engine/battery hybrid systems, the mechanical power available from the heat engine is combined with the electrical energy stored in a battery to propel the vehicle. These systems also require an electric drivetrain to convert electrical energy into mechanical energy, just like in an EV.

Hybrid electric systems can be broadly classified as series or parallel hybrid

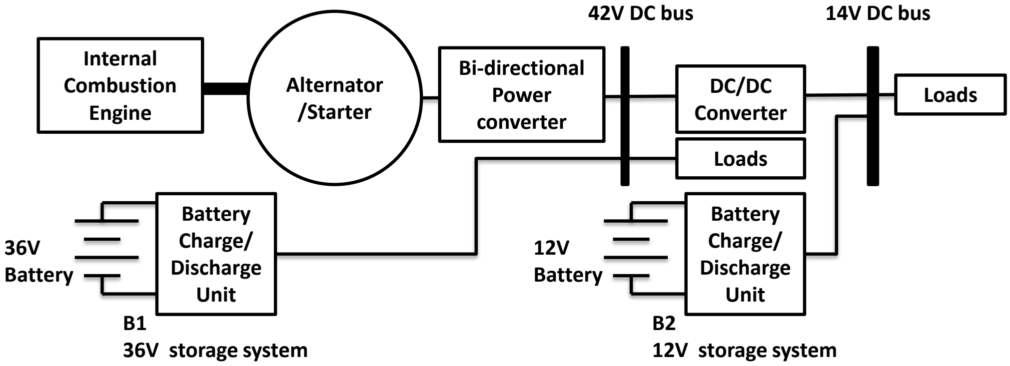

Figure 1.5: The concept of a dual voltage automotive power system architecture of the future MEC.[EEM04]

systems [Cha93], [ERT97]. The series and parallel hybrid architectures are shown in Figures 1.6 and 1.7, respectively. In series hybrid systems, all the torque required to propel the vehicle is provided by an electric motor. On the other hand, in parallel hybrid systems, the torque obtained from the heat engine is mechanically coupled to the torque produced by an electric motor. In an EV, the electric motor behaves exactly in the same manner as in a series hybrid. Therefore, the torque and power requirements of the electric motor are roughly equal for an EV and series hybrid, while they are lower for a parallel hybrid.

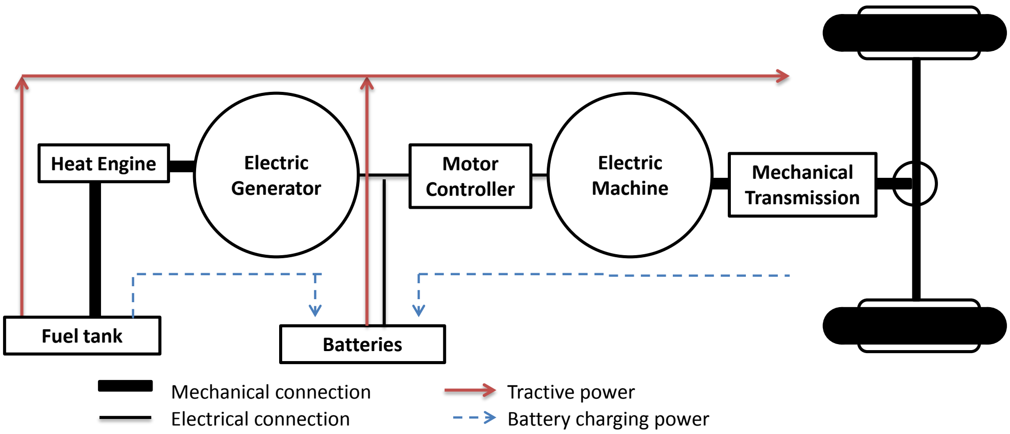

Figure 1.6: Series HEV architecture [EEM04].

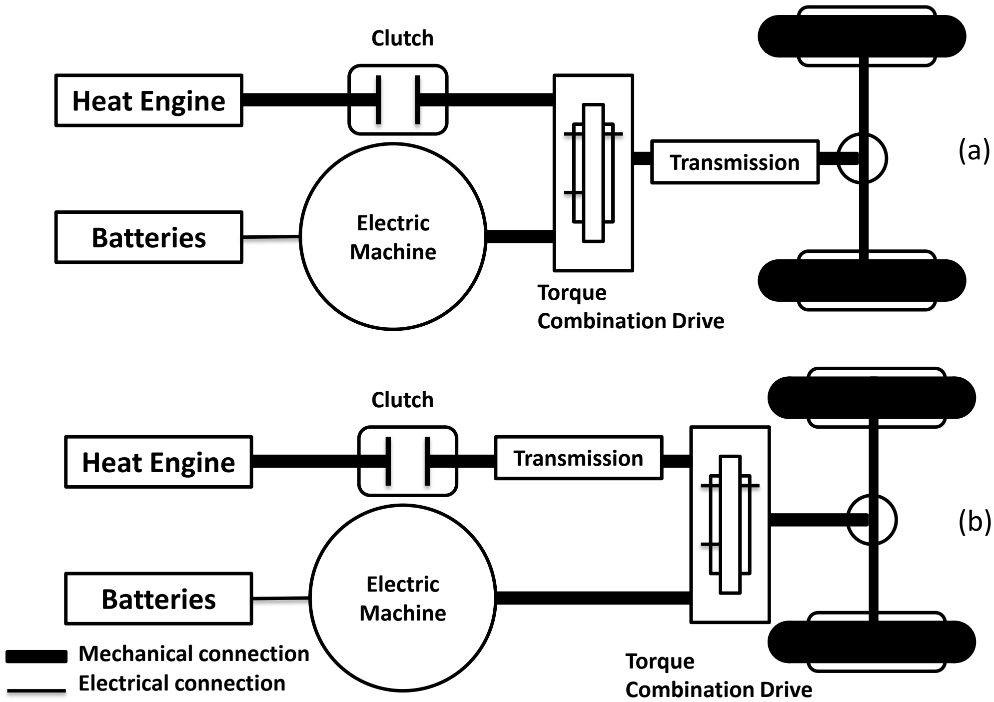

Figure 1.7: Parallel HEV architecture: (a)engine-motor-transmission configuration, (b) engine-motor-transmission configuration [EEM04].

1.2.2.3 Practical models of architectures in Hybrid Electric Drive-trains

Most practical models try to combine the benefits of the control strategies defined above. This is similar to the manner in which a series-parallel hybrid uses the advantage of both the series and parallel setups. Therefore, the most advanced practical HEVs are series-parallel charge sustaining-depleting models. Below, we explain two of practical control strategies that have been implemented in actual vehicles [A.H85].

Toyota Prius:

The Toyota prius is a full size car. The engine uses a strategy similar to a parallel charge depleting strategy in the sense that the engine turns on only when the car is traveling above 12 mph. However, the control strategy is charge sustaining. In this sense, it is similar to the charge sustaining control strategy. If the battery SoC is below 50%, the engine is loaded so that the battery is replenished to this threshold value. Also, if the SoC is way above 50%, the electric motor is loaded more to bring this value down. The Toyota Prius is optimized for low fuel consumption and extremely low emissions in the “around town” driving scenario. Still, the highway fuel economy is about 38 mpg. Below are the characteristics of the vehicle:

- 1254 kg curb weight
- 52 KW gasoline engine
- 33 KW electric motor
- 6.5 Ah Ni-MH battery pack
  38 modules for total voltage of 237.6 V
  Total power 1778 W-h
  Mass 53.3 Kg

Honda Insight:

The Honda Insight is a 2-seat coupe that uses its 1L engine as the principal power source, with additional power provided by a 10KW electric motor. The control strategy does not allow the engine to idle, but the engine works at all speeds. The Insight is capable of 100 mph speeds while averaging between 60 and 70 mpg overall. Such high fuel economy values are also attributed to the fact that the vehicle is very aerodynamic. Below are the characteristics of the vehicle:

- 856 Kg curb weight
- 50 KW gasoline engine
- 10 KW electric motor
- 6.5 Ah Ni-MH battery pack
  20 modules for total voltage of 144 V
  Total power 936 W-h
  Mass 35.2 Kg

In summary, the choice of control strategy greatly influences the performance, fuel economy, and emissions of a vehicle. In addition, as can be seen from the graphs, series control strategies allow for larger variations in the battery state of charge. This is intuitive since, in series hybrids, all torque is provided by the electric motor. Therefore, it is expected that the battery SoC varies more since the batteries are used more. It is important to notice that all control strategies that have been implemented in actual vehicles are charge sustaining. The reason is that the performance of the vehicle should never be compromised at the cost of better fuel economy.

1.2.3 Battery and other energy storage devices in EVs

This section has dealt with the modeling of three of the major types of energy storage devices, namely, batteries, fuel cells and ultracapacitors.

1.2.3.1 Modeling of Batteries

Precise battery models are required for several applications such as for the simulation of energy consumption of electric vehicles and portable devices, or for power system applications. The major challenge in modeling a battery source is dealing with the non-linear characteristics of the equivalent circuit parameters, which require lengthy experimental and numerical procedures. The battery itself has some internal parameters, which need to be taken care of [KH97]. In this section, a battery thevenin model will be presented.

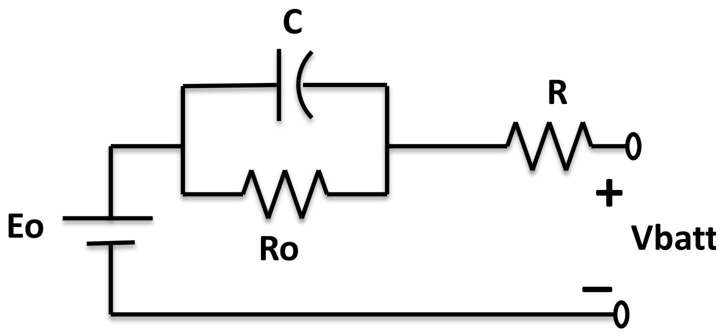

Figure 1.8: Thevenin battery model [EEM04].

The thevenin model of battery consist of electrical values of the open circuit voltage (E_o), internal resistance (R), capacitance (C) and the over voltage resistance (R_o) [KH97],[Cha00]. As observed in Figure 1.8,capacitor C depicts the capacitance of the parallel plates and resistor R_o depicts the non-linear resistance offered by the plate to the electrolyte [Cha00].

In this model, all the elements are assumed to be constants. However, in actuality, they depend on the battery conditions. Thus, this model is not the most accurate, yet it is the most widely used. In this view, a new approach to evaluate batteries is introduced. The modified model is based on operation over a range of load combinations [MLP+01]. The electrical equivalent of the proposed model is as depicted in Figure 1.9.

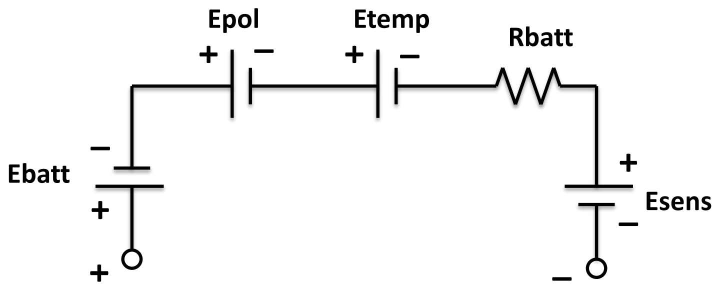

Figure 1.9: Main circuit representation of modified battery model.

As is clear from Figure 1.9, the main circuit model consists of the following five sub-circuits:
E_{batt} : This a simple DC voltage source disignating the voltage in the battery cells.
E_{pol} : It represents the polarization effects due to the availability of active materials in the battery.
E_{temp} : It represents the effect of temperature on the battery terminal voltage.
R_{batt} : This is the battery's internal impedance, the value of which depends primarily on the relation between cell voltage and state of charge (SOC) of the battery[MLP+01].
V_{sens} : This is basically a voltage source wit a value of 0V. It is used to record the value of battery current.

Thus, this simulation model capable of dealing with various models of charge /discharge. It is comparatively more precise and can be extended for use with Ni-Cd and Li-ion batteries, which could be applied to hybrid electric vehicles and other traction applications. only a few application need to be carried out in order to vary the parameters, such as load state, current density and temperature[MLP+01].

1.2.3.2 Fuel Cells

Fuel cells have emerged as one of the most promising technologies for meeting the new energy demands. They are environmentally clean, quiet in operation, and highly efficient for generating electricity. This shining new technology provides the impetus towards a huge market for power electronics and its related applications. This chapter aims at discussing the basic operation of fuel cells for vehicular applications. Furthermore, this chapter covers various types of fuel cell systems and their structures along with their typical power electronic converter topologies. Primarily, power electronics plays a vital role in improving flexibility of utilizing fuel cells in different vehicles.

A fuel cell is typically similar in operation to a conventional battery, although they have some distinct physical differences. Primarily, a fuel cell is an electrochemical device wherein the chemical energy of a fuel is converted directly into electric power [KH97], [?]. The main difference between a conventional battery and a fuel cell is that, unlike a battery, a fuel cell is supplied with reactants externally. As a result, whereas a battery is discharged, a fuel cell never faces such a problem as long as the supply of fuel is provided. As is depicted in Figure 1.10, electrodes and electrolyte are the main parts of a fuel cell. The most popular type of fuel cell is the hydrogen-oxygen fuel cell.

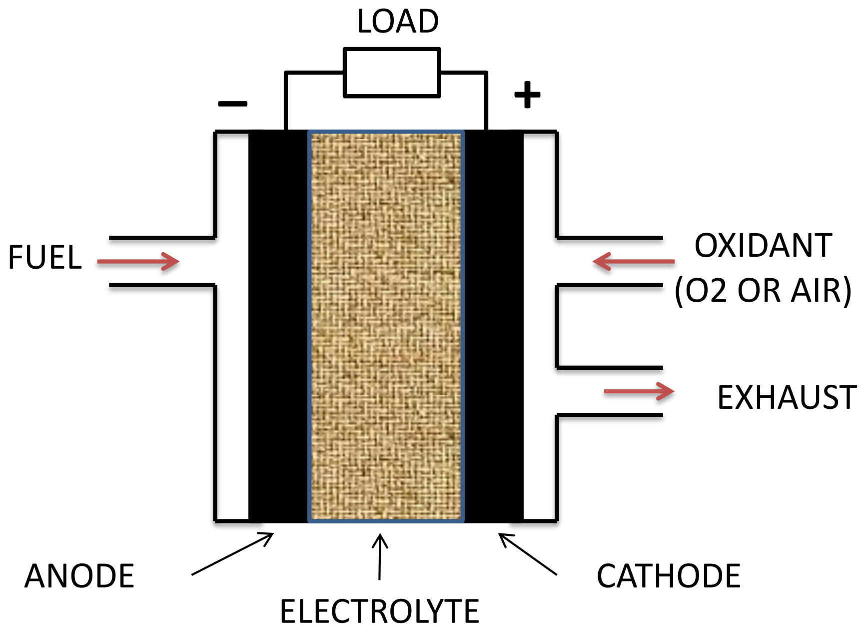

Figure 1.10: Typical schematic diagram of Fuel Cell [EEM04].

The proton exchange membrane (PEM) fuel cell has the potential of becoming the primary power source for HEVs utilizing fuel cells. However, such fuel cell systems are large and complex and, hence, need accurate models to estimate the auxiliary power systems required for use in the HEV. To have a clearer picture of fuel cell model, refer to Figure 1.11, showing the schematic representation of a fuel cell/battery hybrid power system.

The battery pack in Figure 1.11 is used to compensate for the slow start-up and transient response of the fuel processor [JJH+00]. Furthermore, battery can be used for the purpose of regenerative braking in the HEV. Since fuel cell systems are large, complex, and expensive, designing and building new prototypes is difficult [?], [TPV+99]. Therefore, the feasible alternative is to model the

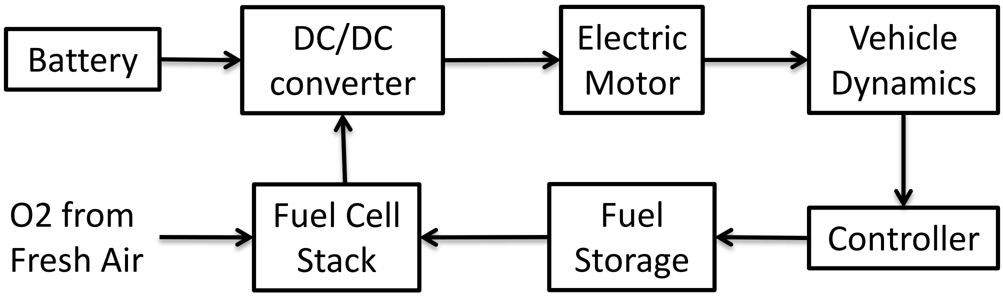

Figure 1.11: Schematic representation of a Fuel Cell/battery power system [EEM04].

system and examine it through simulations. The fuel cell power system consists of a reformer, a fuel cell stack, and a DC/DC (Buck/Boost) or DC/AC power converter. The final output from the power electronic converter is in the required DC or AC form acquired from the low-voltage DC output from the fuel cell stack.

1.2.3.3 Ultracapacitors

Ultracapacitors (also known as super capacitors and double-layer capacitors) work on the electro-chemical phenomenon of a very high capacitance/unit area using an interface between electrode and electrolyte [SN96]. Typical value of such capacitors range from 400 F - 800 F and have low values of resistivity (approximately $10^{-3}\Omega - cm$) [SN96], citeZHJO01. These UCs operate at high energy densities, which are commonly required for applications such as space communications, digital cellular phones, electric vehicles, and hybrid electric vehicles. In some cases, usage of a hybridized system employing a battery alongside the UC provides an attractive energy storage system, which offers numerous advantages. This is particularly due to the fact that the UC provides the necessary high power density whereas the battery provides the desired high energy density.

Combining a battery and a UC to operate in parallel is an attractive energy storage system with many advantages. Such a hybrid systems uses both the high power density of the UC as well as the high energy density of the battery.

Due to the advanced energy storage capabilities of the UC, it can be used for applications requiring repeated short bursts of power such as in vehicular propulsion systems. In a typical scenario, both the battery and the UC provide power to the motor and power electronic DC/AC inverter during acceleration and overtaking, whereas they receive power via regenerative braking during slow-down/deceleration [YP99]. The two most popular topologies for inserting batteries and UCs into drivetrains are as shown in Figures 1.12 (a) and (b).

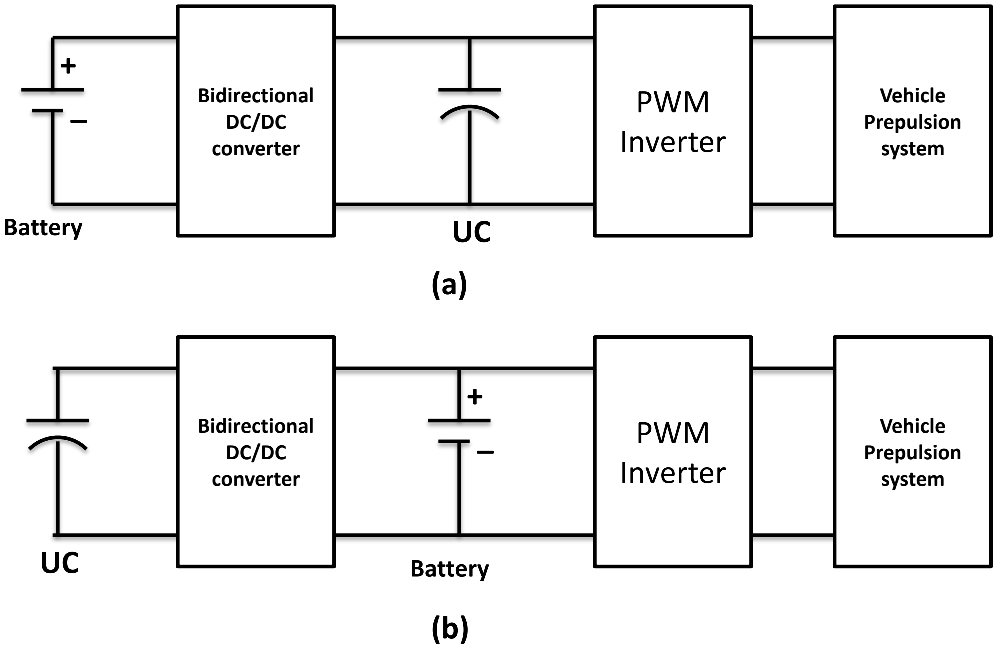

Figure 1.12: Typical topologies of batteries and UCs in drivetrains[EEM04].

1.2.4 Important Properties of Fuel Cells for Vehicles

Various advantages of fuel cells, including reliability, simplicity, quietness of operation, and most importantly low pollution, have made the fuel cells attractive in different low and medium power applications. One such major application is the automotive industry, where all the above-mentioned factors play a vital role. Generally, hydrogen is considered to be the primary fuel to be used for automotive fuel cell based applications. However, due to the danger of carrying hydrogen aboard the vehicle, the automotive industry is considering alternate fuel sources. These alternate fuels are generally natural gases, which can be reformed to get nearly pure hydrogen.

In conventional cars, electric loads are currently about 1.2KW. Hence, small sized batteries are sufficient to supply these loads. But, in the newer cars, known as more electric vehicles (MEVs), electrical systems are replacing mechanical and hydraulic systems. There are also many newly introduced electrical loads, such as electrically assisted power steering, X-by wire, integrated starter/generator, active suspension, and AC power point. Therefore, electrical power in an advanced car can be more than 10kW. As a result, higher voltage batteries, such as the proposed 36V storage system, are required to meet the higher power demands.

On the other hand, hybrid electric vehicles (HEVs) have been developed wherein an electric machine is coupled to the internal combustion engine (ICE) to propel the vehicle. An electric machine is fed from a DC source and its power rating might be up to 80kW. The DC source could be a battery or a fuel cell of suitable capacity. Typical DC link voltage is either about 300V or 140V. Fuel cells could also be considered an advanced version of the battery powered vehicles in automobiles with all-electric drive train.

Fuel cells can be refueled quickly and, at the same time, provide longer operating range. Research result show that the fuel economy of a direct methanol fuel cell vehicle (DMFCV), which is considered the best option for a fuel cell powered car, is approximately 2 times greater than that of a conventional ICE car. In addition, compared to ICE efficiencies of about 10-30%, fuel cells have shown efficiencies ranging between 30-40% for automobile applications. Even higher efficiencies are attainable when fuel cells make use of direct hydrogen as a fuel source. In this case, efficiencies as high as approximately 50% are attainable. Thus, compared to an ICE powered car, the fuel cell car can do about twice the amount of work and, hence, can cover almost double the distance [EEM04].

Chapter 2

Modeling the uncertainties in power system and EVs charging parameters

2.1 EV connection to distribution grid, strategies and modelling

Electric vehicles charging in the power system could be modeled in two dfferent ways. In some studies the overal model is based on studying the connection of one or some limited number of vehicles but it could be a large scale charging of vehicles in other models.

2.1.1 Standards and Guides in electric vehicles

Institute of Electrical and Electronics Engineers (IEEE) has developed several electric vehicle related standards which drive the functionality, capabilities and interoperability of a wide range of products and services.

Standards like IEEE P2030.1 [IEE] for Electric-Sourced Transportation Infrastructure provides guidelines that can be used by utilities, manufacturers, transportation providers, infrastructure developers, and even those who drive EVs to develop and support systems that allow increased use of electric and hybrid vehicles. Another standard called $IEEE1901$ [IEE], specifies the sophisticated modulation techniques required for transmitting data over standard AC power lines of any voltage at transmission frequencies of less than 100 megahertz. The specifications address a wide range of applications, including smart energy, transportation, and local area networks (LANs). For Interconnecting Distributed

Resources with Electric Power Systems, $IEEE1547$ [IEE] highlights interconnections that include both distributed generators and energy storage systems. The series establishes requirements and provides a standard for interconnecting distributed resources with electric power systems and electric and hybrid vehicles. Some other standards like $IEEE802.11$ and $IEEE802.15$ $IEEE802.16$ and $IEEE802.20$ [IEE] focus on wireless connection and communication technologies for data transfer. The WAVE standards ($IEEE1609$ Series) [IEE] define an architecture and a complementary, standardized set of services and interfaces that collectively enable secure vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) wireless communications. Together these standards provide the foundation for a broad range of applications in the transportation environment, including vehicle safety, automated tolling, enhanced navigation, traffic management and many others.

European Standards Organizations provided comprehensive standards for all aspects of electro-mobility which involves vehicles, those responsible for the electrical system and its components, even the ICT community. [CC] These standards are comprehensive and involve connectors and charging systems, electromagnetic compatibility (EMC) of the electric vehicle, smart charging, batteries, communication and regulations.

2.1.2 Single vehicle charging models

For the case in which modelling is based on only one (or some limited numbers of) electric vehicle connection to home considering Vehicle to Home (V2H), driver behaviour, cost reduction and home power constraints are investigated in most of the cases. Cost reduction from the household point of view is the basis of scenarios used in this studies. In this modelling of electric vehicles, to take into account the Vehicle-to-Home (V2H) and Home-to-Vehicle (H2V) capabilities, more emphasis is put on new energy control strategies that has to be developed to avoid new peaks consumption. Some novel controllers like fuzzy logic based controller are applied to integrate an objective State of Charge (SoC) for Vehicle to- Home (V2H) application. In this models, the V2H capability is used when the PHEV is connected to the home to help the grid to meet the household loads during peak period. The SoC objective in this case could be the minimum SoC that the PHEV has to have when the driver connects the PHEV to the home. Different scenarios can be considered in this model to test the proposed controller application. [BBB+11], [FRB+15]. Figure 2.1 shows a schematic figure of charging a single EV at home.

In this model a control center at home power control center is placed in which all contacts and communication signals from power grid control center are integrated. Power grid control center is connected to home control center via the

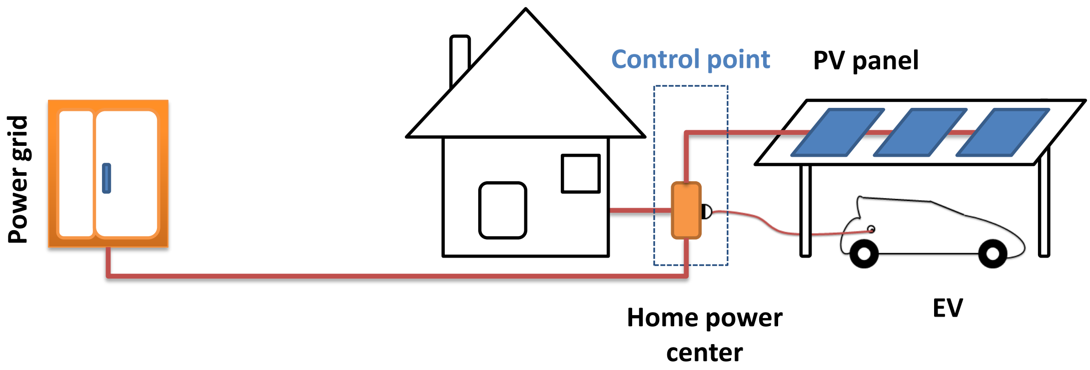

Figure 2.1: A schematic figure of connecting single vehicle to home.

distribution grid control centers.

All other electrical components including power loads and generation units like Photovoltaic panels or other types of sources of energy at home should be connected to home power center. In addition, this power control system is a center in which all communication signals of control scenarios are sent to loads and generation units.

Control strategies of power distribution for all normal loads like lighting, washing machines, refrigerator, cooling and heating system are integrated in this control system.

The aim of the home power control is to figure out which energy fits the best for its electrical consumption. There exists a choice between the renewable energy source, the grid, or the electric vehicle battery.

Some common pros and cons of all studies based on this modelling are summarized here:

Advantages:

1. From the households point of view, these models can be applied to satisfy better all requirement in energy control like the total energy billing for home including different components like EVs, PVs, ...

2. All different charging scenarios for a particular household with specified EV, home load profile and household and driver behaviour can be studied in these models in order to select the best scenario for a particular case.

3. This models could be applied in some cases with no need to future technological improvements. Most of the requirements seem to be covered by the current technologies like Smart Home, Internet of Things(IoT), ...

Disadvantages:

1. Number of electric vehicles are limited, in most cases one electric vehicle.
2. Number of homes are limited, in most cases one home.
3. Electric characterization of vehicles is imposed to be limited because of EVs number so this models can not cover all kind of EVs.
4. Vehicle driver behaviours are imposed to be limited because of EVs number, so these models cannot cover all drivers behaviours.
5. Parking location which is an important parameter in EVs charging is imposed to be fixed by this models, so they can not cover the diversity in parking for all drivers.
6. Traffic data are not considered in this models.
7. From the power system point of view, only some limited constraints like peak period are considered by households. All other constraints of the grid cannot be studied in this models.

An example [BBB+11] of this type of modelling is in minimizing the energy cost for a Plug-in Hybrid Electric Vehicle in a home in which the cost of three sources are compared in real time: renewable source, grid, and battery. The batterys cost is calculated with the following equation :

$$C_{bat} = \frac{V_f(t)C_f(t) + E_g(t)C_g(t) + C_{bat}(t-1)E_{bat}SOC(t-1)}{SOC(t)E_{bat}} \tag{2.1}$$

Where

V_f is the fuels volume (l),
C_f is the fuels cost (€),
E_g is the grids energy (Wh),
C_g is the grids cost (€/Wh),
C_{bat} is the batterys cost (€/Wh),
E_{bat} is the batterys energy (Wh),
SOC is the batterys State of Charge (%).
All these parameters are given for a given time t.

The objective of the control strategy in the simulation done based on these modelling was to minimize the total energy cost. From this study, the total energy cost savings was found to be 20 %.

2.1.3 Large scale charging models

For the cases in which modelling is based on a large scale charging of electric vehicles in the grid, the model is different and parameters are generally figured out to fit a larger number of electric vehicles with a vast diversity in characters .

As mentioned in the previous section, a major part of disadvantages in single EV model comes from missing of diversity in the characters in model which could be removed by taking into account a larger diversity of characters in EVs by the proposed model in this section.

Power grid's constraints like Over Load (OL) in branches, Under Voltage (UV) and Over Voltage (OV) at buses are provoked by power system's suppliers. In addition some other factors like power quality should also be regarded at any cases by power system controllers. All these constraints require a model to cover EVs charging in large scale.

The second type model is basically constructed on the base of these facts to satisfy both vehicle driver behaviour and power system constraints together in the one model. Figure 2.2 shows a schematic diagram of this model. In this model, distributed generation including Photo Voltaic (PV) panels and wind power generation are considered as shown. PV power generation could be installed either at home or in a centralized PV power plant as shown in the figure.

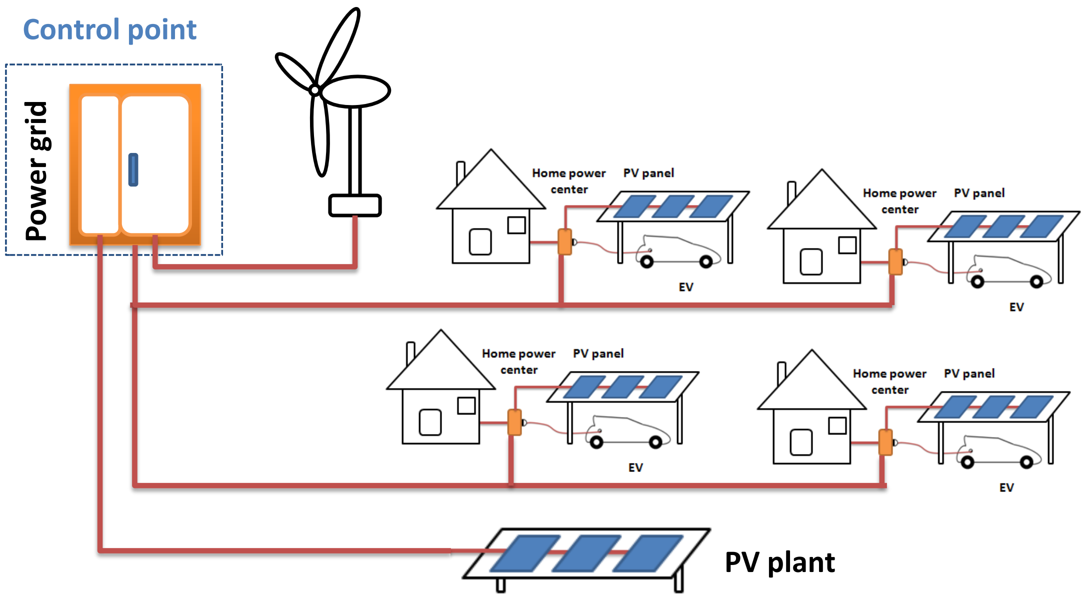

Figure 2.2: A schematic of EVs large scale integration into power grid model

In order to study the impact of increase in Electric Vehicles Penetration Rate (EV_{pr}) on power system, this model which is based on large scale connection of EVs to distribution grid seems to be more appropriate to be applied. Power system constraints are evaluated with increasing in the number of EVs connected to the grid to achieve the maximum value of EV_{pr} depending on the power system constraints. Some common pros and cons of all studies based on this modelling are summarized here:
Advantages:

- From the power system's point of view, these models can be applied to satisfy better all requirements in energy control required in charging EVs in the region.
- Power system constraints can be considered in these models.
- With larger number of EVs, a higher diversity in the parameters like driver behaviour, EVs characters and parking location could be guaranteed.
- Traffic data can be considered in these models.

Disadvantages:

- As the parameters are different for each EV, a huge amount of data enters in simulations. These data cannot be applied by the model via the simple methods and need a more complicated strategies to cover all these data. Some mathematical methods are applied in these modelling.
- Control points in the distribution grid need to have data transfer with all EVs, power loads and generation units in real time but the current power grid condition does not support such facilities. So the grid needs to be smarter.

Each model has its advantages and disadvantages as mentioned above. Selecting a model depends on the problem we want to solve. One model which is used for a specific purpose may not be useful for all other purposes.

Generally, the household and power grid points of views are two major factors in selecting the model. For the studies based on the household point of view, the first model and for the cases based on power grid the second one are appropriate.

2.2 Fast and normal charging methods

Two charging method are defined for charging EVs. These two method could be selected for charging an EV based on three parameters. According with these three parameters including the location in which EVs are parked, the possibility of connection and driver decision, EVs could be charged either in a normal or fast charging method. Charging location for example at station, home or work, are important in selecting the method of EVs charging. These charging locations are discussed in next sections. Two definitions of charging method are described here. It should be mentioned that some locations, charging is limited to only one of these method. For example, an EV at charging station is allowed to be charged only in fast charging method. these limitations are explained in scenarios and modelling of EV connection to grid in the next chapters.

2.2.1 Normal charging method

Normal charging method is a method of charging in which EV has enough time to stay in contact with grid for a period of time. For example, in this section, we supposed four hours for normal charging. EVs charging could be postponed for some hours. This case is more related to the "at home location of charging. We assumed that four hour is enough for charging EVs in this method.

With four hours of charging for normal method, the total energy in time t depends on the conditions of EVs in past three hours and the condition of EVs in the current time.

Figure 2.3 demonstrates a schematic diagram to show this dependence in charging.

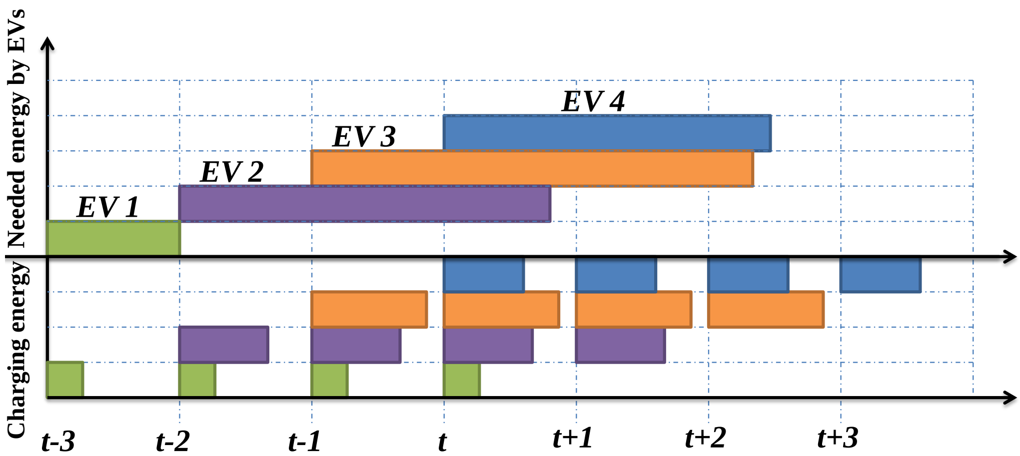

Figure 2.3: Normal charging method for charging four EVs.

We supposed four EVs for each time on top side. In all models of EVs charging in the next sections, EVs maximum and average differences in SOC are the base of scenarios. These values could be constant for all EVs or be specified by a random allocation. Based on these specifications, for all EVs, the values of energy required for charging is specified. These values are modeled with the length of bars in figure. In this figure, these values are supposed to be constant for all EVs.

In bellow side for each time interval, the distribution of energy in charging process is shown. At time t a quarter of needed energy at times $t-1$, $t-2$ and $t-3$ should be considered in charging power rate. Hence the added power to bus i at the given time t with total $EV_n(t)$ numbers is:

$$P_{EV(i,t)} = \sum_{j=1}^{EVn(t)} P_{EV(i,t,j)} \tag{2.2}$$

$$P_{TotalEV(i)} = \sum_{t=-3}^{0} \frac{P_{EV(i,t)}}{4} \tag{2.3}$$

With:
$P_{TotalEV(i)}$: Total added power to bus i.
$EVn(t)$: Total EVs number connected to bus i at time t.
$P_{EV(i,t,j)}$: EV charging power at time t in bus i, for vehicle j.
$P_{EV(i,t)}$: Total EV needed charging power at bus i at time t.

2.2.2 Fast charging method

Battery specifications including capacity of energy for all EVs are the same as normal charging method. All batteries are supposed to have fast charging possibility. Figure 2.4 demonstrates a schematic diagram of charging in fast method.

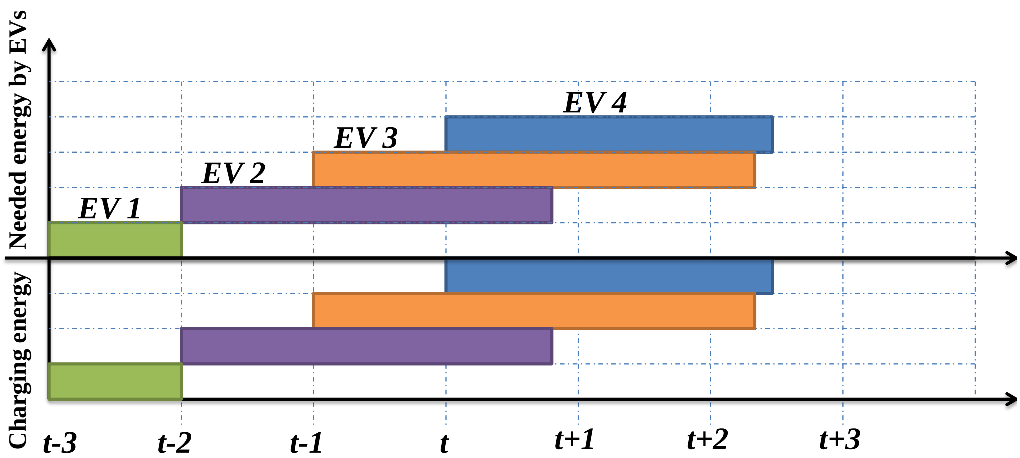

Figure 2.4: Fast Charging method for charging four EVs.

In this schematic figure, we assumed one hour for fast charging duration. For a given time t, total needed power to charge EVn vehicles at bus i depends only on the connected EVs to this bus at time t. This allocation is represented in this equations:

$$P_{EV(i,t)} = \sum_{j=1}^{EVn(t)} P_{EV(i,t,j)} \tag{2.4}$$

$$P_{TotalEV(i)} = P_{EV(i,t)} \tag{2.5}$$

With:
$P_{TotalEV(i)}$: Total added power to bus i.
$EVn(t)$: Total EVs number connected to bus i at time t.
$P_{EV(i,t,j)}$: EV charging power at time t in bus i, for vehicle j.
$P_{EV(i,t)}$: Total EV needed charging power at bus i at time t.

2.2.3 Strong and average EVs charging plan

To evaluate the effect of EVs connection to power grid, the SOC of EVs at arriving and leaving time to/from the parking location is important. These SOCs are applied in modelling the required energy for EV charging. This energy which should be supplied by the grid, determines the power of EV load according with a specified charging model. This load is added to the power demand at the busbar point. Based on the combination of fast and normal charging methods, we suppose two plan for charging EVs; strong and average EV charging plan.

- *Strong EVs charging plan*; in this plan we study en extremely high charging rate. SOC difference in incoming and outgoing EVs is the maximum possible range. This case can show the conditions in which EVs charging is in the highest level. So we can assess the worst possible case of connection EVs to the grid.

- *Average EVs charging plan*; in this plan EVs power rate is in a middle condition. SOC difference in incoming and outgoing EVs is the average of the maximum and minimum possible SOC. With connecting EVs in this condition, we expect to see an image of the general effect of EVs connection to the grid in the average condition.

2.3 Modeling of power system components

In order to be applied in power flow analysis, models of the most common network elements are derived in this section. All analysis in the engineering sciences starts with the formulation of appropriate models. A model is a set of equations or relations, which appropriately describes the interactions between different quantities in the time frame studied and with the desired accuracy of a physical or engineered component or system. Hence, depending on the purpose of the analysis different models of the same physical system or components might be valid. It is recalled that the general model of a transmission line was given by the telegraph equation, which is a partial differential equation, and by assuming stationary sinusoidal conditions the long line equations, ordinary differential equations, were obtained. By solving these equations and restricting the interest to the conditions at the ends of the lines, the lumped-circuit line models (π -models) were obtained, which is an algebraic model. This gives us three different models each valid for different purposes. In principle, the complete telegraph equations could be used when studying the steady state conditions at the network nodes. The solution would then include the initial switching transients along the lines, and the steady state solution would then be the solution after the transients have decayed. However, such a solution would contain a lot more information than wanted and, furthermore, it would require a lot of computational effort. An algebraic formulation with the lumped-circuit line model would give the same result with a much simpler model at a lower computational cost. In many engineering studies the selection of the correct model is often the most difficult part of the study. It is good engineering practice to use as simple models as possible, but of course not too simple. If too complicated models are used, the analysis and computations would be unnecessarily cumbersome. Furthermore, generally more complicated models need more parameters for their definition, and to get reliable values of these requires often extensive work.[And08]

2.3.1 Transmission lines and cables modelling

In Figure 2.5 the general distributed equivalent π model of a line section is characterized by the series parameters;
Where
R' = Series resistance/km per phase (Ω /km)
X= Series reactance/km per phase (Ω /km)
and the shunt parameters;
B = Shunt susceptance/km per phase (siemens/km)
G = Shunt conductance/km per phase (siemens/km)

As depicted in Figure 2.5 the parameters above are specific for the line or cable configuration and are dependent on conductors and geometrical arrangements. From the circuit in Figure 2.5 the telegraph equation is derived, and from this the lumped -circuit line model for symmetrical steady state conditions, Figure 2.6 This model is frequently referred to as the π model, and it is characterized

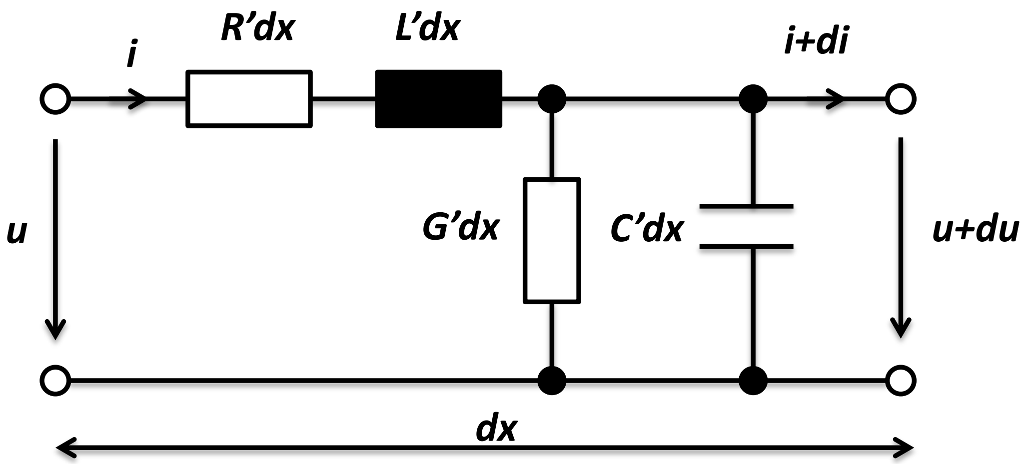

Figure 2.5: Equivalent circuit of a line element of length dx.

by the parameters;

$$Z_{km} = R_{km}+jX_{km} = Seriesimpedance(Y^{sh}_{km} = G^{sh}_{km}+jB^{sh}_{km} = Shuntadmittance(siemens) \tag{2.6}$$

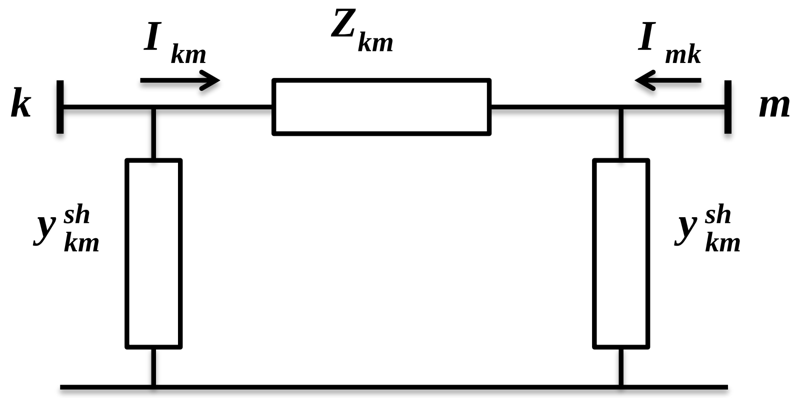

Figure 2.6: π model of a transmission line between nodes k and m.

When formulating the network equations the node admittance matrix will be used and the series admittance of the line model is needed

$$y_{km} = z^{km}_{-1} = g_{km} + jb_{km} \tag{2.7}$$

with

$$g_{km} = \frac{r_{km}}{r_{km}^2 + x_{km}^2} \tag{2.8}$$

and

$$b_{km} = \frac{x_{km}}{r_{km}^2 + x_{km}^2} \tag{2.9}$$

For actual transmission lines the series reactance x_{km} and the series resistance r_{km} are both positive, and consequently g_{km} is positive and b_{km} is negative. The shunt susceptance y_{km}^{sh} and the shunt conductance g_{km}^{sh} are both positive for real line sections. In many cases the value of g_{km}^{sh} is so small that it could be neglected.

The complex currents I_{km} and I_{mk} in Figure 2.6 can be expressed as functions of the complex voltages at the branch terminal nodes k and m:

$$I_{km} = y_{km}(E_k E_m) + y_{km}^{sh} E_k \tag{2.10}$$

$$I_{mk} = y_{km}(E_m E_k) + y_{km}^{sh} E_m \tag{2.11}$$

where the complex voltages are

$$E_k = U_k e^{j\theta_k} \tag{2.12}$$

$$E_m = U_m e^{j\theta_m} \tag{2.13}$$

This can also be written in matrix form as

$$\begin{bmatrix} I_{km} \\ I_{mk} \end{bmatrix} = \begin{bmatrix} y_{km} + y_{km}^{sh} & y_{km} \\ y_{km} & y_{km} + y_{km}^{sh} \end{bmatrix} \begin{bmatrix} E_k \\ E_m \end{bmatrix} \tag{2.14}$$

As seen the matrix on the right hand side of equation 2.14 is symmetric and the diagonal elements are equal. This reflects that the lines and cables are symmetrical elements [And08].

2.3.2 Transformers modelling

We will start with a simplified model of a transformer where we neglect the magnetizing current and the no-load losses. In this case the transformer can be modelled by an ideal transformer with turns ratio tkm in series with a series impedance z_{km} which represents resistive (load-dependent) losses and the leakage reactance, see Figure 2.7. Depending on if t_{km} is real or non-real (complex) the transformer is in-phase or phase-shifting.

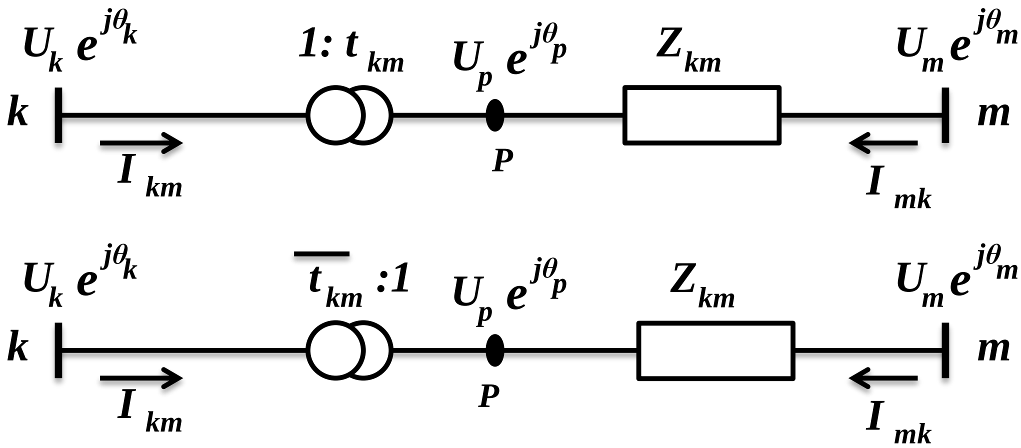

Figure 2.7: Transformer model with complex ratio $t_{km} = a_{km}e^{j\varphi km}$.

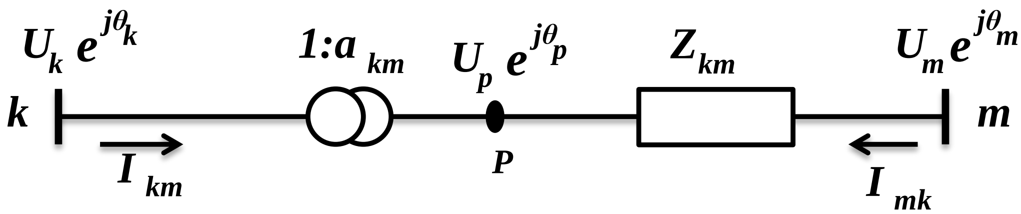

Figure 2.8: In-phase transformer model.

2.3.2.1 In-Phase Transformers

Figure 2.8 represents the equivalent π model for the in-phase transformer. Parameters A, B, and C of this model can be obtained by identifying the coefficients of the expressions for the complex currents I_{km} and I_{mk} associated with the models are;

$$\frac{U_p}{U_k} = a_{km} \tag{2.15}$$

Since $\theta_k = \theta_p$, this is also the ratio between the complex voltages at nodes k and p,

$$\frac{E_p}{E_k} = fracU_p e^{j_p} U_k e^{j_k} = a_{km} \tag{2.16}$$

There are no power losses (neither active nor reactive) in the ideal transformer (the $k-p$ part of the model), which yields

$$E_k I_{km}^* + E_p I_{mk}^* = 0 \tag{2.17}$$

Then applying equations 2.16 and 2.17 gives

$$fracI_{km} I_{mk} = frac|I_{km}||I_{mk}| = a_{km} \tag{2.18}$$

which means that the complex currents I_{km} and I_{mk} are out of phase by 180° since $a_{km} \in R$.

Figure 2.9 represents the equivalent π-model for the in-phase transformer in Figure 2.8. Parameters A, B, and C of this model can be obtained by identifying the coefficients of the expressions for the complex currents I_{km} and I_{mk} associated with the models of Figures 2.8 and 2.9.

$$A = a_{km} y_{km} \tag{2.19}$$

$$B = a_{km}(a_{km} 1) y_{km} \tag{2.20}$$

$$C = (1 a_{km}) y_{km} \tag{2.21}$$

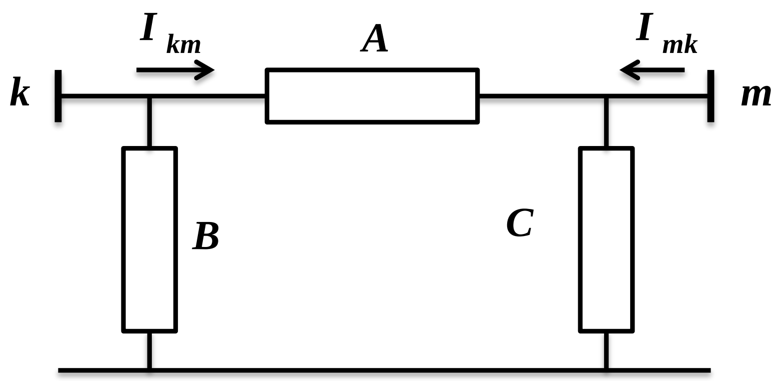

Figure 2.9: π model of a transmission line between nodes k and m.

2.3.2.2 Phase-Shifting Transformers

Phase-shifting transformers, such as the one represented in Figure ??, are used to control active power flows; the control variable is the phase angle and the controlled quantity can be, among other possibilities, the active power flow in the branch where the shifter is placed.

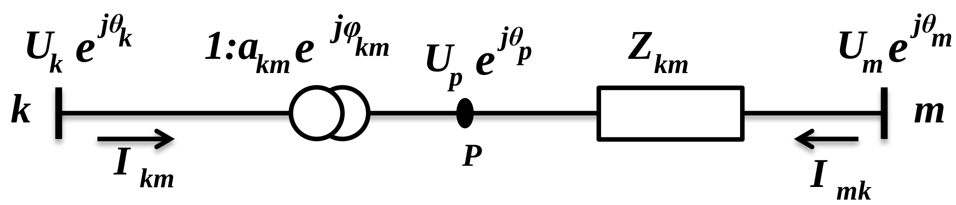

Figure 2.10: π model of a transmission line between nodes k and m.

A phase-shifting transformer affects both the phase and magnitude of the complex voltages E_k and E_p, without changing their ratio.

There is no way to determine parameters A, B, and C of the equivalent π model from the equations like the mentioned equation in last section. A phase shifting transformer can thus not be represented by a π model.

2.3.2.3 Unified Branch Model

The expressions for the complex currents I_{km} and I_{mk} for both transformers and shifters derived above depend on the side where the tap is located; i.e., they are not symmetrical. It is however possible to develop unified complex expressions which can be used for lines, transformers, and phase-shifters, regardless of the side on which the tap is located (or even in the case when there are taps on both sides of the device). Consider initially the model in Figure 2.11 in which shunt elements have been temporarily ignored

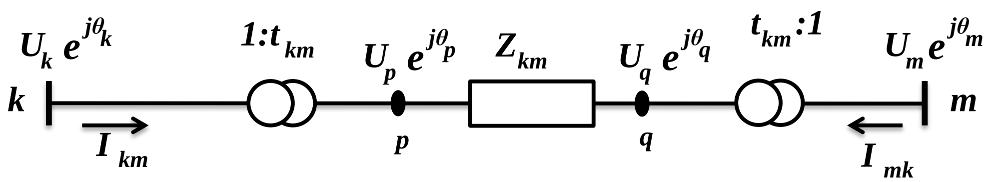

Figure 2.11: Transformer symmetrical model.

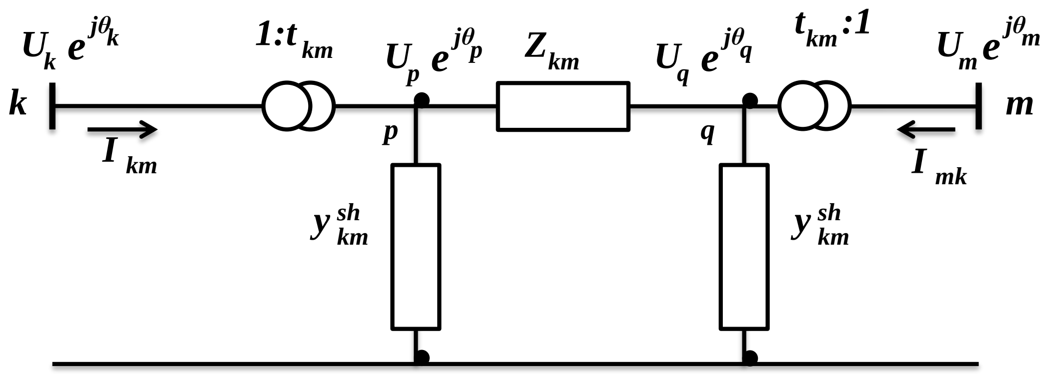

Figure 2.12: Unified branch model extended (π -model).

Figure 2.12 shows the unified branch model. All the devices studied above can be derived from this general model by establishing the appropriate definitions of the parameters that appear in the unified model. Thus, for instance, if $t_{km} = t_{mk} = 1$ is assumed, the result is an equivalent π model of a transmission line; or, if the shunt elements are ignored, and $t_{km} = 1$ and $t_{mk} = a_{mk}e^{j_{mk}}$ is assumed, then the result is a phase shifting transformer with the tap located on the bus m side.

The transformers modelled above were all two-winding transformers. In power systems there are also three-winding and N-winding ($N > 3$) transformers, and they can be modelled in a similar way. Instead of linear relationships between two complex currents and two complex voltages, we will have linear relationships between these quantities modelled by NN matrices.

It should be notes that for N-winding transformers there are leakage reactances between each pair of windings, i.e. in total $N(N-1)/2$ reactances. Since the power ratings of the different windings are not necessarily equal, as in the two-winding case, it should be noted that the power bases for expressing the reactances in $p.u.$ are not always equal [And08].

2.3.3 Shunt Elements modelling

The modelling of shunt elements in the network equations is straightforward and the main purpose here is to introduce the notation and the sign convention to be used when formulating the network equations in the coming sections.

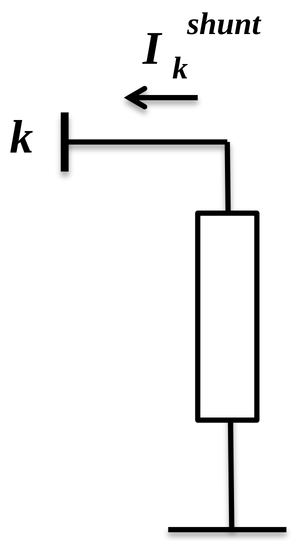

Figure 2.13: A shunt connected to bus k.

As seen from Figure 2.13 the current from a shunt is defined as positive when injected into the bus. This means that

$$I_k^{sh} = y_k^{sh} E_k \tag{2.22}$$

with E_k being the complex voltage at node k. Shunts are in all practical cases either shunt capacitors or reactors. The injected complex power is

$$S_k^{sh} = P_k^{sh} + jQ_k^{sh} = \left(y_k^{sh}\right)|E_k|^2 = \left(y_k^{sh}\right)U_k^2 \tag{2.23}$$

2.3.4 Electric load modelling

Load modelling is an important topic in power system analysis. When formulating the load flow equations for high voltage systems, a load is most often the infeed of power to a network at a lower voltage level, e.g. a distribution network. Often the voltage in the distribution systems is kept constant by controlling the tap-positions of the distribution transformers which means that power, active and reactive, in most cases can be regarded as independent of the voltage on the high voltage side. This means that the complex power $E_k(I_k^{load})$ is constant, i.e. independent of the voltage magnitude U_k. Also in this case the current is defined as positive when injected into the bus, see Figure Figure 2.14. In the general case the complex load current can be written as

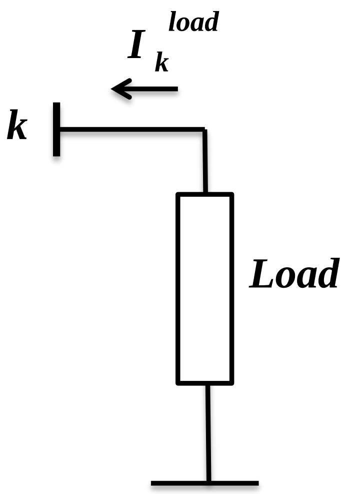

Figure 2.14: Model of a load connected to bus k.

$$I_k^{load} = I_k^{load}(U_k) \tag{2.24}$$

where the function $I_k^{load}()$ describes the load characteristics. More often the load characteristics are given for the active and reactive powers [And08].

$$P_k^{load} = P_k^{load}(U_k) \tag{2.25}$$

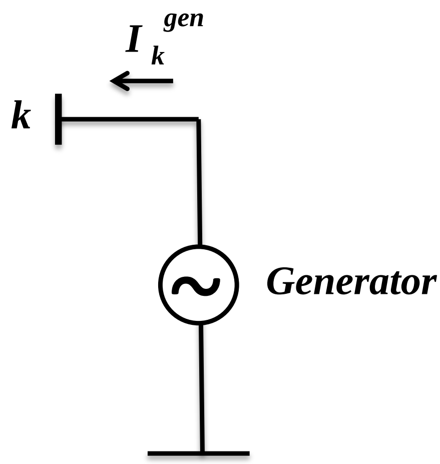

Figure 2.15: Model of a generator connected to bus k.

$$Q_k^{load} = Q_k^{load}(U_k) \tag{2.26}$$

2.3.5 Generator modelling

Generators are in load flow analysis modelled as current injections, see Figure 2.15. In steady state a generator is commonly controlled so that the active power injected into the bus and the voltage at the generator terminals are kept constant. This will be elaborated later when formulating the load flow equations. Active power from the generator is determined by the turbine control and must of course be within the capability of the turbine generator system. Voltage is primarily determined by the reactive power injection into the node, and since the generator must operate within its reactive capability curve it is not possible to control the voltage outside certain limits. The reactive capability of a generator depends on a number of quantities, such as active power, bus voltage and other operating conditions [And08].

2.4 Power flow calculations

2.4.1 Power flow analysis, objectives and problem formulation

A classical problem of circuit theory is to find all branch currents and all node voltages of an assigned circuit. Typical input data are generator voltages as well as the impedances of all branches. If all impedances are constant, the resulting set of equations that describe the circuit is linear. Solution of a simple set of linear equations based on the well-known *mesh/ branch current method* is unique and can be obtained. The power flow problem is conceptually the same problem as solving a steady state ac circuit. The only, though substantial, difference is the set of input data. In power flow analysis, loads are expressed in terms of consumed active and reactive power (*PQ load*) and generators are defined in terms of constant voltage magnitude and active power injection (*PV generator*). Finally, one generator is defined as standard independent voltage source (i.e., as a constant voltage magnitude and phase angle) and is called *slack* or *swing generator*[HS09].In power flow analysis, it is also typical to to represent the circuit as a one line diagram for example as illustrated in Figure 2.16.

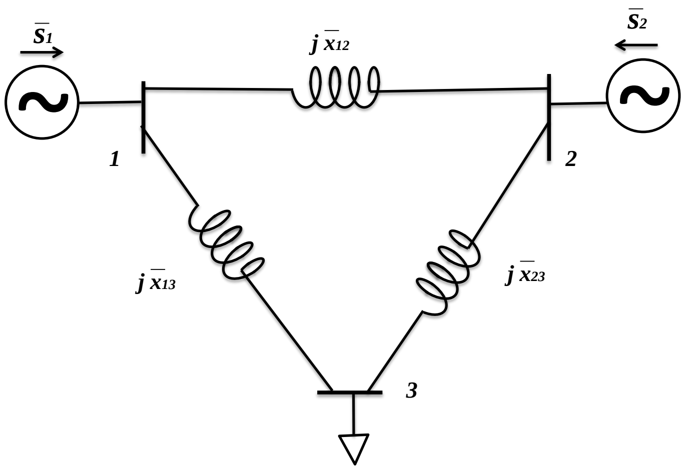

Figure 2.16: Classical power flow problem

For the system shown in Figure 2.16, one can write three complex equations (e.g., the expression of the complex power equation at each bus) or as it is common practice to separate active and reactive power injections, six real equations. Assuming voltage polar coordinates (e.g., $\bar{v} = ve^{j\theta}$) and that the generator at bus 1 is the slack, generator at bus 2 is a PV and the load at bus 3 is a PQ, input data are: $v_1, \theta_1, p_2, v_2, p_3$ and q_3. Thus. Variables are $p_1, q_1, q_2, \theta_2, v_3$and θ_3.

The power flow problem is formulated in order to determine unknown voltage magnitudes and angles. Remaining unknowns, i.e., the power injection, can be straight forwardly computed once all bus voltage are known.

The power flow equation of the system depicted in Figure 2.16 are[Mil10],[HS09]:

$$
\begin{aligned}
0 &= \frac{v_2 v_1}{x_{12}} \sin(\theta_2 - \theta_1) - p_2 \\
0 &= \frac{v_3 v_1}{x_{31}} \sin(\theta_3 - \theta_1) + \frac{v_3 v_2}{x_{32}} \sin(\theta_3 - \theta_2) - p_3 \\
0 &= \frac{v_3^2}{x_{13}} + \frac{v_3^2}{x_{23}} - \frac{v_3 v_1}{x_{13}} \cos(\theta_3 - \theta_1) - \frac{v_3 v_2}{x_{23}} \cos(\theta_3 - \theta_2) - q_3
\end{aligned}
$$

Where the unknowns are v_3, θ_3 and θ_2. Its important to note that the resulting set of equations is intrinsically nonlinear since the load at bus 3 specified as a constant power consumption.

These equations originate from the models of generators and loads. These models are defined based on common practice, as follows.

1. At high voltage level, loads represents an equivalent of sub-transmission systems systems or distribution networks. The equivalent load power consumptions can be generally well approximated as voltage dependent monomials:

$$
\begin{aligned}
p_L &= p_{LO} v^{a_p} \\
q_L &= q_{LO} v^{a_q}
\end{aligned}
$$

   Where p_{LO} and q_{LO} are the active and reactive power consumption, respectively, at the nominal voltage.

2. Synchronous generator turbine governors and automatic voltage controls are able to regulate the generated active power and the voltage at the machine bus, respectively. In steady -state, these controls can be modelled as constant p and v at the generator bus.

3. Since one active power cannot be assigned, the slack generator can only specify the voltage magnitude.

4. Transmission lines and transformers are generally modelled as lumped π -circuits with constant parameters.

2.4.2 Classical power flow equations

Generally speaking, the power flow problem consist in finding the zero of a set of nonlinear equations starting from an adequate initial guess. The power flow equation is a set of equation as follows:

$$\begin{aligned} 0 &= f(x, y) \\ 0 &= g(x, y) \end{aligned}$$

Where differential equations f model dynamic devices such as, for example, under load tap changer, and algebraic equations g define the power balance at network buses.

However, in general, most dynamic devices are initialized after solving the power flow problem. Thus, the most common formulation of the power flow equation is reduced to the algebraic part:

$$0 = g(x) \tag{2.27}$$

The vector of current injected at each node is:

$$\bar{i} = \bar{Y}\bar{v} \tag{2.28}$$

Which leads to write 2.29 as the complex power injection at buses:

$$\bar{s} = \bar{V}\bar{i}^* = \bar{V}\bar{Y}^*\bar{v}^* \tag{2.29}$$

Where $\bar{V} = diag(\bar{v1}, \bar{v2}, \dots, \bar{v_{n_b}})$ and n_b is the number of network buses.
p_h and q_h are defined as neat power injection at the bus h. Thus, using the product of voltage phasors in polar form:

$$p_h = v_h \sum_{k \in \beta} v_k(g_{hk}cos\theta_{hk} + b_{hk}sin\theta_{hk}), \qquad h \in \beta \tag{2.30}$$

$$q_h = v_h \sum_{k \in \beta} v_k(g_{hk}sin\theta_{hk} - b_{hk}cos\theta_{hk}), \qquad h \in \beta \tag{2.31}$$

Where $\theta_{hk} = \theta_h - \theta_k$. A synoptic summary of variables and data for each bus type is shown in Table 2.1

Bus type	Variables	Data
Slack generator	$p.q$	v, θ
PV generator	q, θ	q, θ
PQ load	v, θ	p, q

Table 2.1: Variables and parameters for each bus type in power flow formulation

2.4.3 Numerical iterative methods and software tools in power flow analysis

The mathematical problem of power flow equation is complex as it involves solving a large system of non-linear transcendental algebraic equations. Methods that can be applied to solve these equations are iterative in nature because of the non-linearities involved. Two types of methods are commonly used: the Gauss-Seidel method and and the Newton- Raphson method. The main advantage of Gauss-Seidel method, is the ease of implementation and the low number of calculation required in each iteration. This is what made them successful in past decades, where the power and memory capacity of computers was very limited.

However, the calculation process is very long even when we use the acceleration of convergence including the choice of optimal value of coefficients. Furthermore, this method is depends heavily on the initial values chosen.

In Newton- Raphson method,initially, we assume that all nodes are PQ buses. Hence the known quantities are the active power P and reactive power Q and the unknown quantities are the voltage magnitude V and the phase angle θ.

Convergence of Newton - Raphson method is quadratic, i.e., the error is divided by a factor nearly equal to two, which allows very fast convergence. The disadvantage of this global method is that each iteration requires the solution of a system of 2n equations with as many unknown, which is computationally extensive. Many variations of this method have been developed to reduce the computation time associated with solving the linear system defined by the Jacubian matrix.

2.5 Monte Carlo method; a general probabilistic algorithm

The “Monte Carlo method” is a general probabilistic algorithm for estimating the probability of an event based on a number of random trials.

2.5.1 Randomized Algorithms and Probability

A randomized algorithm is an algorithm that makes at least one decision based upon a random choice, rather than a fixed rule. At first glance, it may seem surprising (or even unbelievable) that incorporating an element of chance into an algorithm can result in a correct and efficient algorithm, but as we will see in this chapter, there are many situations where randomness is extremely effective. Randomized algorithms generally depend upon the laws of probability, and therefore before we begin studying randomized algorithms, it makes sense to formally define some of the terms and concepts of probability.

- An experiment is any procedure that can be repeated any number of times, and has a well-defined set of outcomes. (In order to be interesting from a statistical perspective, the result of the procedure is generally not known in advance.)

- An sample outcome (often denoted s) is a member of the set of outcomes of an experiment.

- The sample space (often denoted S) is the complete set of all possible sample outcomes of an experiment.

- An event is any set of sample outcomes. When the outcome of an experiment is a member of this set, the event is said to occur.

- Two events are independent if the occurrence of one of the events is not related to the occurrence of the other. For example, if we flip a fair coin twice, then the event "first flip is heads" is independent of the event "second flip is heads". However, the events "first flip is heads" and "first flip is tails" are not independent, because the occurrence of one of these events depends on whether the other has occurred. In this case, the correspondence is absolute but this is not always the case.

- A trial is the actual "execution" of an experiment. For example, the procedure of tossing a coin and observing whether the result is heads or tails is an experiment, but the act of actually flipping the coin is a trial.

- A population is the set of all unique trials. This set may be infinite. For example, the population of all coin tosses is infinite, because we can perform as many unique trials as we like by flipping the coin repeatedly. In other situations, the population may be finite for example, if our experiment is to ask a person enrolled in S-Q whether their last name contains the letter e then the set of unique trials is the set consisting of one trial for each person enrolled in the course.

- A sample is a set of trials. A random sample is a set of trials selected at random from the population. For example, consider the act of rolling a 6-sided die. The procedure consisting of rolling the die and reporting which face is visible is the experiment; and each time we actually perform this procedure we are performing a trial. We can roll the die as often as we like, and every time we roll the die the outcome (i.e. which side of the die is showing) must be one of the 6 sides. Each possible side of the die is a possible sample outcome, and these six possibilities constitute the entire sample space. We can define a number of possible events for this experiment for example, rolling any particular number, or rolling an odd number, or rolling a number less than four [DE03].

2.5.2 Monte Carlo Simulation

Monte Carlo Simulations (MCS) are one of the most common randomized algorithms. A Monte Carlo Simulation is a method of estimating the value of an unknown quantity by making use of the principles of inferential statistics. In brief, the guiding principle of inferential statistics is that a random sample tends to exhibit the same properties as the population from which it is drawn. For example, if you flip a coin 10 times, and it comes up heads every single time, then you might start to form an opinion that the coin is not fair, and that it is biased towards coming up heads you might begin to believe that the population of all possible flips of this coin contained more heads than tails. If you flip the same coin 100 more times, and it still comes up heads every single time, it would probably be hard to convince you that the coin was fair at all. On the other hand, if you flipped the coin 100 times and roughly half of the time it came up heads, then you would probably believe that it was a fair coin or at least not unfair to any obvious degree. In both cases, your belief whether the coin is fair or not is based on the intuition that the behavior of a sample of 100 flips is similar to the behavior of the population of all flips of your coin. Luckily, this belief is not without basis in fact and we can make use of this fact to achieve good estimates of probabilities with relatively little effort [DE03].

2.5.3 Accuracy of a Monte Carlo Simulation

When we use Monte Carlo algorithm to perform a Monte Carlo simulation, we are trusting that fate will not give us an unusual or freakish sample. We are trusting that the true probability is reflected in our observations. In the long run, we can generally rely upon this assumption, although it is important to know how many samples we will have to take before this assumption holds. While we trust in luck to ensure that our sample is not wildly unusual, we must also realize that it is extremely unlikely that fate will provide a sample that is exactly like the population. Consider the example of flipping a fair coin 1000 times. While it is likely that the number of heads and tails will be close to 500, it is also unlikely that they will both be exactly 500. What is far more likely is that the number of heads will fall in some range around 500. This leaves us with two questions to ponder:

1. How many samples do we need to take in order to safely assume that we have taken "enough" samples?

2. How accurate do we believe that our estimate is, given a certain number of samples?

for a coin, based on a set of random trials. As you might guess, the answers to these two questions are related; the more sure we want to be that our sample is good, the more samples we need to take, and the more samples we take, the more likely it is that we will get a more accurate estimate. Unfortunately, it is never possible to achieve perfect accuracy through sampling unless you sample the entire population, no matter how many samples you take, we can never be sure that the sample set is typical until we verify every last element of the population (and since we are usually dealing with infinite populations, this is simply impossible). Of course, this is not to say that our estimates are not perfectly correct. We might arrive at the exactly correct value, but the trouble is that we cant know that our estimate is correct. All we can measure is how likely it is to be correct. The relationship between the sample size and our estimate of the accuracy of an estimate arrived at from a sample is given by the following equations:[DE03]

$$e = \frac{z}{2\sqrt{n}} \tag{2.32}$$

$$n = (\frac{z}{2e})^2 \tag{2.33}$$

In these equations;

n is the sample size,

e is the "margin of error", which is the fraction by which we believe our estimate may be incorrect.

z is a function of how confident we desire to be in our estimate of e, the probability that our estimate is within e of the true value.

Computing z is a laborious process. However, Table 2.2 contains values of z for some common confidence levels [DE03].

Description	Value		
z	1.96	2.58	3.29
Confidence Level (%)	95	99	99.9

Table 2.2: Confidence levels and z.

2.5.4 Computing the Margin of Error

Returning to our example of flipping a coin 1000 times, if the coin comes up heads exactly 500 times; our estimate of the probability of the coin coming up heads is 0.5. However, now we can also compute our "margin of error" for this estimate. With 95% confidence, we can say that our estimate is accurate to within 3.1%:
$e = 0.031$
Similarly, we can compute our "margin of error" with a 99% level of confidence, using the same method, but with a z of 2.58:
$e = 0.041$

Notice that our margin of error has increased. In order to gain more confidence in our estimate, we have had to widen the margin. Note that the only way to achieve 100Returning to the coin example, if our estimated p is 0.5, and our margin of error (based on 1000 trials, at a 95% level of confidence) is 0.031, then we can restate our estimate as 0.5 ∓ 0.031 (with a 95% level of confidence). This way of expressing the estimate together with the margin of error is called a confidence interval.

In this case, based on our 1000 trials, we can say that we are 95% confident that the true probability of the coin coming up heads is within the range from 0.469 to 0.531. The true probability might be outside this range, but we are 95% confident that it is not. Note that if our margin of error is large enough (either because we are requiring a very high confidence level, or the number of samples is too small), the confidence interval may include values outside the range from 0 to 1. These values should be discarded, because they are not valid probabilities [DE03].

2.5.5 Computing the Number of Trials

In the last section, we computed the confidence interval for a sample of 1000 trials. In this section, we will ask the problem from the other perspective. In order to get an estimate of the probability p of a coin (i.e. the probability that the coin will come up heads) that is accurate to within 5%, with a 95% level of confidence, how many trials do I need to perform? Returning the equation:

$n = 384$

Therefore, we can be 95% confident that an estimate of p based on 384 coin flips will be accurate to within 5% of the true p. If we want to be more confident, or to achieve a more accurate estimate with the same level of confidence, then more coin flips will be necessary [DE03].

2.6 Power system and EVs modelling; Applying a case study

In last section, for each part of the system the related model is prepared. Now we try to put together all these models in a single model to see the overall model of the system. Figure 2.17 shows this model in which all data from different sources are gathered together. All data from power system model, geographical and traffic information and the social data from the region are shown in this figure. In order to handle all these data, after some initial checking in the source data, these data are integrated into the Matlab [MAT] software to run simulations for the algorithms of scenarios.

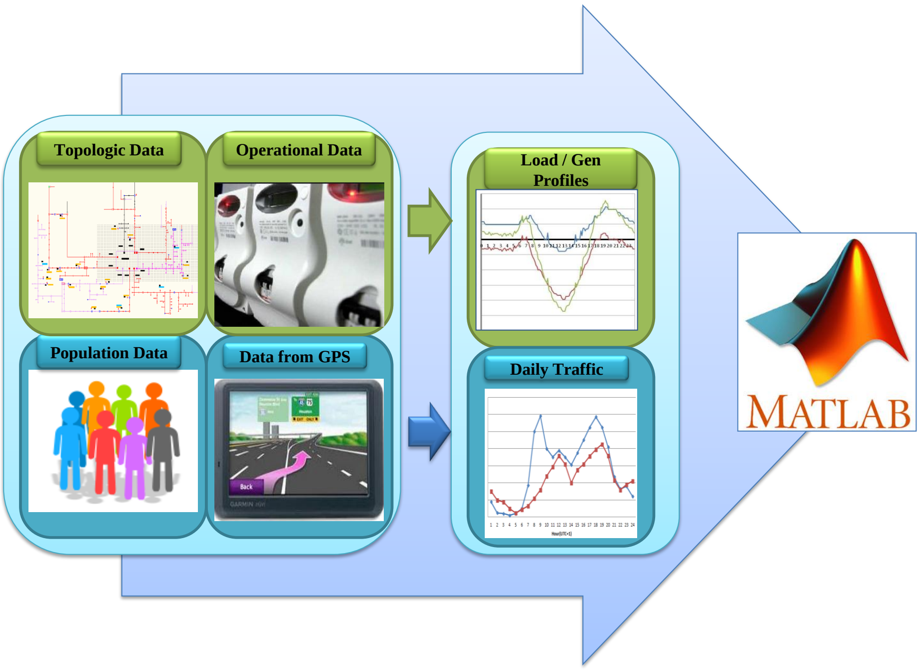

Figure 2.17: Modelling all data from different areas and simulation in Matlab

In the next parts of this section, a case study is applied to model the power system and EVs with all data from a real case study from Monza, a city in the northern Italy. This model is applied in the next chapters to study proposed methods in connecting EVs to power grid.

2.6.1 Power system uncertainties specification in case study

Power systems have uncertainties coming from multiple sources, including forecast errors of load, renewable generation including wind and solar generation, uninstructed deviation and forced outage of traditional generators, and unscheduled loss of transmission lines [MLS+11]. With increasing amounts of wind and solar generation being integrated into the system, these uncertainties have been growing significantly. It is critically important to build the power system model by taking into account sources of uncertainties.

2.6.1.1 Power systems uncertainties sources

Modeling and computation of engineering aspects of power systems is subject to many sources of uncertainty**??**;

- the form of the assumed mathematical model is often open to question.
- The topology of the model. Even though we may know how to represent every component in the system, we may not be sure of what to represent.
- The value of the model parameters may be unknown or subject to error.
- Inputs into the model may be subject to "noise". For example, the value of a given system load may only be represent able as an uncertain variable.
- Numerical modeling using finite arithmetic introduces errors in the modeling process that can, under some conditions, overwhelm the accuracy of a model. In addition, environmental, regulatory and technology change considerations often introduce uncertainties that are of greater significance, yet less quantifiable in nature.

2.6.1.2 A case study; specifications of parameters in modelling the power system

In the power system, Parameters of models, in particular load and generation models, are rarely known exactly. In this study load and generation uncertainties are considered in building the power system model.

The power system applied in evaluating the proposed models in next chapters, is composed of one HV/MV and 289 MV/LV Buses. This distribution grid supplies Monza city, an urban area in northern Italy. All the characteristics of the power system are designed so that the system should be capable to serve this urban region with a high population density. From power system point of view, these urban characteristics are translated to shorter length of lines and bigger capacity in the lines and transformers. Table 2.3 shows the overall view of this distribution system. .

Description	Value / Specification
Type	Urban Distribution Power System
Population	80 000
Served area	11 000 km^2
HV/MV Bus	2
HV/MV Transformer	2 including a 40 MVA and a 78 MVA , 132/23 KV
MV Feeder	17 Feeder
MV/LV Bus	289 Bus
MV/LV Transformers	273 Transformer 23 / 0.4 KV
Total Customers	44399 including 44316 LV and 83 MV customers
Max. Power demand	54 MW
Generation capacity	1,162 KW PV

Table 2.3: Overall view of power system case study.

Single Line Diagram (SLD) of the used distribution power system as case study is shown in Figure 2.18 including all HV/MV and MV/LV Buses.

In Figure 2.19 a sample profile for a MV customer is shown.

Figure 2.20 in top shows a sample load profile for all 17 MV feeders in the case study. At bottom, two load profiles for two HV/M transformers are presented. We use these profiles to make a normalized load profile with maximum value of consumption in each feeder. This normalized profile is presenting the load profile in feeder for all buses. In next step the load profile for each bus is made by multiplying this normalized profile in maximum power in each bus.

This maximum power in each bus is composed of the maximum power registered by the MV/LV transformers at each bus plus the MV consumers connected to these buses. In some cases the number of connected transformer to buses are more than one. Figure [next] shows total load and power generation in each bus.

2.6.1.3 Operational data from meters

Location of different meters in the distribution grid is shown in Figure 2.21. Some meters i.e. M1 and M3 have the possibility to sense the power flow in both directions, but some other meters i.e. M2 and M4 have only one direction sensing

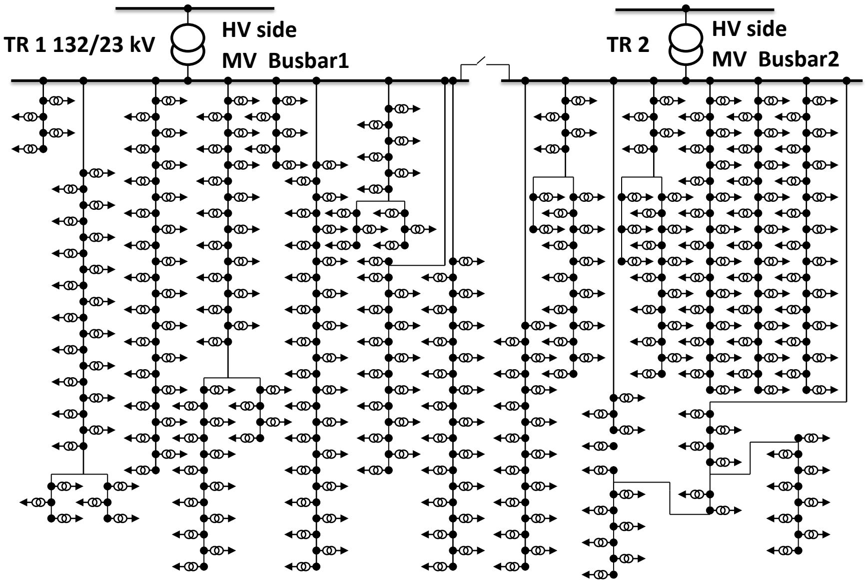

Figure 2.18: Single Line Diagram (SLD) of the case study.

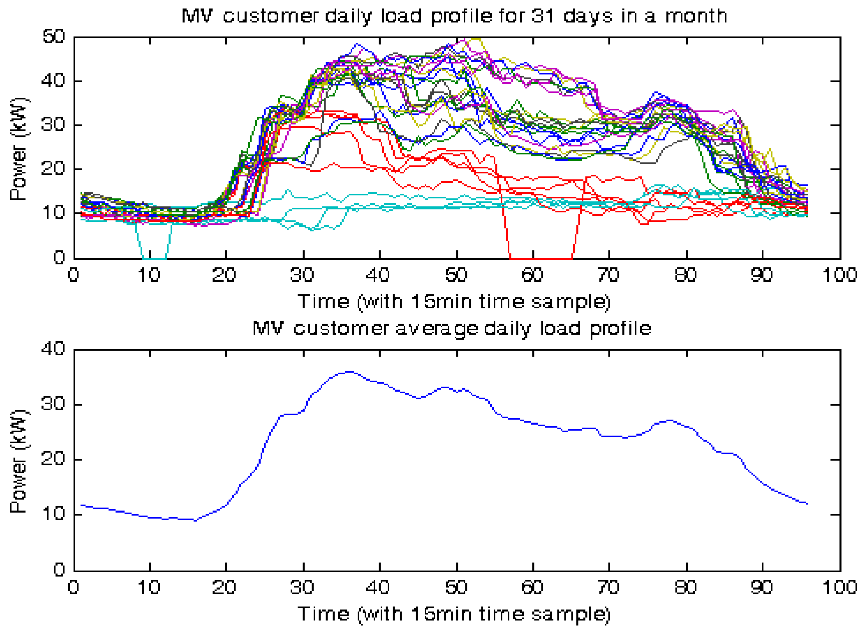

Figure 2.19: An example of MV customer load profile.

capability. It is shown in the figure by one or double direction on the meters. Some meters i.e. M3 have the responsibility to measure the power flow from/to the customers, these customers are some big clients like commercial centers, big

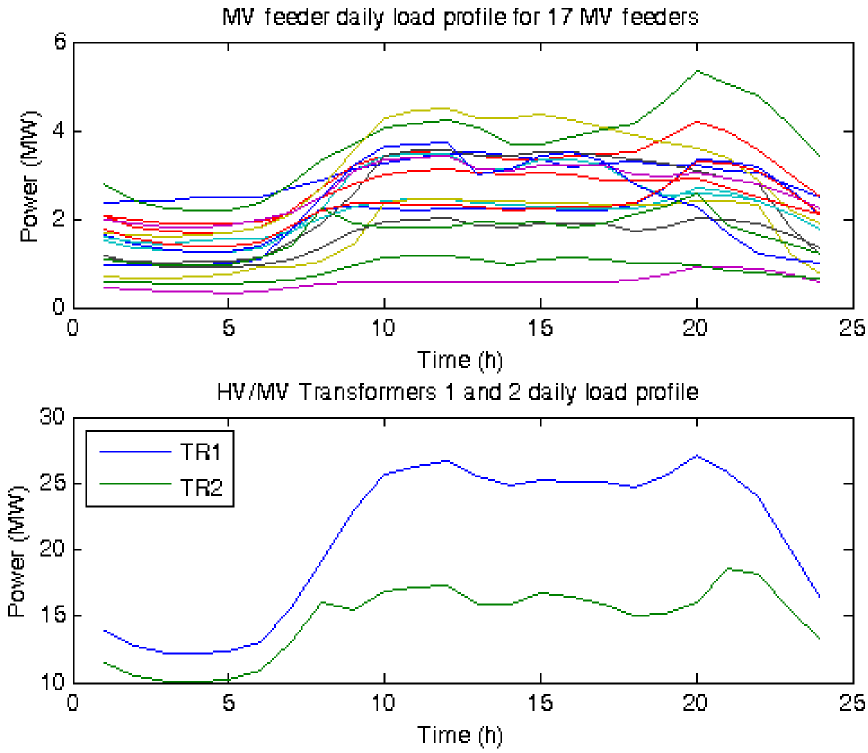

Figure 2.20: MV feeders and HV/MV transformers load profile.

buildings or sometimes small factories inside or near urban region which might have generation plants beside them. In this figure, M1 is the meter on the bus in LV side of transformer normally they use double direction to measure the power flow from/to the bus; M2 is one direction feeder meter which measure the power flow to the related feeder.

2.6.1.4 A case study; modelling uncertainties by using GPDF

Modelling uncertainties in the power system depends on the source of uncertainty and the method of modelling the power system parameters. In the next chapters, an stochastic model of EVs large-scale integration into power system is proposed. Based on the proposed model, all uncertainties in power system are applied with their Probability Density Functions (PDF). The model is explained in next chapters, but the PDF of each uncertainty is defined in this section. All data provided from a real case study are used to show better the modelling. The case study is the urban case study we applied before in the previous sections. This data are extracted in a way to support the stochastic method and probability

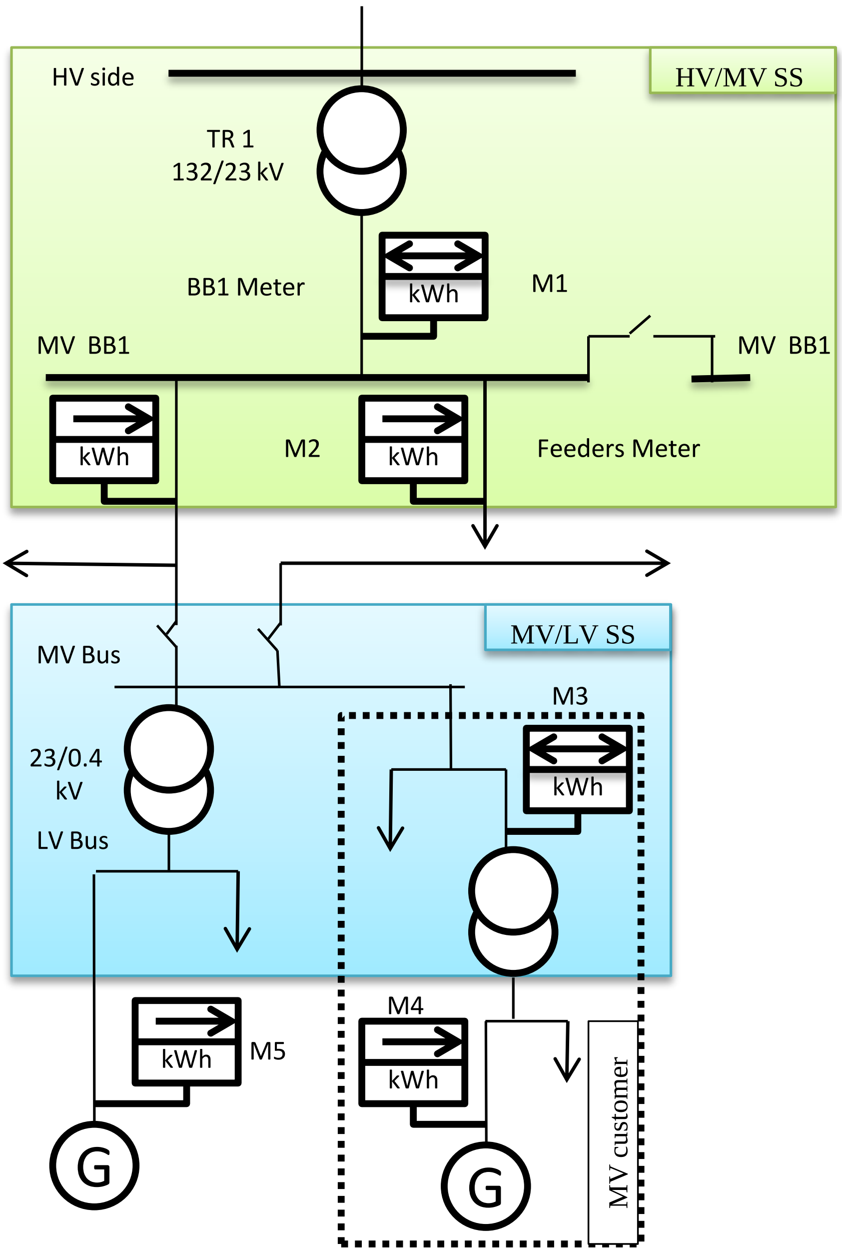

Figure 2.21: location of different meters in the grid.

functions based model in the next chapters.

All data from power demand and generation are converted to Gaussian Probability Distribution Function (GPDF)inputs.

To model the uncertainties in power generation and power demand at buses, we need to have two parameters; the maximum power value and characters of the

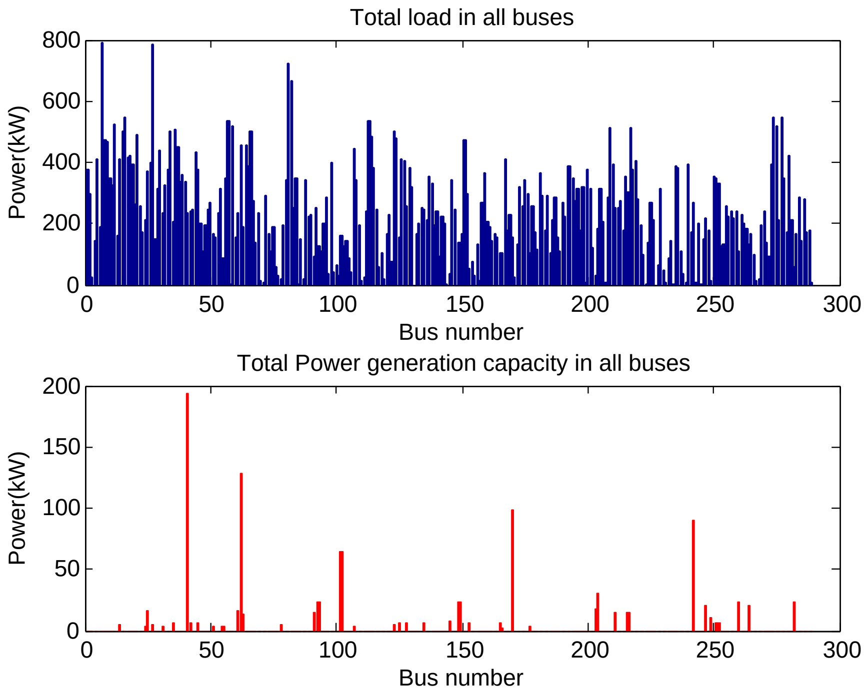

Figure 2.22: Maximum value of total initial load and generation in all 289 buses.

GPDF of the bus. In the applied case study, load profile of feeders is provided and its GPDF is applied as the GPDF of all buses connected to the feeder. The maximum power value is provided for all buses. Applying these two parameters, the probability distribution of the power demand could be achieved. This maximum power in each bus is composed of the maximum power registered by the MV/LV transformers at each bus plus the MV consumers connected to these buses. In some cases the number of connected transformer to buses are more than one. Figure Figure 2.22 shows maximum values of load and power generation in each bus.

Feeders load profiles are shown before in Figure 2.20. In top of the figure, a sample load profile for all 17 MV feeders in the case study is shown. At bottom, two load profiles for two HV/M transformers are presented. We use these profiles to make a normalized load profile with maximum value of consumption in each feeder. This normalized profile is presenting the load profile in feeder for all buses. In next step the load profile for each bus is made by multiplying this normalized profile in maximum power in each bus. Figure 2.23 shows Gaussian probability density function for each feeder. In Table 2.4 PDF data for 17 feeder load profile are listed.

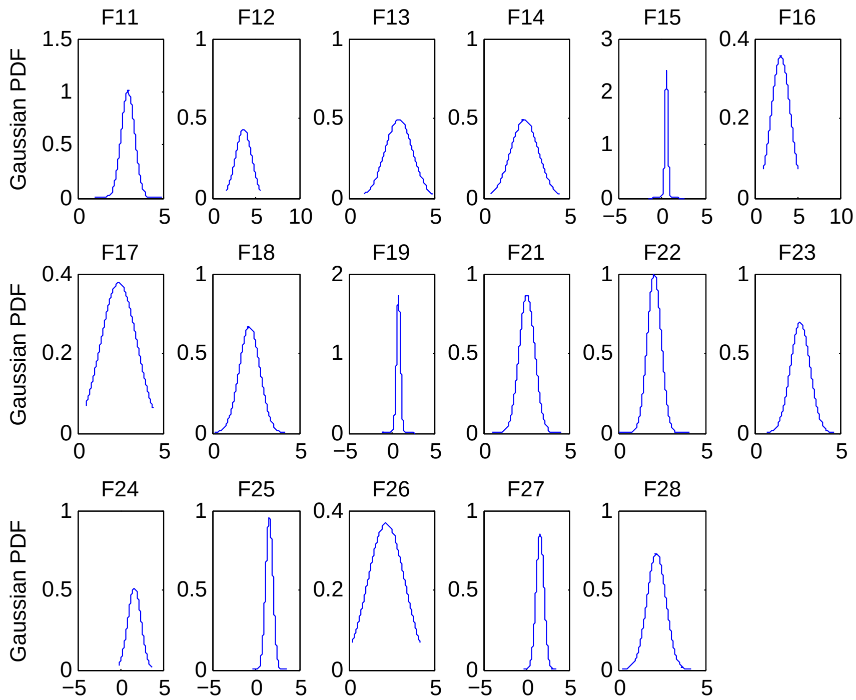

Figure 2.23: Gaussian PDF for 17 feeders.

Feeder	11	12	13	14	15	16	17	18	19	21	22	23	24	25	26	27	28
Average	3	3.6	3	2.4	0.6	3.1	2.4	2.2	0.9	2.6	2.1	2.7	1.7	1.6	2.2	1.7	2.2
STD	0.4	0.9	0.8	0.8	0.2	1.1	1.1	0.6	0.2	0.5	0.4	0.6	0.8	0.4	1.8	0.5	0.6
Max	3.5	5.4	4.2	3.5	0.9	4.5	3.6	3.3	1.2	3.1	2.7	3.4	2.4	2	3.7	2.6	3.3
Min	2.4	2.2	1.7	1.3	0.3	1.6	1	1.3	0.5	1.9	1.4	1.8	0.7	0.9	1	1	1.4

Table 2.4: Overall view of power system case study.

2.6.2 Annual average daily traffic modelling

In the Italian vehicular fleet a percentage of about 1.5 % is equipped with a GPS device. All recorded data are collected by these vehicles during a period of one month in the Florence province [GG12]. This data are used to study traffic analysis on different municipal areas. For each municipality, the number of vehicles belonging to the resident people, equipped with the GPS devices is estimated. This allows normalizing the calculated parameters. All these traffic data are reported versus time. Furthermore, the normalized parameters can be taken as indicators to assess traffic and migration behavior in a municipality as well as to compare different size municipalities.

These data are extracted for another purpose by an insurance company for Florence city which is geographically matched with Monza city, our case study. A set of normalized data from GPS data are integrated with the real data from our case study to make the traffic data for Monza city. Figure 2.24 shows annual daily traffic for a Weekday and Weekend day.

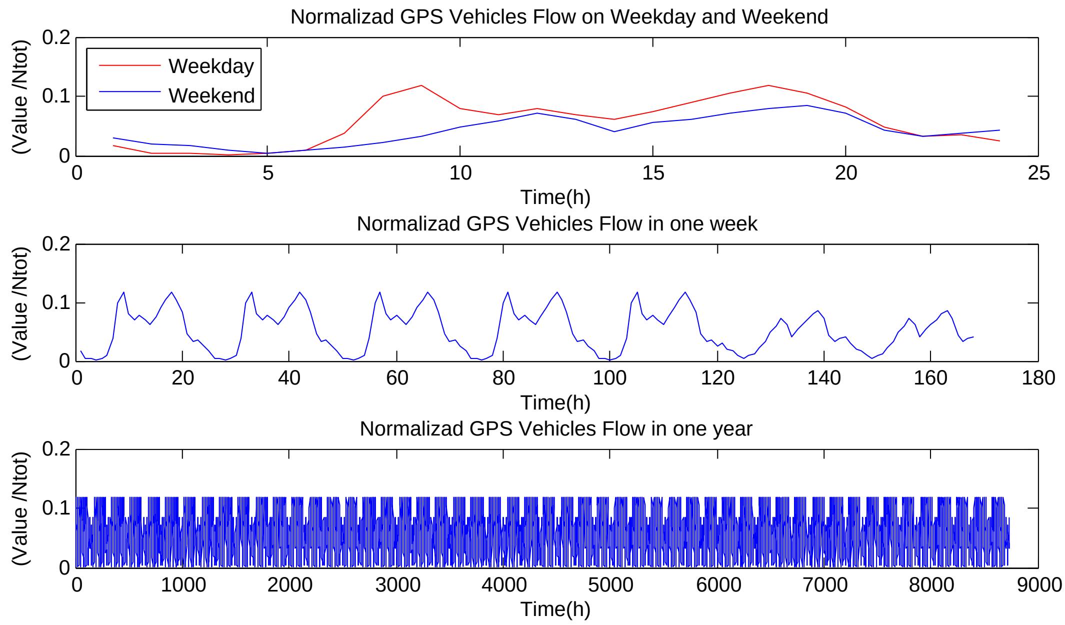

Figure 2.24: Annual daily traffic for a Weekday and Weekend day with normalized GPS vehicle flow values [GG12].

Parked vehicles are the vehicles which are not in movement. Parked vehicles curve is get from traffic curve. Figure 2.25 shows annual daily parked vehicles curve for a Weekday and Weekend day.

2.6.2.1 Annual average daily traffic GPDF model

In the MCS and all other models based on the stochastic methods, the Gaussian Probability Distribution Function of the annual average daily traffic is applied. This model is provided from the daily traffic curve for one year. Figure 2.26 shows the Gaussian probability distribution function for traffic curve. Parked vehicles are the vehicles which are not in movement. Figure 2.27 shows Gaussian probability distribution function for parked vehicles.

Table 2.5 summarizes parameters of GPDF for parked and in move EVs.

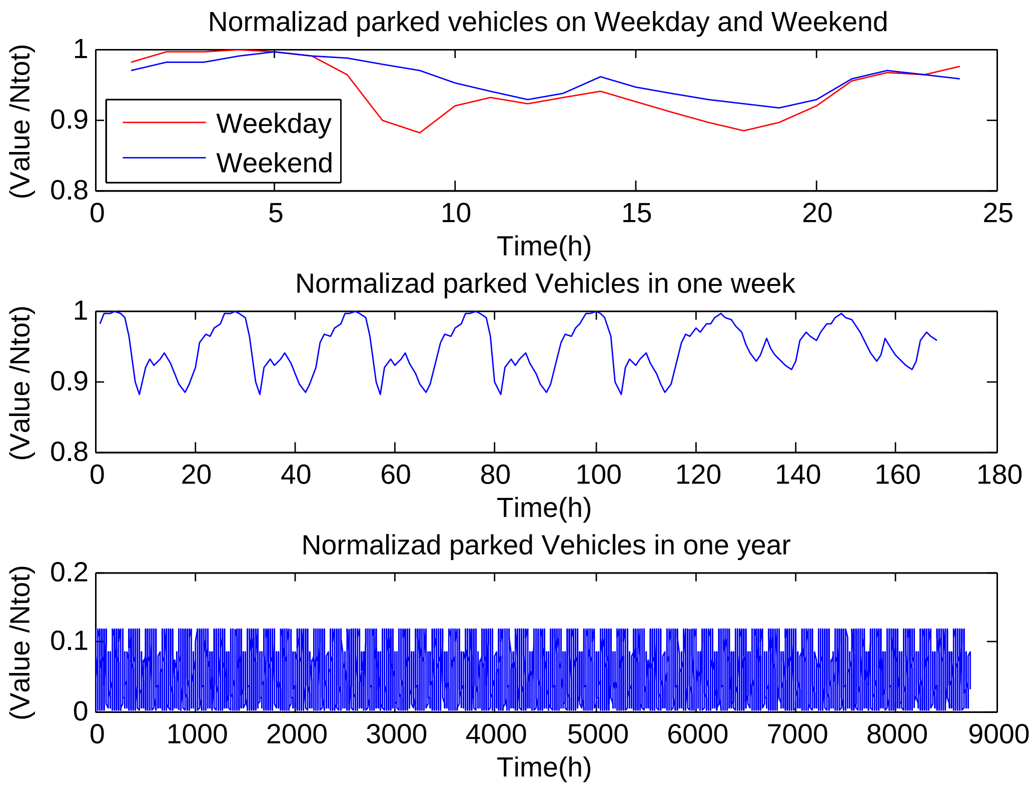

Figure 2.25: Annual daily normalized parked vehicles for a Weekday and Weekend day [GG12].

Description	Average	Standard deviation	Maximum Value allowed	Minimum Value allowed
Traffic curve	0.0529	0.0352	0.1180	0.0020
Parked vehicles curve	0.9471	0.0352	0.998	0.882

Table 2.5: Gaussian PDF parameters in traffic and parked vehicle curves.

2.6.3 Electric vehicles uncertainties specification in case study

In order to study all EVs impact on the power grid, an extended variety of EVs with different characters must be considered. Table 2.6 shows EV characters including batteries capacity and charging rates for normal and fast charging.

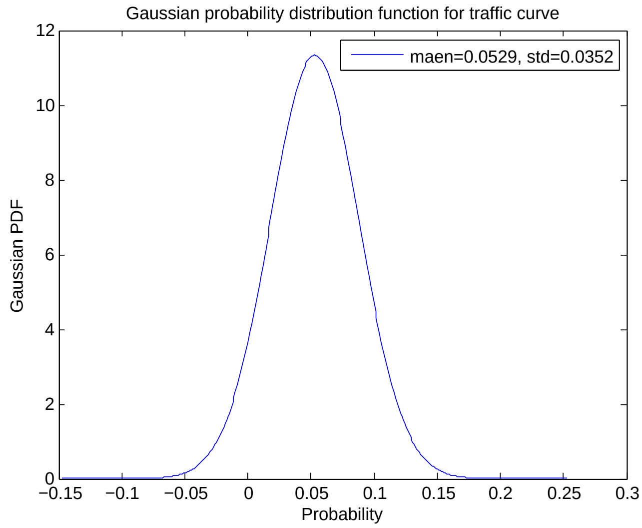

Figure 2.26: Gaussian probability distribution function for traffic curve.

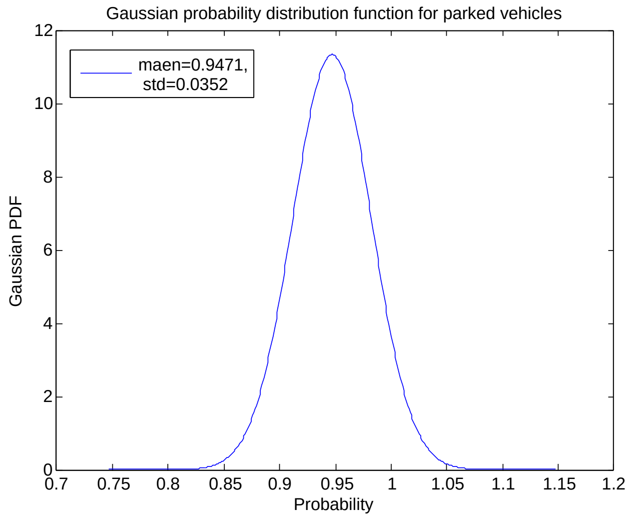

Figure 2.27: Gaussian probability distribution function for parked vehicles.

These characters are taken from a European study on EVs characters and drivers behaviours **??**. Energy consumption average is 0.16 kWh/km [BBB+11], means that driver can drive about 109 km with one full charged EV with the average battery capacity. We considered usable energy between ranges 15% and 85%. Fast and slow charging are two possible modes in charging EVs.

EV character	Average	Max. Value	Min. Value
Battery capacity (kWh) (100% SOC)	25	85	5
Charging rated power for slow charging mode(kW)	3.5	10	2
Max. charge power (kW)(fast charge)	20	32	10
Duration for max charge power (min)(fast charge)	30	45	25
Battery SOC(%)	50	85	15

Table 2.6: EV characterization for normal and fast charging modes [ND10].

2.6.3.1 Electric vehicles uncertainties GPDF model

EVs specified characters illustrated in Table **??** are provided directly from the survey results. To apply the GPDF model of these specifications, we need another parameter, the standard deviation. Table 2.7 shows the GPDF model of all EV uncertainties.

EV character	Average	SD	Max. Value	Min. Value
Battery capacity (kWh) (100% SOC)	25	17.5	85	5
Charging rated power for slow charging mode(kW)	3.5	1.5	10	2
Max. charge power (kW)(fast charge)	20	5.00	32	10
Duration for max charge power (min)(fast charge)	30	5.00	45	25
Battery SOC(%)	50	25	85	15

Table 2.7: EV characterization for normal and fast charging modes GPDF model [ND10].

2.6.4 Driver behaviour uncertainties specification in case study

Drivers are a source of uncertainty in charging EVs. Drivers behavieurs as the controller of all non technical characters of EVs including batteries SOC, distance to charging station, charging location and charging duration. Therefore the drivers behavieur is a key point in modeling EV charging. Results of an report which examines the traffic patterns and human behaviours of drivers from across Europe, are applied in this study in modeling EVs drivers behaviours. The data analyzed in this survey was collected using a targeted online questionnaire that was filled in by a total of 1,621 people from a number of countries in Europe, from a range of backgrounds, providing a sound basis from which to draw conclusions and perform analysis. When an EV is in parked state, three question should be answered before EV start charging; first question is about the location of EV, *"where is EV parked?"*. Second question is about the possibility of access to charging socket, *"is there the possibility to charge EV in parked place?"* and the third question which is related with the EV driver behavior; *"Would EV Driver decide to charge in this location or not?"*.

To answer to each of these questions we applied the finding of an internet survey made within the framework of the MERGE project **??** for some European countries. Table 2.8 shows the location of survey responders vehicles when they are parked for the longest period of time in a given day.

Location	Weekday (%)	Weekend (%)
At home in a garage	37	44
At home in a driveway	19	28
At home on the street outside my home	17	20
At home but in a parking space away from my home	4	4
At work	20.5	3
At an intermediate location, such as a rail station	1.5	.5
At a shopping district	1	.5

Table 2.8: Location of vehicle for longest period of inactivity [ND10].

Results of a another question in this survey, asking if drivers could provide a standard domestic electricity socket to the place their car is parked for the longest period of the day. 57% of drivers reported that they could provide a supply of electricity to their car where it is parked for the longest period on weekdays, rising to 65% at weekends. Among them, only 23% on weekdays has access to socket to recharge with no need to an extension cable. This percentage is 27% at weekends. Table 2.9 shows their answers to the question *"Could you provide a standard domestic electricity socket to your vehicle where it is parked for the longest period?"*.

Based on another results of this survey the EV drivers behavior we can have the preference of drivers about the charging location. The results revealed that there are three major types of behaviors regarding EV charging, as presented in Table 2.10. The asked question was *"Where do you / would you choose to refuel your vehicle?"*. These percentages are related to EV answers.

Answers	Weekday (%)	Weekend (%)
Yes there is an electrical socket	57	65
No: there is no access to electricity	43	35

Table 2.9: Access to electricity at parking space [ND10].

Location	Responses(%)
At a service station or recharging station	10
At work	20
At home	70

Table 2.10: Driver behavior for charging location preference [ND10].

Based on this survey, 70% of responders said that at least 60% of the journeys they undertake in a typical week are part of a regular cycle of similar journeys that occur at approximately the same time every week.

We regroup EVs in four group of parking location.

1. *"At home"* group which is including three first groups in Table 2.8.
2. *"At work"* group for parked at work location.
3. *"Near station"* group which is including parked EV inside shopping center and intermediate location. These cases are EVs in two last groups in Table 2.8.
4. *"No Charge access"* group which is related to EVs parked t home on the street outside home.

Based on this new group definition we have these percentages as shown in Table 2.11.

2.6.4.1 Driver behaviour uncertainties specification GPDF model

In stochastic model all driver behaviours uncertainties specified in case study are applied in GPDF model with their percentage values. In some uncertainties, are applied with no change, like Table 2.10 and Table 2.11.Uncertainties of Table 2.9 change as shown in Table 2.12.

Location	Week Average(%)
At home	64.5
At work	15.5
Near station	2.1
No charge access	17.9

Table 2.11: Four groups of charging location .

Location	Week Average(%)
Yes there is an electrical socket	59.29
No: there is no access to electricity	40.71

Table 2.12: Access to electricity at parking space [ND10].

2.6.4.2 Probability bar definition

In some parts of this work, a random selection between elements is needed. If these elements have not the same probability to appear in result, the probability of each element is considered in random selection. In this way we applied a "probability bar" for the group of random elements. Probability bar is an interval of continues domain between 0 and 1. This interval is composed of small probabilities of elements. Figure 2.28 shows an example of six elements with their probability in above side. Below side of figure shows the probability bar with its elements in different colors. We use this bar to take a random selection of elements proportional to their probability. In Appendix 5.6 an example, shows the random selection by using the probability bar.

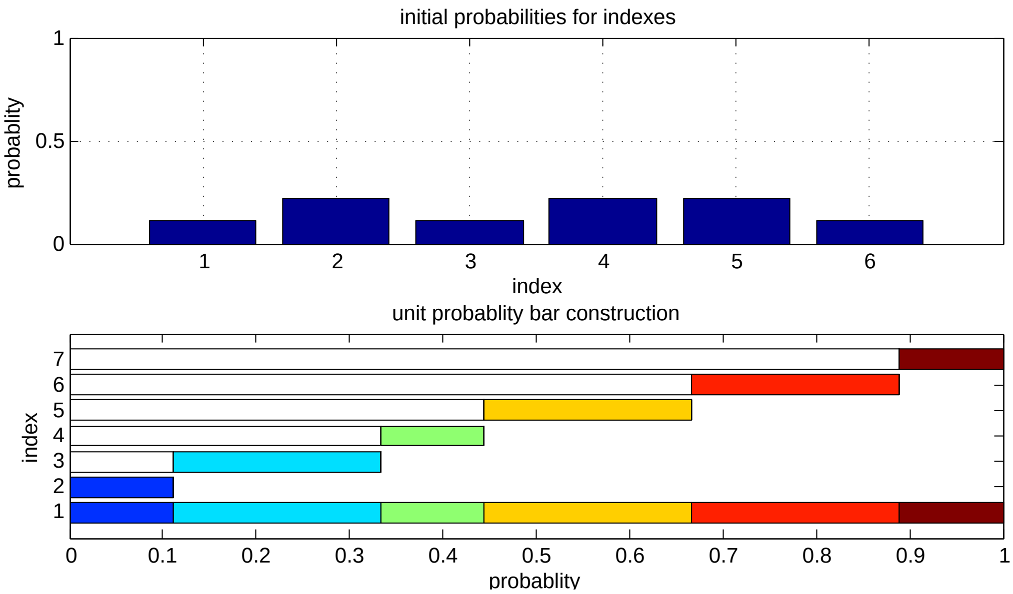

Figure 2.28: Probability bar.

Chapter 3

Comprehensive modeling of uncertainties in EV integration into power system

3.1 Strategies and models for EV connection to grid impact study

The development of Electric Vehicles as a flexible, movable load with storage capacity is an evolution of the electrical system. The development of electric vehicles could cause a significant increase in peak power demand, resulting in the need to develop advanced generation facilities that emit a lot of CO2, and the appearance of reinforcement needs for transmission and distribution grids.

For example, the French public authorities anticipate a fleet of 1,000,000 electric vehicles in 2020. The annual energy consumption would then be limited to 2.5 TWh, i.e. 0.5% of the annual demand. Assuming that a third of the vehicles would be recharged simultaneously with an option to recharge slowly, the power required will be 1 GW. If there are 1.2 million simultaneous 24 KW rapid recharges, however, the required power will rise to 30 GW [Mal12].

One option might be to give the user the choice between a soft charge (which is better for the battery, the electrical system, leads to a reduction in CO2 emissions and cheaper) or a rapid charge (which is considerably more expensive and could be reserved for emergencies).

The analysis of the impact of electric vehicles on the distribution grid must take into account the fact that vehicle charging can occur at a time different from that of the national peak load but still contribute significantly to the local peak load, for example in a supermarket car park or a residential area, and therefore require significant reinforcement from the distribution grid.

Impact analysis of EV battery charging on the power system distribution transformers shows that EVs load can effect the load loss, temperature and aging acceleration factor of distribution transformer [KK12a], [AAJ12], [KK12b] ,[TBCH12].

Another study shows relationship between the transformer life consumption and the total harmonic distortion (THD) of the battery charger current [GM03] [THB12].

Some other studies are applied stochastic modelling approach to study the effect of EVs increase in the distribution network [SVN14], [?], [TLPSB12].

Studies have been carried out to assess the EV load impacts in terms of changes in power losses, bus voltages, and real and reactive power demands at the distribution systems with different types of load models [HM13], [LX13],[TGI14], [RACYC13]. Losses in power system could be increased by increase in EV penetration rate. Some studies show the EV benefits at home using vehicle to grid (V2g) concept in to decrease the total final cost of energy including electricity factor and petrol costs to run a plug in hybrid electric vehicle (PHEV) [BBB+11].

In this chapters, we created two main model to assessed the impact of EV integration into the power system in different scenarios. Generally we can say that increasing EV penetration rate in power system changes the load profile of the system. Consequently, this changes cause in some effects on power system parameters. Power system constraints like maximum loads on branches and minimum under voltage on buses could be crossed by increasing in EV penetration rate. By applying smart charging scenarios, we can decrease these effects. In this way, we control the charging time and the charging power rate to consider these constraints.

This chapter, presents a daily traffic curve based model and investigates different scenarios to assess the power system capacity for serving electric vehicles charging in urban regions. The goal is to make a model for studying two charging scenarios for integrating electric vehicles into the power system in large scales. Power system constraints impose a maximum admissible penetration rate on electric vehicles in the area. For each scenario this maximum penetration rate is assessed.

This model covers all uncertainties related to the electric vehicles drivers behaviours variants. These uncertainties include the state of charge in batteries, the charging mode (normal / fast), the charging location, time and rate. All these uncertain properties are considered in the EVs charging model through a probability density function.

Daily traffic curves inform about the situation of the electric vehicle which is either moving or parked. For electric vehicles in the parked situation, different parking locations are considered based on the results of an internet survey for European drivers behavior. Different charging locations, including charging stations, home, shopping centers and work parking, have been considered.

In this study two charging scenarios have been investigated in order to assess the impact of charging on the power system. The first scenario is based on a dumb charging of EV, while in the second one a smart charging system in term of charging time, duration and power rate is considered.

This proposed model is based on a stochastic method using Monte Carlo Simulation. Probability density functions of all data from power demand and generation profiles are applied, in which renewable energy resources of the distribution power grid are included.

The proposed model, is performed for a real case of European city in northern Italy. Annual average of daily traffic curve from the recorded data during a period of one month is used. These data are collected from around 1.5 percent of the vehicular fleets that are equipped with GPS devices.

3.2 A simple model for EVs impact study on grid based on daily traffic curve without considering uncertainties

In this section, a model for studying impact of EVs large-scale integration into power system is proposed. In this model, all load profils and generation time series are applied for a 24 hours. Traffic data are used in modeling the number of EVs during this period.

3.2.1 Mathematical model

The problem is to find states in which integration of EVs large scale into grid, caused problems for power system constraints. These states includes times in the 24 hours of study and locations in the grid in which the constraints are crossed. Objective is finding these states for given Electric Vehicles Penetration Rate (EV_{pr}). In the next step, we apply this model to investigate a proposed method for controlling EVs charging in order to ameliorate these states of crossing constraints in the grid. The mathematical problem is :

Finding

$$States_{cross}(times, buses, lines)$$

In which;

$$\begin{cases} UV_{bus} \neq 0 \\ \text{or} \\ OV_{bus} \neq 0 \\ \text{or} \\ OL_{branches} \neq 0 \end{cases} \tag{3.1}$$

$$With: \qquad EV_{pr} = fix$$

$$Considering:$$

$$\begin{cases} \text{Large-Scale EVs integration} \\ \text{Traffic Data} \\ \text{Drivers Behavieurs} \end{cases} \tag{3.2}$$

Parameters are:
$States_{cross}$: States(conditions) of crossing grid constraints.
EV_{pr}: Electric Vehicles Penetration Rate (%).
UV_{bus}: Number of under voltage buses with STn connected station to buses.
OV_{bus}: Number of over voltage buses with STn connected station to buses.
$OL_{branches}$: Number of over load branches with ST_n connected station to buses.

3.2.2 Power system and EVs charging modelling

From the power system point of view, power demand and generation are two parameters which should be modeled in EVs connection to grid.

We start with modelling the power demand of one bus which supply a part of the region. This power demand includs the initial power demand by the conventional loads and the power demand caused by EVs;

$$P_{TotalDemand}(j,t) = P_{InitialDemand}(j,t) + P_{EVDemand}(j,t) \tag{3.3}$$

In this equation, $P_{EVDemand}(j,t)$ is the total power demand caused by integration EVs to bus j. Adding this power demand to the $P_{InitialDemand}(j,t)$, which represents the initial power demand of the bus j for time t, the total power demand of the bus or $P_{TotalDemand}(j)$ is achieved.

$P_{EVDemand}(j,t)$ is composed of two parts:

$$P_{EVDemand}(j,t) = P_{EVfast}(j,t) + P_{EVnormal}(j,t) \tag{3.4}$$

In this equation, $P_{EVfast}(j,t)$ is the total power demand caused by integration EVs to bus j in fast mode of charging. Adding this power demand to the $P_{EVnormal}(j,t)$, which represents the total power demand caused by integration EVs to bus j, for time t, in normal mode of charging, $P_{EVDemand}(j,t)$ is achieved. For each one we have:

$$P_{EVfast}(j,t) = \sum_{i=1}^{EVnf} P_{EVf}(i,j,t) \tag{3.5}$$

$$P_{EVnormal}(j,t) = \sum_{i=1}^{EVnn} P_{EVn}(i,j,t) \tag{3.6}$$

In this equation, $P_{EVf}(i,j,t)$ and $P_{EVn}(i,j,t)$ are power demand caused by connecting the single EV i to bus j, for time t, in fast mode and normal mode of charging respectively.$EVnf$ and $EVnn$ are the number of EVs connected to bus j in fast mode and normal mode of charging respectively.

Normal charging is possible in two locations; home and parking so for $P_{EVnormal}(j,t)$, we have:

$$P_{EVnormal}(j,t) = \sum_{i=1}^{EVnh} P_{EVnh}(i,j,t) + \sum_{i=1}^{EVnp} P_{EVnp}(i,j,t) \tag{3.7}$$

In this equation, $P_{EVnh}(i,j,t)$ and $P_{EVnp}(i,j,t)$ are power demand caused by connecting the single EV i to bus j,for time t, in normal mode of charging at home location and parking location respectively.$EVnh$ and $EVnp$ are the number of EVs connected to bus j in normal mode of charging at home location and parking location respectively.

For power generation in bus j, we have:

$$P_{TotalGen}(j,t) = \sum_{i=1}^{Gn} P_{Gen}(i,j,t) \tag{3.8}$$

In this equation, $P_{TotalGen}(j,t)$ is the total power generation on bus j. $P_{Gen}(i,j,t)$ is the power generation of the single generation unite i on bus j for time t. Gn is the total number of generation units connected to bus j.

For specifications of EVs, mean values are allocated. For a given time t, the allocated value to each parameter is achieved from a the average values of parameters presented before in **??**.

EVs parameters, including SOC% and batteries capacities for EVs at arriving time to parking are allocated by mean values. Drivers behavieurs parameters including charging mode and charging location are allocated based on the percentage of each parameter for all drivers.

EVs could be in "parked" or "movement" state. For a given time t, normalized parked curve gives the number of parked EVs.
Main assumption in charging EVs:

1. For all time intervals, we assumed that SOC % for all EVs in the parking is defined according with a presumption specified in the scenarios. The fact that all EVs may dont change their charging status for some hours (especially in slow charging mode), is been considered in this assumption. The difference between SOC at arrival time to the parking and outgoing from parking is specified in this way to cover a range of SOC % for all EVs in parking position.

2. All EVs are in use during this simulation, so all EVs at parking state contribute in charging process.

3. The EV could be charged in fast or slow mode according with their location and EV driver decision. We assumed two plans for fast/normal charging. In one scenario the only location for fast charging is "Shopping district and intermediate location". This is a more "normal charging base" scenario. In another "fast charging base" scenario we assumed 50% of "at work" and "At home but in a parking space away from my home" EVs to have the possibility to be charged in fast mode. This two "plans" and "modes" are explained in more details in next sections.

4. Total population for Monza case study is 80 000 [4] and Vehicle Penetration determined as the number of small and family car per person in the region is 0.65 [?].

5. In this study number of EVs in movement is extracted from the traffic curve with considering the total population of the region, EV penetration rate, and vehicle per person index. At a given time, the number of EVs in movement, are applied to get the number of EVs need to be charged in next time. We supposed for one hour period of time, the number of arriving EVs to park to be equal to the EVs going out from parking location and this number is equal to the EVs in movement in this period of time. It should be mentioned that not all EVs are parked in the parking; they could be parked in garage, in parking location, or even at street. Based on the parking location and access to charging socket, EV could be charged. EV drivers decision is the final factor that is checked before EV starts charging.

6. When EVs arrive to parking location, the traveling distance is not the same for all EVs. They can have a random traveled distance. In addition, the SOC at the arriving time is different for all EVs. SOC for outgoing EVs from the parking location could be different too. SOC for an outgoing EV depends on the initial SOC at arriving time, duration of stay and charging power rate. All these variables are modeled in the difference between SOC at arrival and at outgoing time. In this part of study we fixed this value but in the next chapter, a random analysis base scenario is applied to consider all these variables.

7. In the urban environment, we assumed the total population of each given bus to be a proportional to the served power by this relative bus. Hence, the total EV in each region is a proportion of population, consequently, the total EV connected to each bus could be considered as a function of the power consumed by the relevant bus. We use the normalized load profile extracted from daily traffic curve and by multiplying it in a coefficient of the number of EV connected to this bus, the real load profile of EV is extracted. Figure 3.1 shows this distribution in a schematic diagram.

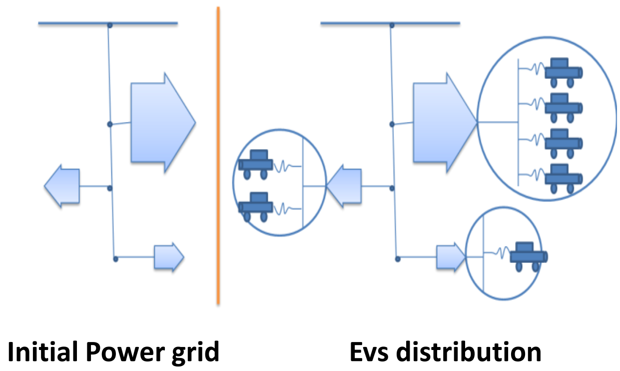

Figure 3.1: EV connection to each bus is proportional to total power connected to this bus.

3.2.3 Two scenarios; dumb and smart charging model

In order to study the effect of large-scale integration of EVs into the power system, two scenarios are considered. Both scenarios are based on average EVs charging plan. In scenarios one, EVs charging is done according with a dumb charging while scenarios two is supposed to use a smart charging for EVs. All these scenarios have the some common steps in their process. Figure 3.2 shows the general flowchart algorithm of the scenarios.

Another case with strong EVs charging plan is discussed in Appendix 5.6. Two scenarios for dumb and smart charging is compared in terms of total losses and total power demand.

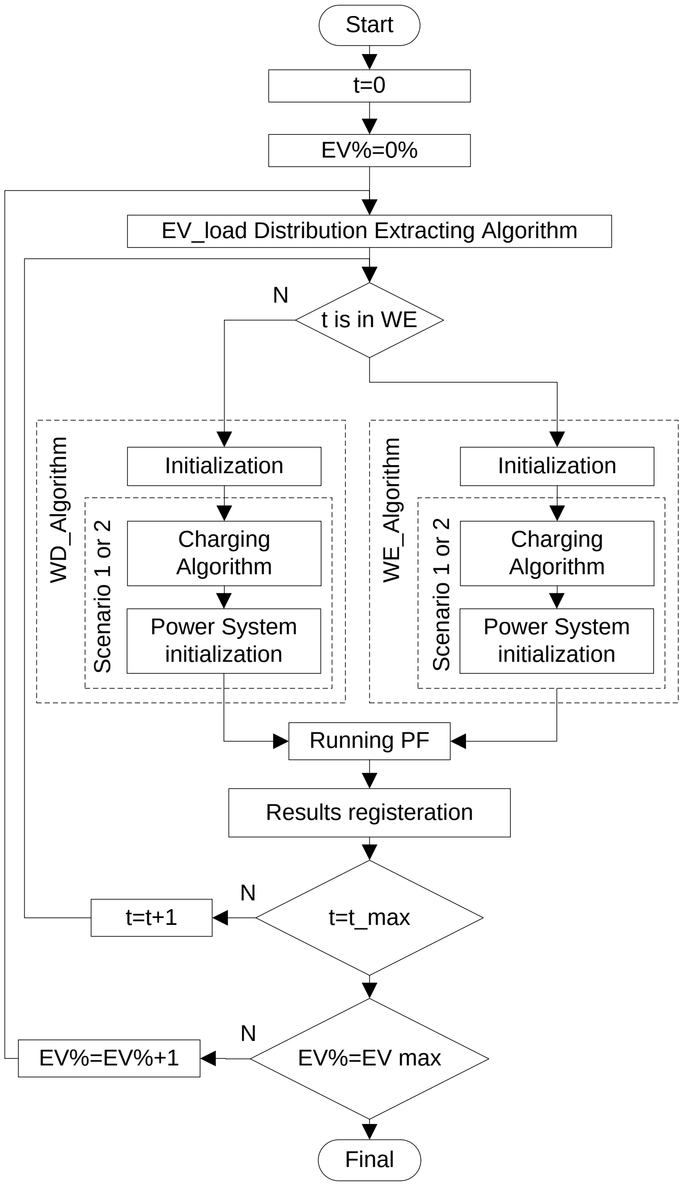

Figure 3.2: Flowchart algorithm of EV charging.

In this figure, descriptions of some parameters are;
WE: Weekend day
WD: Normal Week Day

t_{max}: final time index in load profile
EV_{max}: final EV percentage in the region determined by initialization

3.2.3.1 Dumb charging with average EVs charging plan

In the first scenario, charging process of EVs starts when they are plugged in without any control on the charging start time. They stop charging as soon as the State of Charge (SOC) of the battery has gone over the specified value specified as complete charged situations. In this study a battery with 85% SOC is considered as a charged battery.

Figure 3.3 shows the results of simulations with this scenario for $EVpr =$ 0%,10% and 15%. As we can see in this figure, generally the integration of EVs caused increase in the total power demand. EVs load has increased the peak power demand at time 21:00. Total active loss in the grid is shown in the bellow side of the figure. As we can see, total loss is increased with augmentation in EV_{pr}.

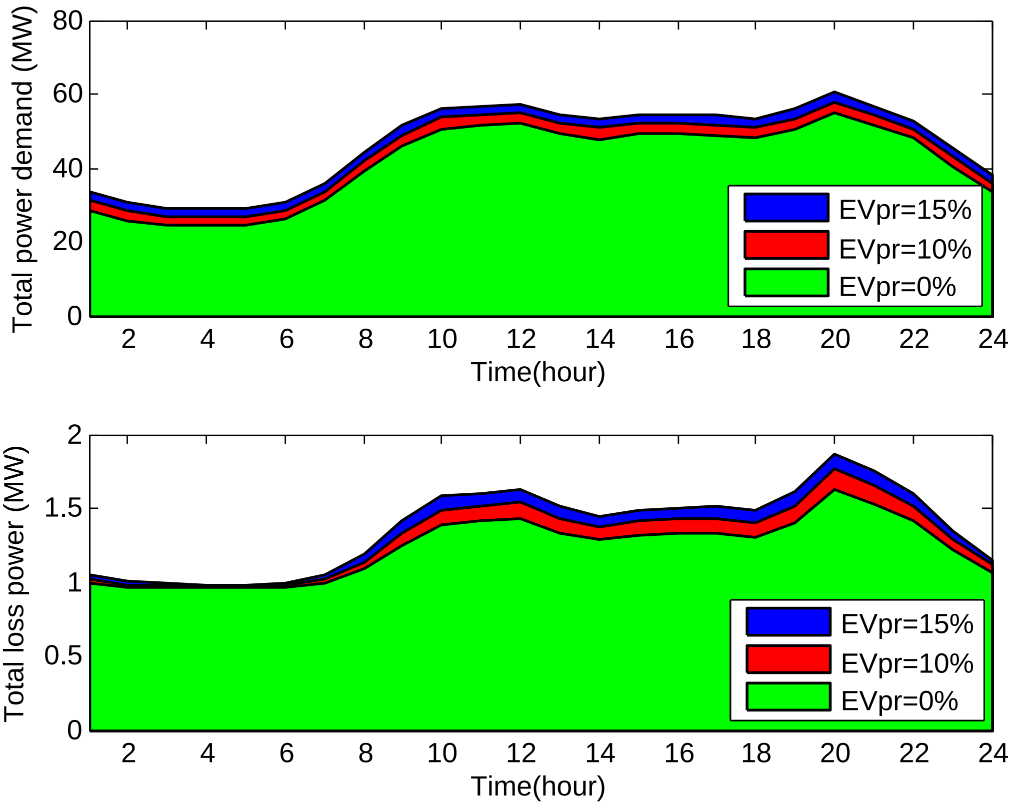

Figure 3.3: Total power demand and loss increase in peak with scenario1.

3.2.3.2 Smart charging with average EVs charging plan

In this scenario a smart model of EVs charging is evaluated. Comparing with dumb charging, smart charging scenario includes a time analyzing factor in deciding for a given time, whether EV charging could be done or should be postponed.

For a given time t, the power demand is compared with the daily average power demand on bus. The values bigger and lower than average are considered as a "peak" and "off-peak" respectively. All connected Evs to buses with a power demand less than average daily power demand are allowed to start charging. For the rest EVs, charging process is postponed until the end of peak period. As mentioned before, for all buses in a feeder, the power profile of feeder is applied in extracting buses power profile. So there are 17 different profiles with different peak and off-peak intervals. Figure 3.4 shows a schematic diagram of postponing EVs charging. In this charging model, two peaks and two off-peaks intervals are supposed. In top side of figure, the EVs number needed to be charged in each interval are illustrated in different colors. In the bellow side, EVs charging in peak period is postponed to the next possible off-peak period.

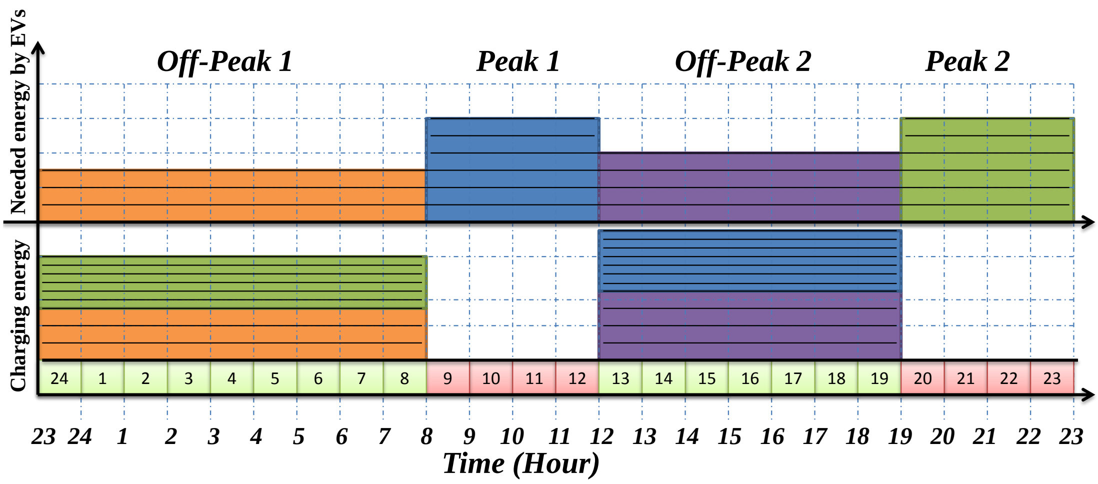

Figure 3.4: Postponing Evs charging at peak times to off-peak time in smart scenario.

3.2.3.3 Applying a case study and results comparison

Two scenarios are evaluated by applying the described case study in the first chapter. Figure 3.5 compares the total power demand in three cases including the initial case without EVs, dumb charging of EVs and smart charging of EVs.

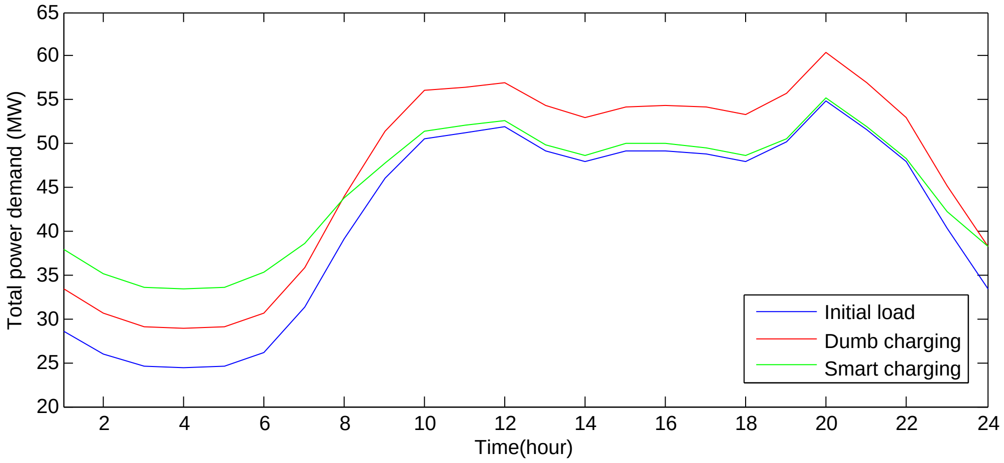

Figure 3.5: Total power demand for initial case, without control and with control on EVs charging.

Figure 3.6 compares the total power losses in the power system for these three cases.

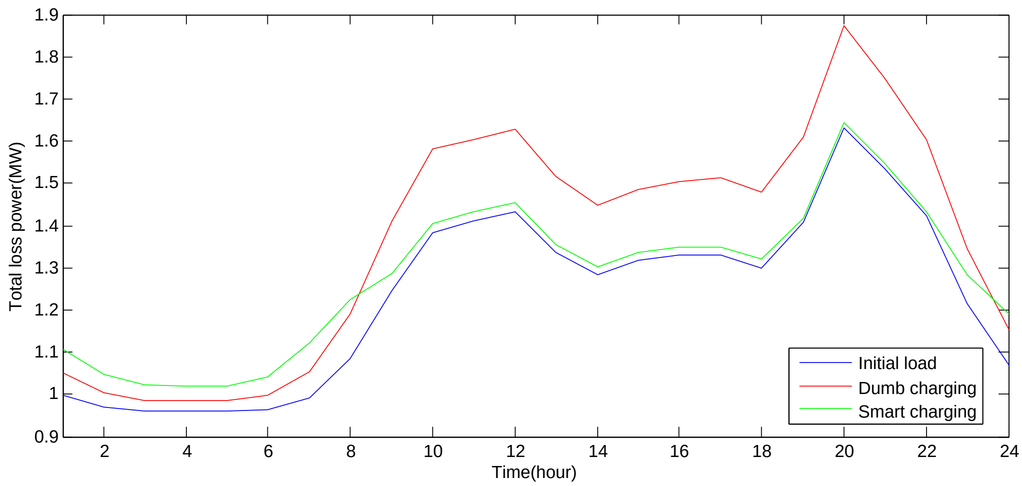

Figure 3.6: Total power losses in the grid for initial case, without control and with control on EVs charging.

In order to evaluate scenarios, two factors are compared for different scenarios; the power shaving factor and standard deviation of the power demand profile. The formula for the population standard deviation of a finite population can be applied to the sample, using the size of the sample as the size of the population. This estimator, denoted by SD, is known as the standard deviation of the sample, and is defined as follows:

$$SD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{3.9}$$

Where $\{x_1, x_2, \ldots, x_N\}$ are the observed values of the sample items and $\bar{x}$ is the mean value of these observations, while the denominator N stands for the size of the sample: this is the square root of the sample variance, which is the average of the squared deviations about the sample mean[Dac12].

Power shaving factor, denoted by PSF, is known as the peak to average power ratio of samples, and is defined as follows:

$$PSF = \frac{MaxP}{AvrP} \tag{3.10}$$

$MaxP$:Max value in daily power curve
$AvrP$:Average of daily power curve

Power shaving factor effects directly on the power reserves of the system, more the power shaving factor increases , more the generations should be increased in the system to feed the system in the peak hour times. The distribution system companies prefer to have a smaller power shaving factor. Standard deviation could be used to evaluate the quality of the delivered power, more the standard deviation decreases, more the power quality increases [Saa09].

Table 3.1 shows results of comparison of power shaving factor, standard deviation of power demand and total losses in the grid. Results are compared for two scenarios of EVs charging; dumb and smart charging.

Description	Dumb Charging	Smart Charging
Standard Deviation (SD) of power demand (MW)	11.1508	7.2349
Power Shaving Factor (PSF) of power demand (MW)	1.2989	1.2288
Total losses in the grid (MWh)	32.7565	30.7116

Table 3.1: Dumb and smart charging scenarios comparison

Standard Deviation (SD) of power demand has improved to 35% by applying the smart charging model to EVs. Power Shaving Factor (PSF) of power demand and total losses in the grid are decreased to 5

3.3 A comprehensive model considering uncertainties in grid and EV parameters

In this section, a comprehensive model is proposed to study the EVs large integration into power system and to find the maximum EV_{pr} accepted by the grid. In this model, uncertainties in grid and EV parameters are observed.

3.3.1 Mathematical model

The problem is to find the maximum Electric Vehicles Penetration Rate (EV_{pr}) with the minimum possibility to lead in any problem on power system constraints. That means we are looking for the limit value of allowed EVs to be integrated into power system. This value is a percentage of total vehicles in the region. The proposed model is working based on the Monte Carlo Simulation (MCS) algorithm. In fact the power system constraints are evaluated by a Monte Carlo Simulation Success/Fail index.

The mathematical problem is :

Finding

$$MaxEV_{pr}$$

$$With: \qquad UV_{bus} = 0, \quad OV_{bus} = 0, \quad OL_{branches} = 0$$

$$Considering:$$

$$\begin{cases} \text{Large-Scale EVs integration} \\ \text{Traffic Data} \\ \text{Drivers Behavieurs} \\ \text{Power System uncertainties} \end{cases} \tag{3.11}$$

Parameters are:
EV_{pr}: Electric Vehicles Penetration Rate (%).
UV_{bus}: Number of under voltage buses with STn connected station to buses.
OV_{bus}: Number of over voltage buses with STn connected station to buses.
$OL_{branches}$: Number of over load branches with ST_n connected station to buses.

Solution is a percentage value which determines the percentage of total vehicles in the region which are electric vehicle type.

Figure 3.7 illustrates details of the proposed model for finding the maximum EV_{pr}. Based on this model, all power system parameters, including power generations and substations loads are allocated randomly. EVs parameters including EVs positions, charging power, SOC of batteries and drivers behavieurs are also allocated based on a random selection from the probability density function of each one. In this way, the allocation algorithm is working independantly for MCS iterations.

3.3.2 Power system and EVs charging modelling

From the power system point of view, power demand and generation are two parameters which should be modeled in EVs connection to grid.

We start with modelling the power demand of one bus which supply a part of the region. This power demand includes the initial power demand by the conventional loads and the power demand caused by EVs;

$$P_{TotalDemand}(j) = P_{InitialDemand}(j) + P_{EVDemand}(j) \tag{3.12}$$

In this equation, $P_{EVDemand}(j)$ is the total power demand caused by integration EVs to bus j. Adding this power demand to the $P_{InitialDemand}(j)$, which represents the initial power demand of the bus j, the total power demand of the bus or $P_{TotalDemand}(j)$ is achieved.

$P_{EVDemand}(j)$ is composed of two parts:

$$P_{EVDemand}(j) = P_{EVfast}(j) + P_{EVnormal}(j) \tag{3.13}$$

In this equation, $P_{EVfast}(j)$ is the total power demand caused by integration EVs to bus j in fast mode of charging. Adding this power demand to the $P_{EVnormal}(j)$, which represents the the total power demand caused by integration EVs to bus j in normal mode of charging, $P_{EVDemand}(j)$ is achieved. For each one we have:

$$P_{EVfast}(j) = \sum_{i=1}^{EVnf} P_{EVf}(i,j) \tag{3.14}$$

$$P_{EVnormal}(j) = \sum_{i=1}^{EVnn} P_{EVn}(i,j) \tag{3.15}$$

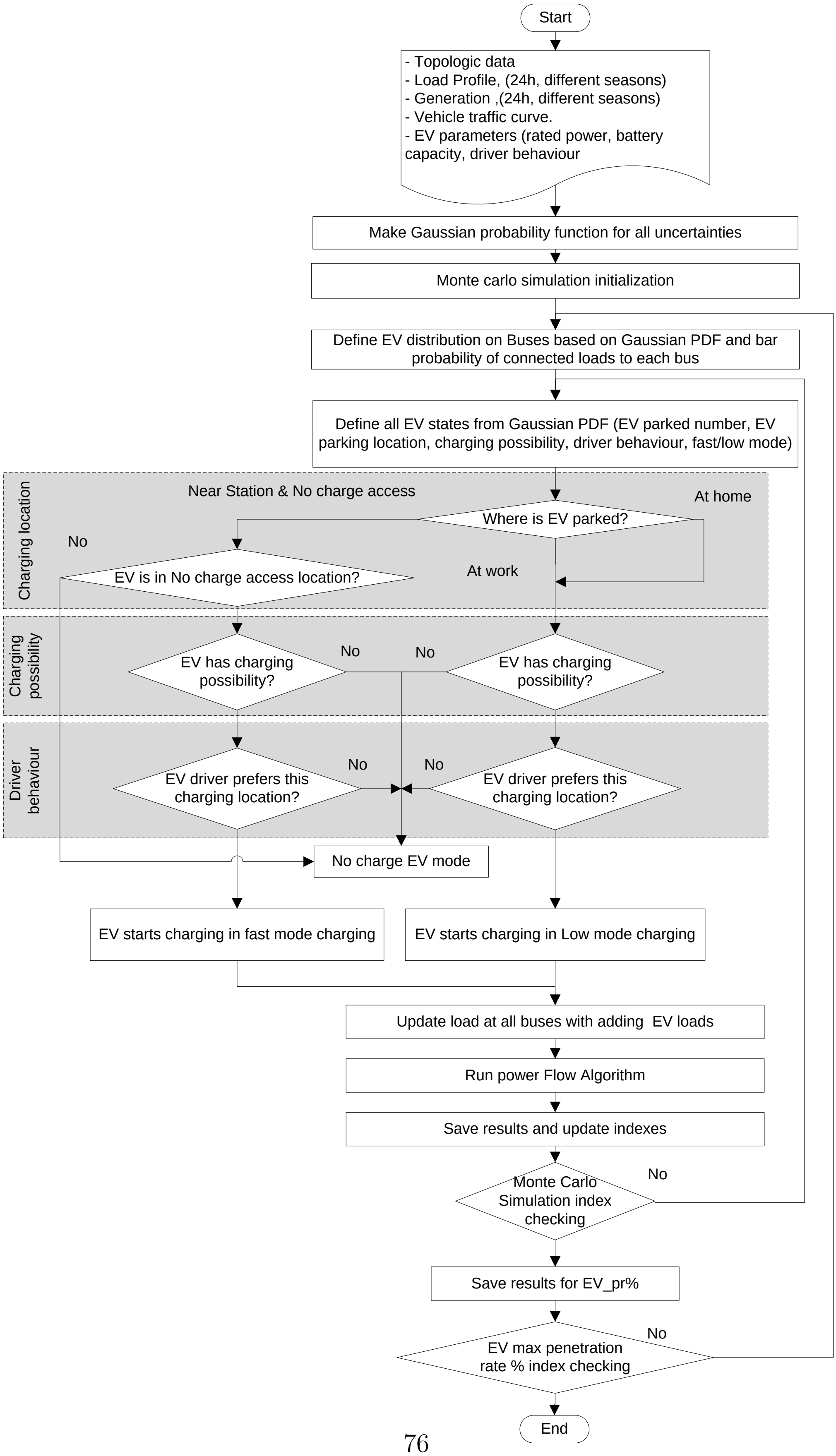

Figure 3.7: General flowchart algorithm for EV normal plan charging.

In this equation, $P_{EVf}(i,j)$ and $P_{EVn}(i,j)$ are power demand caused by connecting the single EV i to bus j in fast mode and normal mode of charging respectively.$EVnf$ and $EVnn$ are the number of EVs connected to bus j in fast mode and normal mode of charging respectively.

Normal charging is possible in two locations; home and parking so for $P_{EVnormal}(j)$, we have:

$$P_{EVnormal}(j) = \sum_{i=1}^{EVnh} P_{EVnh}(i,j) + \sum_{i=1}^{EVnp} P_{EVnp}(i,j) \quad (3.16)$$

In this equation, $P_{EVnh}(i,j)$ and $P_{EVnp}(i,j)$ are power demand caused by connecting the single EV i to bus j in normal mode of charging at home location and parking location respectively.$EVnh$ and $EVnp$ are the number of EVs connected to bus j in normal mode of charging at home location and parking location respectively.

For power generation in bus j, we have:

$$P_{TotalGen}(j) = \sum_{i=1}^{Gn} P_{Gen}(i,j) \quad (3.17)$$

In this equation, $P_{TotalGen}(j)$ is the total power generation on bus j. $P_{Gen}(i,j)$ is the power generation of the single generation unite i on bus j. Gn is the total number of generation units connected to bus j.

In the proposed model, all power generation and demand values are allocated randomly in MCS method. For example in each iteration, the allocated generation to each unit is achieved from a random selection based on the GPDG of the unit generation profile. next equation shows this allocation:

$$P_{Gen} \sim rand\{P_{gen}GPDF\} \quad (3.18)$$

In this equation, P_{Gen} is the allocated value to power generation of the unit. $P_{gen}GPDF$ is the GPDF specification of the unit generation profile.

In the same way, for all power demand on buses, values are allocated randomly in MCS method. In each iteration, the allocated power demand to each bus is achieved from a random selection based on the GPDG of the bus load profile. next equation shows this allocation:

$$P_{InitDemand} \sim rand\{P_{demand}GPDF\} \quad (3.19)$$

In this equation, $P_{InitDemand}$ is the allocated value to initial demand power of bus. $P_{demand}GPDF$ is the GPDF specification of the load profile at related bus.

Also, for specifications of EVs,values are allocated randomly in MCS method. In each iteration, the allocated value to each parameter is achieved from a random selection based on the GPDG or the probability bar of the parameter. next equation shows this allocation:

$$P_{EV} \sim rand\left\{EV_{SOC}\right\} \cap rand\left\{EV_{Batt}\right\} \cap rand\left\{EV_{ChMode}\right\} \cap rand\left\{EV_{ChLocat}\right\} \tag{3.20}$$

In this equation, P_{EV} is the allocated values to EV parameters. EV_{SOC} and EV_{Batt} are the GPDF specification of the EVs at arriving time to parking for SOC% and batteries capacities respectively. EV_{ChMode} and $EV_{ChLocat}$ are the random bar specifications of EVs drivers behavieurs for selection of charging mode and charging location respectively.

All these allocations are performed in an independent selection. The final specification of the EVs parameter is a random selection of these four parameters in a separate random allocations.

3.3.3 Monte Carlo parameters specifications

According with flowchart algorithm of the model, EV and power system characters are allocated in each iteration. Then the program runs the power flow analysis. This cycle is repeated in each Monte Carlo Simulation iteration. Based on definition, a "Success" iteration is the iteration in which the power flow analysis results consider all constraints of power system including Over Load (OL) in branches, Over Voltage (OV) and Under Voltage (UV) in buses. "Failure" iteration is the iteration in which at least one of the above mentioned power system constraints are crossed. Success/Failure evaluation test is done at the end of iteration. Program repeats Monte Carlo Simulation for each EV penetration rate and results are saved at the end of each simulation for a specified EV penetration rate.

$$MCS_{SuccessIndex}(n) = \frac{N_{success}(n)}{N_{success}(n) + N_{failure}(n)} \tag{3.21}$$

$With$

$MCS_{SuccessIndex}(n)$: MCS success index for n number of total iterations.

$N_{success}(n)$: The number of success iterations for n number of total iterations.

$N_{failure}(n)$: The number of failure iterations for n number of total iterations.

During each MCS iteration, a random distribution of power demand and generation is assigned on buses. Results of power flow analysis with the composed power demand including initial power and the power caused by EVs charging is evaluated. Power system constraints are checked at the end of each iteration. These constraints are Over Load (OL) in branches, Under Voltage (UV) and Over Voltage (OV) at buses. By checking these parameters, MCS Success/Failure index is determined. An iteration is considered as success iteration if non of these three constraints are crossed. Otherwise it's a failure iteration.

3.3.4 Two plan for charging; normal and fast charging

Normal charging base plan: In this plan we supposed a more basic model for the possibility of fast charging mode for EVs. In this plan only the parked EVs in "near station" mode location are able to be charged in fast charging mode. These cases are related to shopping centers or intermediate parking. Other EVs including "At home" and "At work" are considered as normal charging mode. This "normal charging based plan" is the subject of scenario one and two.

Fast charging base plan: In this plan we study two scenarios with a larger contribution for fast charging mode. We supposed some fast charging possibilities at home and works. In this plan we assumed 50% of "at work" and "At home but in a parking space away from my home" EVs to have the possibility to be charged in fast mode. In fact we assumed some charging stations in 50% of parking. These parking could be private or public parking. In fact for some parking near residential regions for the vehicles in "At home" location we assumed a possibility to install fast charging stations. For EVs at "service station and recharging station" the only possible charging mode is fast charging. This plan is the foundation of scenarios number three and four. Table 3.2 summarized these values.

3.4 Case Study Application of the comprehensive model

3.4.1 Two scenarios; dumb and smart charging

In order to assess the proposed model on the power system case study, two scenarios are tested; dumb and smart scenario.

	Fast charging plan		Normal charging plan	
Ch. Location	Fast mode	Norm mode	Fast mode	Norm mode
At home	33	67	0	100
At work	50	50	0	100
Near station	100	0	100	0
No charge access	0	0	0	0

Table 3.2: Allocated probabilities for normal and fast charging (all values in %)

In the charging process, time of start and stop of charging is defined based on the conditions. These conditions could be forced by the control charging center or home power control center. These conditions are defined in the smart charging scenarios. For dumb charging scenarios the only important factor is SOC of battery in EVs. This factor determines the start and stop time of charging. In dumb charging scenario, EVs start charging as soon as they are plugged in to the grid and stop charging when battery is full.

3.4.1.1 Dumb EVs charging

Dumb charging model is a scenario of charging in which we have no control on the parameters of charging. EVs start charging process when they are connected to the grid. In this case, grid has no control on the power demand of the EVs charging. Depending on the initial SOC and characters of EVs, charging parameters are determined.

3.4.1.2 Smart EVs charging

To make a smart charging scenario we need to return back to the characteristics of load profile in the region. The case study from previous chapter is applied in this section. In this case study, load profiles in feeders, are the reference profile for loads of the relevant bus.

These load profiles have two different peaks. First peak starting from 8:00 and turning down at 12:00, in this study is called "peak1". This peak is related to work period peak in the morning when peoples are at work. Second peak is between 19:00 and 23:00 and is called "peak2". This is the time when people are at home or restaurant with families or friends. Lighting and normal home uses are the most important components of load in this period. The average load increase for these periods is about 20% of maximum load in the whole day hours. In addition two off-peak periods constitute the rest of total hours of a day including from 12:00 to 19:00 period and 23:00 to 8:00 period. These two terms are denominated “off-peak1” and “off-peak2”, respectively.

In order to have a smart charging scenario we suppose a new charging model for the EVs at work and at home. According to this scenario, EVs charging is shifted to the next hours if the charging time is inside intervals peak1 or peak2. In fact the EV charging load is added to off-peak1 and off-peak2 for the expected charging in peak1 and peak2 periods respectively. Figure 3.8 describes this scenario in a schematic example. In top side of this Figure, the area of rectangles indicates the total energy expected for charging EVs. This energy is supplied by the power system. In below, the proposed scenario for postponing EV charging is demonstrated. These retarded charging cause increase in the usual power de-

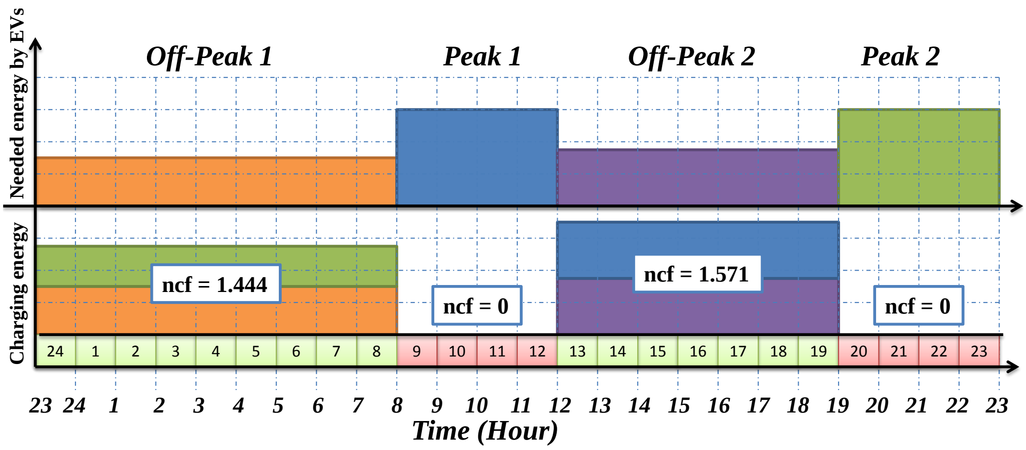

Figure 3.8: Different peak and off-peak periods for smart EVs charging.

mand in off-peak1 and off-peak2. To make this more precise, a coefficient called “normal charging factor” or “ncf” is defined for the number of EVs connected in off-peak. ncf for a off-peak is the sum of total expected hours in last peak plus the expected hours in the current off-peak divided by the expected hours in the current off-peak. These definitions for two off-peaks1 and 2 is: For off-peak1:

$$ncf = \frac{h_{peak1} + h_{0ff-peak1}}{h_{0ff-peak1}} = \frac{4+7}{7} = \frac{11}{7} = 1.571 \tag{3.22}$$

With:
h_{peak1}: expected hours in peak1
$h_{0ff-peak1}$: expected hours in 0ff-peak1 expected hours in 0ff-peak1.

For off-peak2:

$$ncf = \frac{h_{peak2} + h_{0ff-peak2}}{h_{0ff-peak2}} = \frac{4+9}{9} = \frac{13}{9} = 1.444 \tag{3.23}$$

With:
h_{peak2}: expected hours in peak2
$h_{0ff-peak2}$: expected hours in 0ff-peak1 expected hours in 0ff-peak2.
The probability of being in peak time for an EV is proportional to the ratio of the below hours:

$$P_{peak} = \frac{h_{peak1} + h_{peak2}}{h_{total}} = \frac{8}{24} = 33\% \tag{3.24}$$

With:
h_{total}: Total peak and off-peak hours

$$P_{peak} = \frac{h_{0ff-peak1} + h_{0ff-peak2}}{h_{total}} = \frac{16}{24} = 67\% \tag{3.25}$$

The probability of being in off-peak1 or off-peak2 for an EV is proportional to the ratio of the below hours:

$$P_{off-peak1} = \frac{h_{off-peak1}}{h_{off-peak1} + h_{off-peak2}} = \frac{7}{16} = 44\% \tag{3.26}$$

$$P_{off-peak2} = \frac{h_{off-peak2}}{h_{off-peak1} + h_{off-peak2}} = \frac{9}{16} = 56\% \tag{3.27}$$

This scenario is considering only EVs in normal charging mode. For fast charging mode EVs, there is no condition. In fact, EVs in fast charging mode start charging as soon as they are plugged in. We have this assumption because of the nature of fast charging modes in which the locations are generally at stations and could not be postponed. In fast mode conditions, driver arrives at station and need to charge EV immediately. Figure 3.9 illustrates the flowchart algorithm of smart charging.

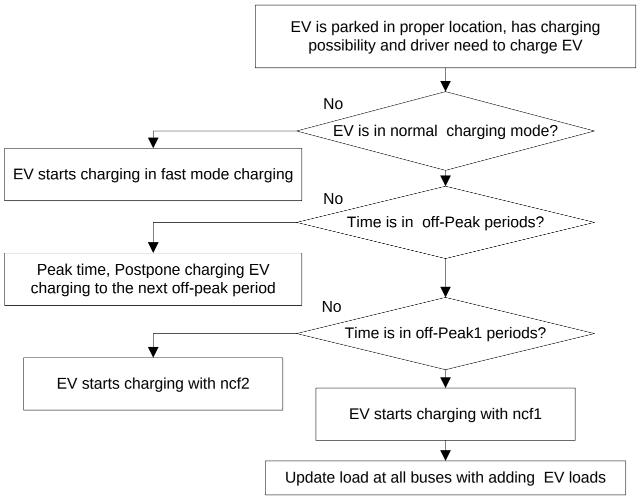

Figure 3.9: Smart charging determination.

3.4.2 A criterion definition for MCS results evaluation

In order to qualify the EV_{pr} in general, we fix a limit for $MCS_{SuccessIndex}(n)$ percentage. For EV_{pr} cases with $MCS_{SuccessIndex}(n)$ less than this specified percentage, we suppose "failure for EV_{pr}vase" In this study , we fixed this specified value to 99% of $MCS_{SuccessIndex}(n)$ values. Figure [next] shows the success percentages points for each EV_{pr}.

To find the exact value of EV_{pr} we supposed a limit line with $MCS_{SuccessIndex}(n)$ equal to 99%. we use a normal curve fitting method to find the related curve of discrete values of $MCS_{SuccessIndex}(n)$ for different EV_{pr}. The cross section of fitted curve and Y=99 Table 3.3 summarized data from dumb normal charging scenario. This table includes total losses and number of max crossed buses or branches from power system constraints.

Description	Results
Max EV penetration rate (for 99% success)	7 %
Under voltage Buses NO in the worst failed case	1 buses
Over voltage Buses NO in the worst failed case	0 buses
Over load Branches NO in the worst failed case	0 branches
Total real Losses(MW) in the worst failed case	1.8870

Table 3.3: Worst case in dumb normal charging mode with EV_{pr}=7%

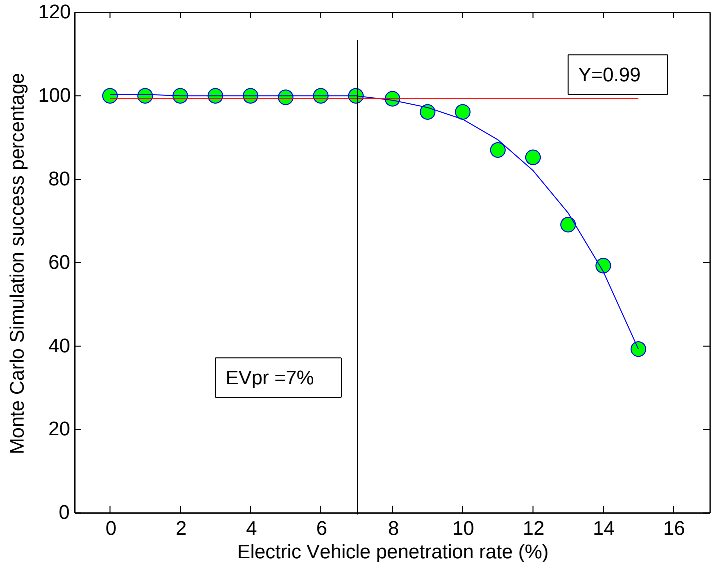

Figure 3.10: A criterion of 99% for MCS results evaluation

3.4.3 Power system and EV data

All power system and EVs data are applied from the case study of the previous chapter. These data are explained in the uncertainties modelling of the power system and EVs parameters.

3.4.4 Results analysis and comparison

In this section results of applying the the comprehensive model on the case study are discussed. These results are provided for two scenarios; dumb and smart charging. Using the proposed comprehensive as a investigation tool, the charging control scenario (smart charging scenario) is tested on the case study. This smart charging method is compared with dumb charging method in terms of EV_{pr} and power system constraints. Compared power system constraints are voltage drop on buses and over load in branches.

3.4.4.1 EV_{pr} comparison

Figure 3.11 demonstrates $MCS_{SuccessIndex}(n)$ for EV_{pr} increase. Two dumb and smart charging scenarios are compared. In dumb scenario, the maximum EV_{pr} accepted by the MCS criterion is 7%. This maximum value is ameliorated by applying smart charging to 14%.

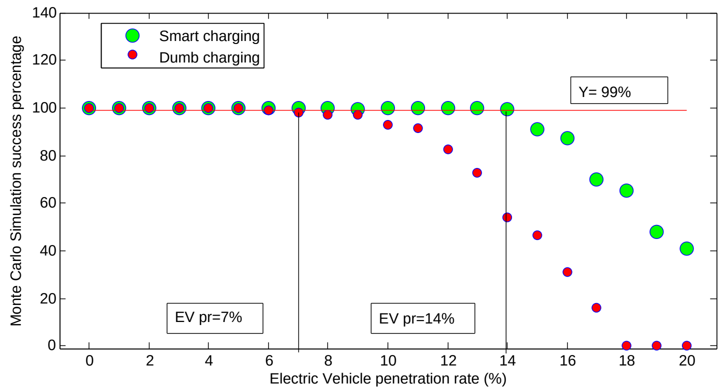

Figure 3.11: Increase in EV_{pr} by applying a smart charging.

Table 3.4 resumes results of simulations for dumb and smart charging scenarios. These results are provided for two plans; normal and fast charging plans. Fast charging plan has smaller EV_{pr} compared to normal plan. Applying a smart charging, EV_{pr} is increased in both normal and fast plans.

Plan	Dumb charging	Smart charging
Normal plan	7%	14%
Fast plan	3%	6%

Table 3.4: Maximum EV_{pr} in dumb and smart charging for two plans

3.4.4.2 Power system constraints comparison

Figures 3.12 and 3.13 show the maximum number of power system constraints for smart and dumb charging scenarios. These constraints are the constraints which are crossed in simulation. As we can see over loads in branches are more significant for EV_{pr} increase in first steps. It should be reminded that the case study is an urban type in which over load in branches are more common than under voltage.

3.4.4.3 Voltage drop on buses display

Figure 3.14 displays voltage value on some buses. Voltages on all buses are sorted from small to bigger and only the buses number with coefficient five are

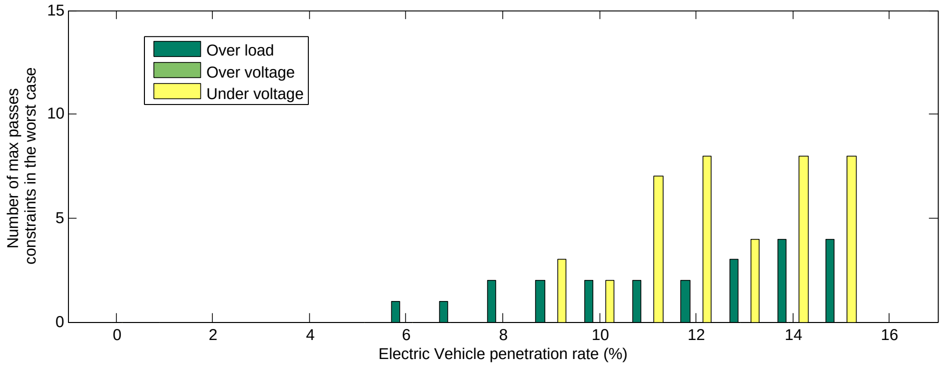

Figure 3.12: Power system constraints comparison for dumb charging scenarios.

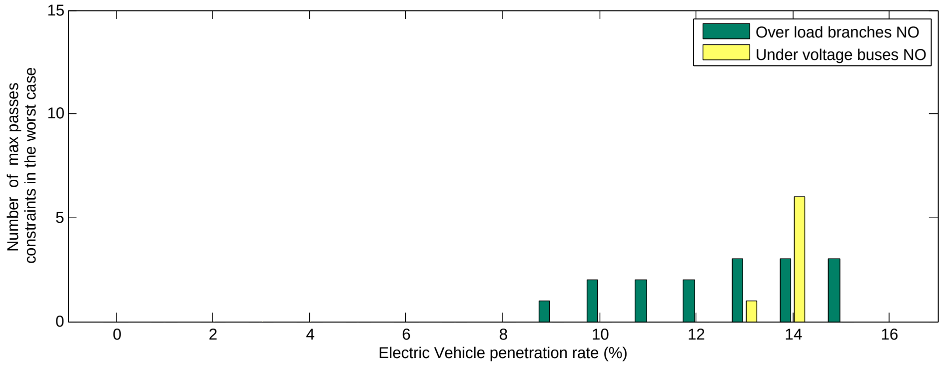

Figure 3.13: Power system constraints comparison for dumb charging scenarios.

selected to be shown. For each EV_{pr} the case with minimum average in bus voltages is selected. As we can see bus voltages are not very small. This case study is an urban case and we did not expect a big voltage drop on buses. The most challenging constraint in urban power grid is over load in branches.

In Appendix 5.6 , the fast plan charging algorithm is presented. The maximum iteration for Monte Carlo Simulation is fixed to 10000 iterations.

In this section, two proposed models, the simple deterministic and comprehensive models are compared.

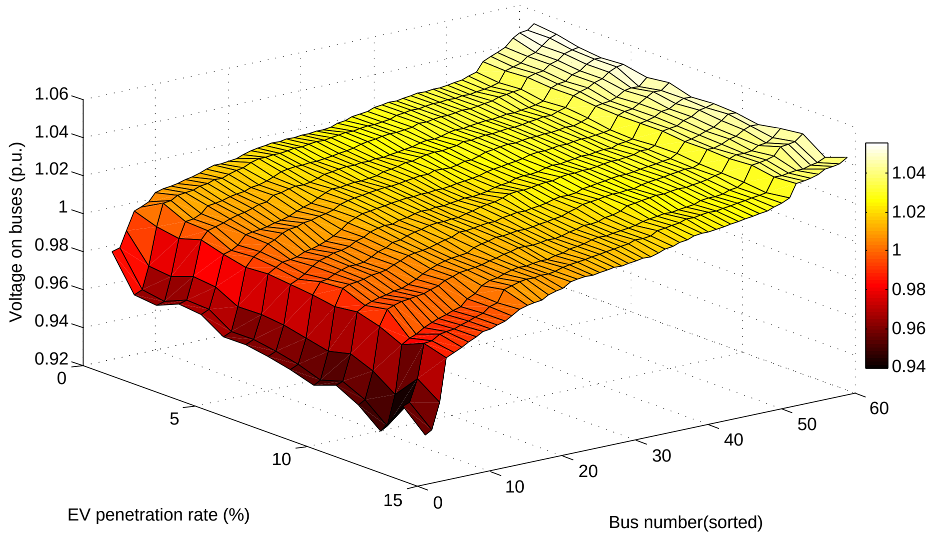

Figure 3.14: Bus voltage drop with decrease in EV_{pr} in dumb charging scenario.

3.5 Conclusion

In this chapter, two charging model are provided to improve the grid parameters in large-scale integration of EVs into power system. The first model is based on a deterministic method. This model is tested on a case study. Applying the first model, Standard Deviation (SD) of power demand, Power Shaving Factor (PSF) of power demand and total losses in the grid are improved by applying the smart charging model to EVs.

The second model is a comprehensive model based on the Monte Carlo method. In this model, power system uncertainties in loads and generations are taken into account. This model cover all the electric vehicles in the urban area with their uncertain behaviour variants of charging including the state of charge in batteries, the charging mode (normal / fast), the charging location, time and rate. All these uncertain properties are considered in the EVs charging model through a probability density function. A random allocation on Gaussian Probability Distribution Function (GPDF) determines these values for each parameter. Drivers behaviours are allocated by a random bar specification. The proposed model is a stochastic model based on the Monte Carlo method. Using the proposed comprehensive model as an investigation tool, the charging control scenario (smart charging scenario) is tested. This smart charging method is compared with dumb charging method in terms of EV_{pr} and power system constraints. Compared power system constraints are voltage drop on buses and over load in branches. Results show that by applying a smart charging for EVs, EV_{pr} could be increased in the region without causing power system constraints crossing.

From the power system point of view, shaving peak loads is important and results of applying two dumb and smart scenario shows that it is necessary to favor slow charging solutions and smart management of charging, which will automatically orient the power demand to off-peak hours. The proposed study tool can be applied to other distribution networks.

Chapter 4

Fast charging stations for electric vehicles planning

Electrification of the transportation sector in urban regions is gradually becoming a global trend. Smart grid development calls for effective solutions, such as electric vehicles, to meet the energy and environmental challenges. Combustion engine vehicles replacement with Electric Vehicles (EV) seems to have the capacity of reducing air pollutions in large cities. Beside the economic incentives for EV drivers and car manufacturing companies, the lack of charging infrastructures and facilities with proper accessibility is important to increase the public motivation for using EVs. In this way installing fast charging stations, which can ensure the easy accessibility to energy, may promote drivers to use more and more the electricity instead of fuel, especially in hybrid electric vehicles. To facilitate large-scale EV applications, optimal locating and sizing of charging stations in smart grids have become essential. In this chapter the fast charging station planning is discussed. In the first step, a stochastic approach based model is proposed to define a priority index in selection between various busbars for installing charging station. In the next step, a proposed model is presented to find the optimal location for charging station applying the Particle Swarm Optimization (PSO) method.

4.1 Fast charging stations planning challenges for smart grid

Due to the environmental concerns, there is a definite development towards new propulsion systems for future cars in the form of electric and hybrid electric vehicles. Although electric vehicles are known as zero emission vehicles, if we consider the fossil fuels sources of energies as the main sources of energy for power system, the environmental advantages of EVs may seems to be unrealistic. But they use batteries as electrical energy storage devices and electric motors to propel the automobile. According to [EVo], electric vehicle registrations in Europe rose by more than 60.9 % in 2014, as compared to 2013. In the next eight years the number of electric vehicles will exponentially increase and will reach 40 millions in EU. By increasing renewable sources of energy like wind and photovoltaic sources in the next years, the percentage of green energy in the power system will be increased. Despite the general advantages of increasing EV for environmental reasons, they are still a good option for decreasing air pollutions in urban regions in which the main part of pollutions is caused by combustion engine vehicles. Fast charging station is based on this hypothesis to centralize the EVs charging in urban regions. Fast charging station gives easy access to drivers to charge their EVs in the cities, urban areas and highways with higher density of EVs. These charging facilities could be installed in the public areas in which the drivers could have access easily like shopping centers, commercial centers, work location parking or even in residential parking. Finding the best location of fast charging station is a new challenge in increasing EVs in urban regions. In power system planning, the charging station should be selected in a smart manner to respect some technical and economic considerations.

Power system constraints should be considered. Charging stations require high power to charge connected EVs to station, especially when the network could be overloaded. Therefore there is the need to model and analyze the impact of charging stations on the grid. Integration of charging station effects on the grid was the subject of some literature. In some studies, authors tried to find the best solution for the problem of location finding for fast charging station to respect technical constraints of the power grid. [**?**], [RKVB13] ,[PL14] , [RACYC13]. In [WXWW13], author proposes a multi-objective EV charging station planning method which can ensure charging service while reducing power losses and voltage deviations of distribution systems. Another study [YRT+13], shows both the network voltage level of low voltage level ($400V$) and medium voltage level ($11kV$)system go beyond the safe voltage operating limits with fast charging of EVs at station.

Geographical constraints like easy access to charging stations should be considered. Drivers should be able to reach the charging station with minimum possible distance from the place in which the EV battery is empty and needs to be recharged. In [Cle12] a limited number of EVs are studied. The minimum distance from station or the minimum total cost for travel could be considered as objective function in substations studies. [Cle12], [ZfWXK12], [RACYC13]. In [HZF+12], according to the characteristics of the electric vehicle charging station planning, authors put forward a kind of Multiple-Population Hybrid Genetic Algorithm (MPHGA) combined with the Standard Genetic Algorithm (SGA) with

Alternative Location and Allocation Algorithm (ALA). According to the multi-objective of the charging station planning, the concept of multigroup is used to do collaborative evolution search.

The total cost for the charging stations including investments, structures cost, and operational cost should be minimized [RKVB13],[PL14].

Drivers behavieurs can affect any study related to modeling EVs as substation studies. Driver behavieur as a keypoint of selection the location of charging is important.

For the internal structures of fast charging station different models could be considered. In some fast DC charging models, an electric vehicle charging station is suitable for the fast DC charging of multiple electric vehicles [AAJ12]. In this model, the station consists of a single grid-connected inverter with a DC bus where the electric vehicles are connected. The control of the individual electric vehicle charging processes is decentralized, while a separate central control deals with the power transfer from the AC grid to the DC bus. The electric power exchange could be independent from communication links between the station and vehicles.

Traffic data of the EVs is another parameter that can affect the substation selection for charging EVs. Traffic networks are considered in some studies. In these cases, candidate place of charging station is optimally found by traffic network along with distribution network. In these models, an electrical vehicle flow capturing location is proposed to maximize the EV traffic flow that can be charged given a candidate construction plan of EV charging stations. [PMH13], [**?**].

Some other studies like [Var14] propose model for electric vehicle charging management for a fast charging station network in a smart grid environment. The basic feature of the proposed model is when EVs are blocked by their preferred station due to the unavailability of charging outlets, they are prompted via a communication system to select their next station, which either provides fixed or elastic charging services. In this model a charging station network that provides service to multiple EV charging-classes is considered.

In [DHS+14], the coordinated operation of EV fast charging stations with Energy storage system is studied. Based on this study, energy storage system is regarded as a promising supplement for electric vehicle fast charging station.

4.2 Stochastic modeling in finding the best location for connecting fast charging stations

Before extracting the complex model for optimal solution in planning charging stations, we start with a simple model. In this modeling of fast charging planning in this section, a model is structured to answer to this question. “Where is the best location to for installing the charging station?" The answer to this question is a selected bus candidate between all buses in the power system. Geographic data including structure of road network will be considered in the next section.

4.2.1 Mathematical model

The problem is to find the buses with capacity to install charging stations with the minimum possibility to lead in any problem on power system constraints. That means we are looking for the buses in which installing charging station causes less problem to power system. Number of stations planed to be installed in the region (ST_n) is supposed to be constant value. The proposed model has this ability to work without determining the ST_n. In this case it could be decided at the end. Means that after finding the best buses to connect stations we can decide the number of stations needed to be connected to power grid. Results of the used model in this study are a list of buses numbers in which the buses in top of the list have priority to be a proper candidate for installing the station. In this priority list, buses are arranged according with a Monte Carlo Simulation Success/Fail index. The index is evaluated only in case the bus has a connected station. Index definition is:

$$BUSst_{index}(i) = \frac{Nst_{success}(i)}{Nst_{total}(i)} \tag{4.1}$$

$With$

$BUSst_{index}(i)$: Station installation success index for bus i.
$Nst_{success}(i)$: Number of success MCS with at least one station connected to bus i.
$Nst_{total}(i)$: Total cases with at least one station connected to bus i.

During each MCS iteration, a random distribution of stations is assigned on buses and results of power flow analysis with the composed power demand including initial power and the power caused by EVs charging is evaluated. Power system constraints including Over Load (OL) in branches, Under Voltage (UV) and Over Voltage (OV) at buses are checked at the end to determine the Success/Fail of the iteration.

The mathematical problem is :

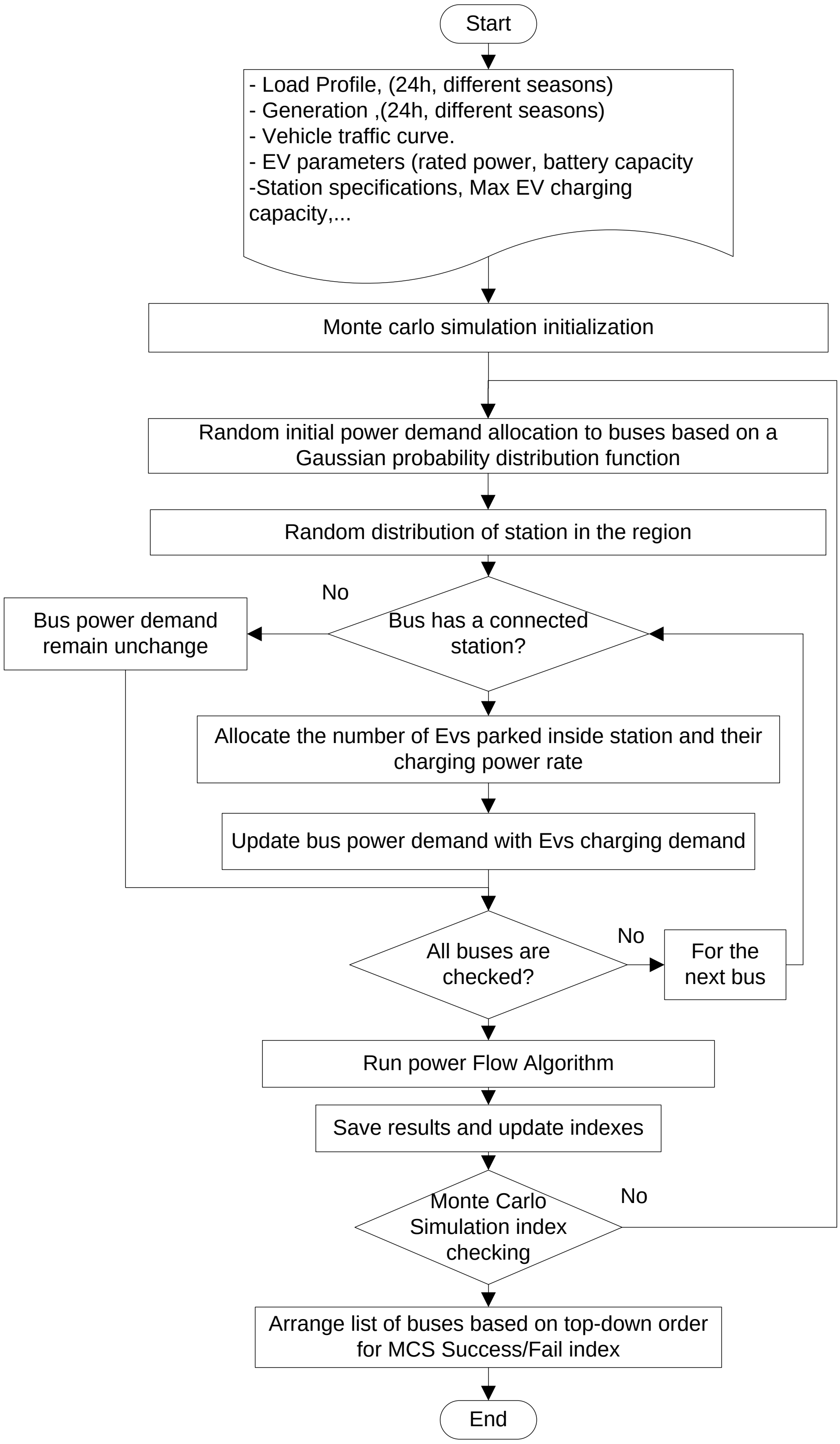

Figure 4.1: Finding the best buses to install charging station in grid.

Finding

$$[bus_1, bus_2, bus_3, bus_{ST_n}] \quad With \quad Max \quad BUSst_{index}(i) \mid$$

$$UV_{bus} = 0, \quad OV_{bus} = 0, \quad OL_{branches} = 0$$

With

EV_n =constant value
ST_n =constant value

ST_n: Station number in the grid
EV_n: The maximum EVs possible to charge in the station at the same time.
UV_{bus}: Number of under voltage buses with STn connected station to buses.
OV_{bus}: Number of over voltage buses with STn connected station to buses.
$OL_{branches}$: Number of over load branches with ST_n connected station to buses.

Solution is $[bus_1, bus_2, bus_3, bus_{ST_n}]$ with $bus_1, bus_2, \ldots$ being the list of buses in which stations are installed. Figure 4.1 illustrates details of the proposed model for finding the best buses to install fast charging stations. Based on this model, all power system parameters, including power generations and substations loads are allocated randomly. EVs parameters including EVs positions, charging power, SOC of batteries and drivers behavieurs are also allocated based on a random selection from the probability density function of each one. In this way, the allocation algorithm is working independently for MCS iterations.

4.2.1.1 Power system and EVs charging modelling

From the power system point of view, power demand and generation are two parameters which should be modeled in EVs connection to grid.

We start with modelling the power demand of one bus for iteration n in MCS. This power demand includes the initial power demand by the conventional loads and the power demand caused by EVs;

$$P_{TotalDemand}(j,n) = P_{InitialDemand}(j,n) + P_{EVDemand}(j,n) \tag{4.2}$$

In this equation, $P_{EVDemand}(j,n)$ is the total power demand caused by integration EVs to bus j. Adding this power demand to the $P_{InitialDemand}(j,n)$, which represents the initial power demand of the bus j, for iteration n, the total power demand of the bus or $P_{TotalDemand}(j,n)$ is achieved.

$P_{EVDemand}(j,n)$ is composed of two parts:

$$P_{EVDemand}(j,n) = P_{EVfast}(j,n) + P_{EVnormal}(j,n) \tag{4.3}$$

In this equation, $P_{EVfast}(j,n)$ is the total power demand caused by integration EVs to bus j in fast mode of charging. Adding this power demand to the $P_{EVnormal}(j,n)$, which represents the the total power demand caused by integration EVs to bus j, for iteration n in normal mode of charging, $P_{EVDemand}(j,n)$ is achieved. For each one we have:

$$P_{EVfast}(j,n) = \sum_{i=1}^{EVnf} P_{EVf}(i,j,n) \tag{4.4}$$

$$P_{EVnormal}(j,n) = \sum_{i=1}^{EVnn} P_{EVn}(i,j,n) \tag{4.5}$$

In this equation, $P_{EVf}(i,j,n)$ and $P_{EVn}(i,j,n)$ are power demand caused by connecting the single EV i to bus j in fast mode and normal mode of charging respectively.$EVnf$ and $EVnn$ are the number of EVs connected to bus j, for iteration n, in fast mode and normal mode of charging respectively.

Normal charging is possible in two locations; home and parking so for $P_{EVnormal}(j,n)$, we have:

$$P_{EVnormal}(j,n) = \sum_{i=1}^{EVnh} P_{EVnh}(i,j,n) + \sum_{i=1}^{EVnp} P_{EVnp}(i,j,n) \tag{4.6}$$

In this equation, $P_{EVnh}(i,j,n)$ and $P_{EVnp}(i,j,n)$ are power demand caused by connecting the single EV i to bus j, for iteration n, in normal mode of charging at home location and parking location respectively.$EVnh$ and $EVnp$ are the number of EVs connected to bus j in normal mode of charging at home location and parking location respectively.

For power generation in bus j, for iteration n, we have:

$$P_{TotalGen}(j,n) = \sum_{i=1}^{Gn} P_{Gen}(i,j,n) \tag{4.7}$$

In this equation, $P_{TotalGen}(j,n)$ is the total power generation on bus j, for iteration

n. $P_{Gen}(i,j,n)$ is the power generation of the single generation unite i on bus j, for iteration n. Gn is the total number of generation units connected to bus j, for iteration n.

In the proposed model, all power generation and demand values are allocated randomly in MCS method. For example in each iteration, the allocated generation to each unit is achieved from a random selection based on the GPDG of the unit generation profile. next equation shows this allocation:

$$P_{Gen} \sim rand\{P_{gen}GPDF\} \tag{4.8}$$

In this equation, P_{Gen} is the allocated value to power generation of the unit. $P_{gen}GPDF$ is the GPDF specification of the unit generation profile.

In the same way, for all power demand on buses, values are allocated randomly in MCS method. In each iteration, the allocated power demand to each bus is achieved from a random selection based on the GPDG of the bus load profile. next equation shows this allocation:

$$P_{InitDemand} \sim rand\{P_{demand}GPDF\} \tag{4.9}$$

In this equation, $P_{InitDemand}$ is the allocated value to initial demand power of bus. $P_{demand}GPDF$ is the GPDF specification of the load profile at related bus.

Also, for specifications of EVs,values are allocated randomly in MCS method. In each iteration, the allocated value to each parameter is achieved from a random selection based on the GPDG or the probability bar of the parameter. next equation shows this allocation:

$$P_{EV} \sim rand\{EV_{SOC}\} \cap rand\{EV_{Batt}\} \cap rand\{EV_{ChMode}\} \cap rand\{EV_{ChLocat}\} \tag{4.10}$$

In this equation, P_{EV} is the allocated values to EV parameters. EV_{SOC} and EV_{Batt} are the GPDF specification of the EVs at arriving time to parking for SOC% and batteries capacities respectively. EV_{ChMode} and $EV_{ChLocat}$ are the random bar specifications of EVs drivers behavieurs for selection of charging mode and charging location respectively.

All these allocations are performed in an independent selection. The final specification of the EVs parameter is a random selection of these four parameters in a separate random allocations.

4.2.2 Applying the model on a case study

The proposed model based on MCS is applied on a real case study described before in the previous chapter. MCS parameters and a summary of applied case study is illustrated in Table 4.1.

Parameter description	Value
The number of MCS iteration	5000
The number of target charging station (ST_n)in the region	15
The maximum number of EVs possible to charge in the station	20
The maximum ST_n possible in one bus	1
Number of candidates buses for installing ST_n stations	279

Table 4.1: MCS settings and other parameters used in the case study.

Figure 4.2 demonstrates Success/Fail index values according with the definition for $BUSst_{index}$ for the case with ($ST_n = 15, EV_n = 20$). In this method, all buses could be a candidate for installing the charging station. Based on the proposed algorithm, after running the MCS iterations, a $Success_{index}$ allocation is done for each bus. List of buses with related $Success_{index}$ is arranged in descending order for the $Success_{index}$. So that the buses on the top of the list has a higher $Success_{index}$. This list is the priority list in which the bus with higher priority for installing charging station is located in the top of the list. The first (ST_n number are selected as the final result of algorithm. In the top part of the figure, the $Success_{index}$ value is shown in blue for all buses. In the bottom part, the final results of the algorithm are shown in blue and the buses with lower priority for installing charging stations are shown in green.

Figure 4.3 shows the same results but with different zoom. This figure shows only some buses in order to have a more obvious image.

4.2.3 Comparing results and sensitivity analysis to the input parameters

Input parameters including ST_n and EV_n are two main parameters in charging station. These parameteres could be specified based on the investment factors of substations including the initial and operational costs of stations. In this section the impact of these two parameters on the technical constraints of the power system is studied.

In order to investigate the effect of ST_n an EV_n on the selection of buses for installing stations, two studies are accomplished with different parameters. In

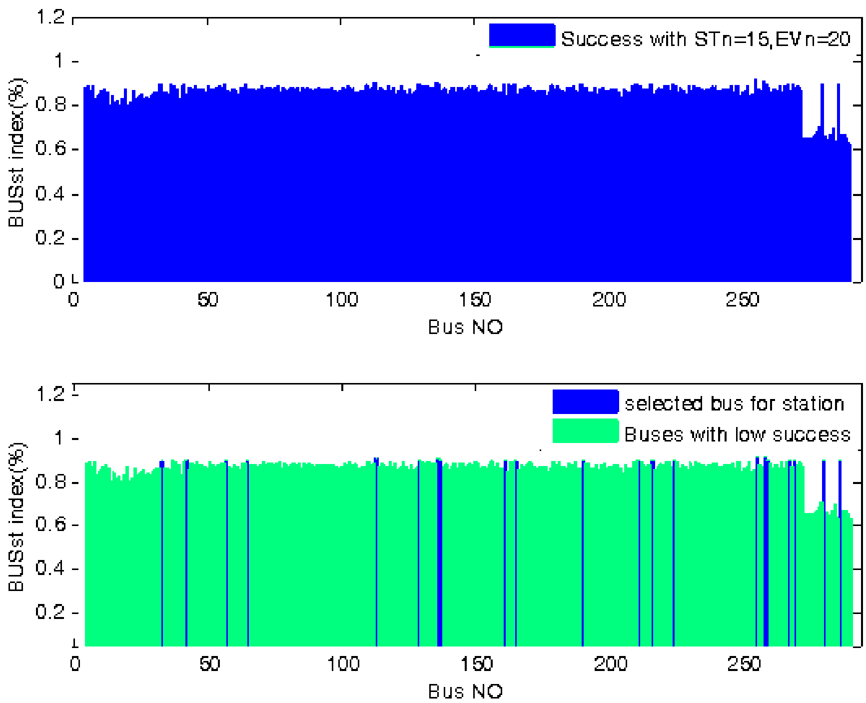

Figure 4.2: Success and Selected bus with higher priority for installing charging stations. ($ST_n = 15, EV_n = 20$).

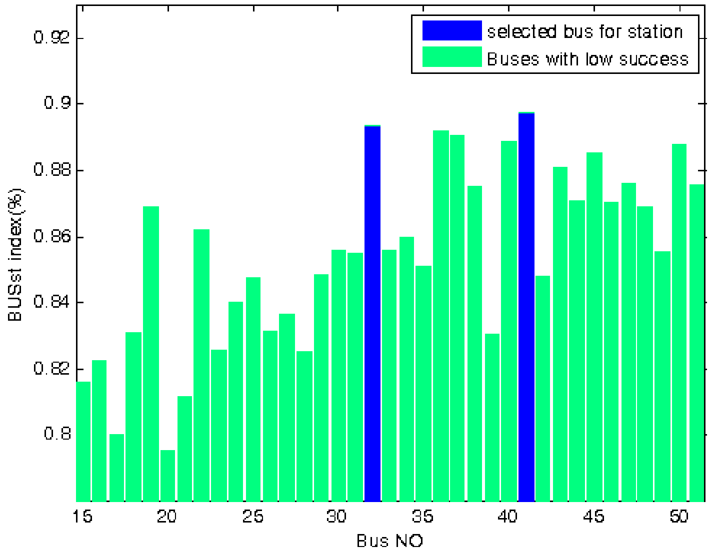

Figure 4.3: Selected bus with higher priority for installing charging stations. ($ST_n = 15, EV_n = 20$).

first, a case study with specified ST_n and three different EV_n is tested. In the second case, EV_n is assumed as a fix and three different ST_n are tested.

As results of the first case, Figure 4.4 shows $BUSst_{index}$ for ST_n = 15,20 and 25 stations and $EV_n = 20$. Results show that for three different ST_n and with the same EV_n, the priority list is different and the final result is not the same for three value of ST_n parameters. As demonstrated in Figure, although some buses have higher index in 15 station case, meaning that they could be a proper bus for installing the station, in other cases they are in lower priority.

Table 4.2 compared two cases with $ST_n = 20$ and 25 with the case $ST_n = 15$ as the reference case. In should be mentioned that in the priority list, the first 25 stations are compared in this table.

Case description	The number of ST	%
Case with $ST_n = 20$ and $EV_n = 20$	6	24
Case with $ST_n = 25$ and $EV_n = 20$	11	44

Table 4.2: Results of priority list comparison with the case of $ST_n = 15$ and $EV_n = 20$ as the reference

As shown in the table, final results are not the same and could be different to 44% from case with $ST_n = 20$ to case with $ST_n = 25$. Hence its important to determine the number of stations in the region before any other design in the characteristics of the stations with using this model. In the same way, the impact of different cases with different values for EV_n parameter with the same values for EV_n is studied.

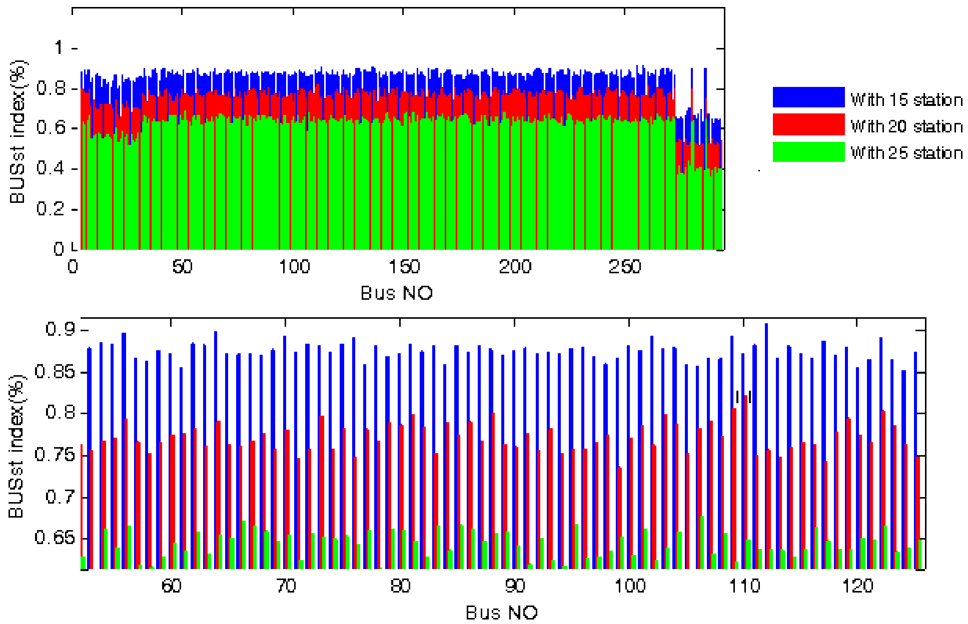

Figure 4.4: Priority changes by changing station numbers.($EV_n = 20EV$)

Figure 4.5 shows $BUSst_{index}$ for $ST_n = 20$ stations and $EV_n = 10$, 20 and 30. As demonstrated in this figure, in general, the $BUSst_{index}$ is smaller for cases with higher EV_n value. Results show also a difference in the final result list. Meaning that although some buses have higher index in 10 EV case, meaning that they could be a proper bus for installing the station, in other cases they have lower priority. Table 4.3 shows this difference for three cases.

Case description	The number of ST	%
Case with $ST_n = 20$ and $EV_n = 20$	11	55
Case with $ST_n = 20$ and $EV_n = 30$	12	60

Table 4.3: Results of priority list comparision with the case of $ST_n = 20$ and $EV_n = 10$ as the reference

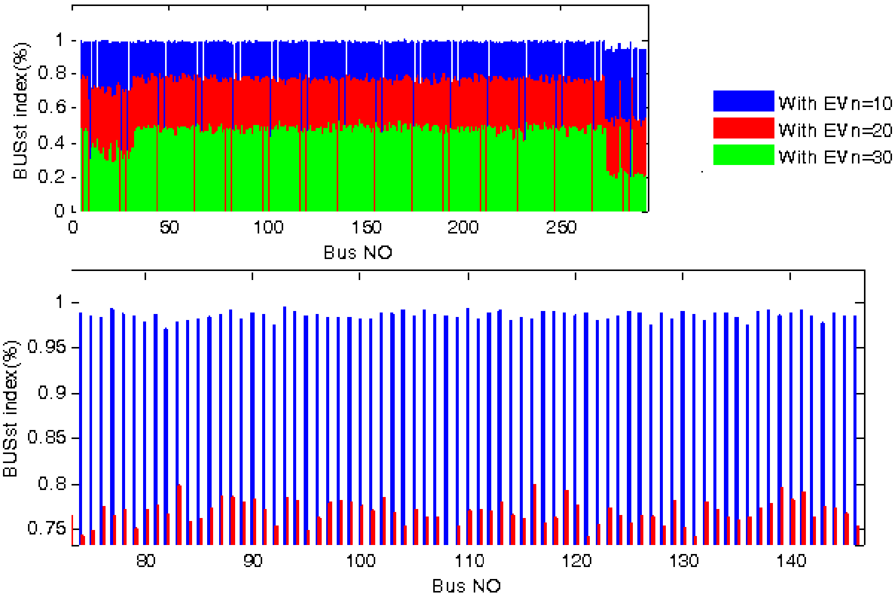

Figure 4.5: Priority changes by changing station numbers.($ST_n = 20$)

Two cases with $EV_n = 20$ and $EV_n = 30$ are compared with the case with $ST_n = 15$ and $EV_n = 20$ as the reference case. As we can see in this table, changing the number of EVs to two times more than the initial values in the stations, could change to 55% the final results. we can conclude that its important to determine the number of stations in the region before any other design in the characteristics of the stations with using this model.

Another conclusion is on the higher difference between results of the two cases withe constant ST_n and EV_n values in general. As we can see in two results tables, impact of changing EV_n is more than changing ST_n. That shows a higher sensitivity of the station specifications to EV_n more than ST_n.

4.3 Finding the optimal number of fast charging stations using Particle Swarm Optimization (PSO) method

In this section, scenarios are investigated to assess the power system capacity to serve electric vehicles charging stations in an urban region. The goal is to find the maximum possible number of charging station and the best location for installing these stations. In fact two main questions are how many stations can be served and where these stations can be installed. The question is about the capacity of power grid to accept charging power caused by this maximum number of charging station. Some buses have limited accessibility because of geographical information of the region. These limitations are taken into account to find the best location for installing charging stations.

In this section, a stochastic method based on Monte Carlo Simulation is applied. All data from power demand and generation profiles including renewable energy resources of the distribution power grid are modeled as probability density functions. Some uncertain behavior variants in EVs charging at stations including the state of charge in batteries, charging location, time and rate as well as some other properties of EVs are considered in EVs charging model through a probability density function.

In order to solve the problem of maximal number of stations in a region, the proposed method finds the optimal solution using Particle Swarm Optimization algorithm. Both over current in branches and voltage drops on bus voltages are taken into account as power system constraints. In order to cover different possibilities for charging locations, EV charging has been made possible at charging station, home, shopping centers and work parking. Annual average daily traffic curve is used to find EVs in movement and in parking mode.

4.3.1 Mathematical model

Let n_{bus} be the bus numbers in the region. From the mathematical point of view, the problem is finding the maximum ST_n points possible to be connected to n_{bus} points considering the power system constraints. Solution of this problem is a list of buses from n_{bus} list in which the ST_n station could be installed.
The summary of the ST_n problem; Finding

$$Max\ ST_n \quad | \quad UV_{bus} = 0, \quad OV_{bus} = 0, \quad OL_{branches} = 0$$

With

$$ST_n = \text{constant value}$$

ST_n: Station number in the grid
EV_n: The maximum EVs possible to charge in the station at the same time.
UV_{bus}: Number of under voltage buses with ST_n connected station to buses.
OV_{bus}: Number of over voltage buses with ST_n connected station to buses.

$OL_{branches}$: Number of over load branches with ST_n connected station to buses.

Solution is: $[bus_1, bus_2, bus_3, bus_{ST_n}]$

with $bus_1, bus_2, \ldots$ being the list of buses in which stations are installed. We use the same assumptions about the characters of stations as last section. EV charging is possible in these assumptions:

- EV charging at home is possible only in normal charging mode.
- EV charging at work is possible only in normal charging mode.
- EV charging at charging station is possible only in fast charging mode.
- EVn is fixed to 20 EV.

In order to solve the presented problem we propose to use the PSO method. Before starting the PSO method and mathematical model in which we are searching the solution, some definitions on Computational Complexity and complexity classes are discussed.

4.3.2 Computational complexity and complexity classes definitions

Computational complexity theory is a branch of the theory of computation in theoretical computer science and mathematics that focuses on classifying computational problems according to their inherent difficulty, and relating those classes to each other. A problem is regarded as inherently difficult if its solution requires significant resources, whatever the algorithm used. The theory formalizes this intuition, by introducing mathematical models of computation to study these problems and quantifying the amount of resources needed to solve them, such as time and storage.

Identifying which combinatorial problems are easy to solve and which are hard is an important and challenging task, which has occupied theoretical computer scientists for many years. In order to translate the everyday expression easy to solve to mathematical theory the concept of polynomial time algorithms has been introduced. An algorithm is said to run in polynomial time if there is a polynomial p such that the algorithm applied to an input of size n always finds a solution in time p(n), that is after performing p(n) simple instructions. Note that we measure the worst case complexity that is the time in which we are sure that the algorithm ends regardless of which input of size n we have fed it. The execution time of a polynomial time algorithm grows slowly enough with increasing input size to be able to be run on a computer, but if the execution time grows exponentially the algorithm is useless for all but the smallest inputs. One of the most accepted ways to prove that a problem is hard is to prove it NP-complete. If an optimization problem is NP-complete we are almost certain that it cannot be solved optimally in polynomial time.

In the theory of complexity [Joh79], the authors classify the decision problems according to the complexity of the algorithms that exist to resolve them. In order to be able to pinpoint the combinatorial optimization problem that must be resolved among other combinatorial problems, the main classes of problems are summarized in Figure 4.6. . In computational complexity theory, NP is one of the

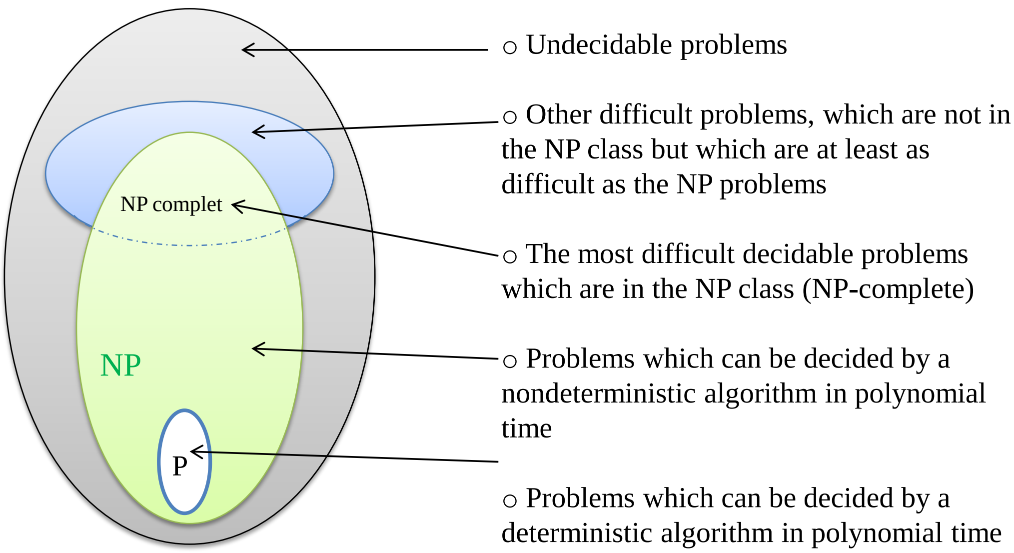

Figure 4.6: Classification of the problems according to the complexity of the algorithms that exist to resolve them (NP = nondeterministic polynomial)

most fundamental complexity classes. The abbreviation NP refers to "nondeterministic polynomial time." Intuitively, NP is the set of all decision problems for which the instances where the answer is "yes" have efficiently verifiable proofs of the fact that the answer is indeed "yes". More precisely, these proofs have to be verifiable in polynomial time by a deterministic Turing machine. In an equivalent formal definition, NP is the set of decision problems where the "yes"-instances can be accepted in polynomial time by a non-deterministic Turing machine. In fact all these problems have a common property: for every input to a problem with solution yes there is a proof that the input has solution yes and this proof can be verified in polynomial time [DK00], [AB09], [Als99], [Kan92].

4.3.3 Complexity class definition for fast charging station problem

The presented problem in last section cannot be solved optimally in polynomial time. For a given configuration, with all the EV, ST_n and power system data, power flow analysis results can verify the solution. So there is a proof that the input (EV_s, ST_n, and power system data) has solution yes and this proof can be verified in polynomial time. The proposed method to solve the problem is applying PSO algorithm to find the optimal solution. In the next section PSO standard algorithm is discussed.

4.3.4 Particle Swarm Optimization method

Particle swarm optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO optimizes a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formula over the particle's position and velocity. Each particle's movement is influenced by its local best known position but, is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions.

PSO is originally attributed to Kennedy, Eberhart and Shi [SE98], [KE95] and was first intended for simulating social behaviour [Ken97]. This algorithm is called particle swarm optimization since it resembles a school of flying birds. Each particle adjusts its flying according to its own flying experience and its companions' flying experience. The algorithm was simplified and it was observed to be performing optimization. The book by Kennedy and Eberhart [KEY01] describes many philosophical aspects of PSO and swarm intelligence.

PSO is a metaheuristic as it makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. However, metaheuristics such as PSO do not guarantee an optimal solution is ever found. More specifically, PSO is a pattern search method which does not use the gradient of the problem being optimized, which means PSO does not require that the optimization problem be differentiable as is required by classic optimization methods such as gradient descent and Quasi-Newton methods. PSO can therefore also be used on optimization problems that are partially irregular, noisy, change over time etc [SE98], [KE95].

4.3.5 PSO algorithm

A basic variant of the PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). These particles are moved around in the search-space according to a few simple formula. The movements of the particles are guided by their own best known position in the search-space as well as the entire swarm's best known position. When improved positions are being discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered.

Formally, let $f: \mathbb{R}_n \to \mathbb{R}$ be the cost function which must be minimized. The function takes a candidate solution as argument in the form of a vector of real numbers and produces a real number as output which indicates the objective function value of the given candidate solution. The gradient of f is not known. The goal is to find a solution a for which $f(a) \leq f(b)$ for all b in the search-space, which would mean a is the global minimum. Maximization can be performed by considering the function $h = -f$ instead.

Let S be the number of particles in the swarm, each having a position $x_i \in \mathbb{R}$ in the search-space and a velocity $v_i \in \mathbb{R}$. Let p_i be the best known position of particle i and let g be the best known position of the entire swarm.
A basic PSO algorithm is then:

For each particle $i = 1, ..., S$ do:
  Initialize the particle's position with a uniformly distributed random vector: $x_i \sim U(blo, bup)$, where blo and bup are the lower and upper boundaries of the search-space.
  Initialize the particle's best known position to its initial position:$p_i \leftarrow xi$
  If $f(p_i) < f(gi)$ update the swarm's best known position: $g \leftarrow pi$
  Initialize the particle's velocity:$v_i \sim U(-|bup - blo|, |bup - blo|)$
Until a termination criterion is met (e.g. number of iterations performed, or a solution with adequate objective function value is found), repeat:
  For each particle $i = 1, ..., S$ do:
    Pick random numbers: $r_p, r_g \sim U(0, 1)$
    For each dimension $d = 1, ..., n$ do:
      Update the particle's velocity:

$$v_{i,d} \leftarrow \omega v_{i,d} + \varphi_p r_p (p_{i,d} - x_{i,d}) + \varphi_g r_g (g_d - x_{i,d})$$

    Update the particle's position: $x_i \leftarrow x_i + v_i$

If $(f(x_i) < f(p_i))$ do:

Update the particle's best known position: $p_i \leftarrow x_i$
If $(f(p_i) < f(g))$ update the swarm's best known position: $g \leftarrow p_i$

Now g holds the best found solution.

The parameters ω, φ_p, and φ_g are selected by the practitioner and control the behaviour and efficacy of the PSO method [KE95],[SE98],[Cle12]. Figure 4.7 shows a vector presentation of PSO algorithm. Particles move from actual

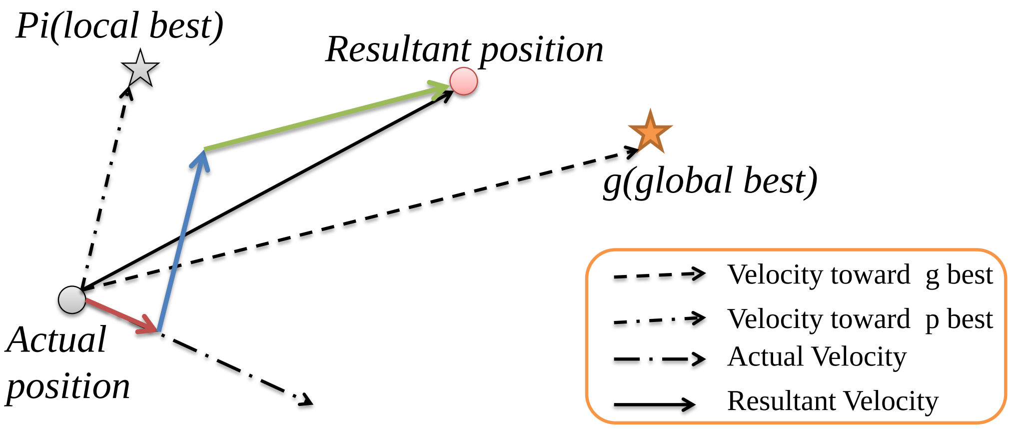

Figure 4.7: PSO algorithm particle movement toward new location.

location to a new location during each iteration. For all particles in iteration n, after one iteration, the particles location and velocity is updated as mentioned in the algorithm. Particles movement toward the global best is demonstrated in Figure 4.8. In this Figure shows two iterations. Global best is supposed to remain in the same location during these two iterations.

4.3.6 Mathematical model

The problem is to find maximum possible ST_n to be installed in the region. As mentioned, this problem is a NP-complete problem. In order to find the maximum ST_n, we made an algorithm based on Particle Swarm Optimization (PSO) method. We applied also MCS algorithm beside the optimization method. The mathematical model in this section is a determination of the problem based on the PSO algorithm definition.

let $f : \mathbb{R}_n \to \mathbb{R}$ be the objective function which must be maximized. The function takes a candidate solution as argument in the form of a vector of zero

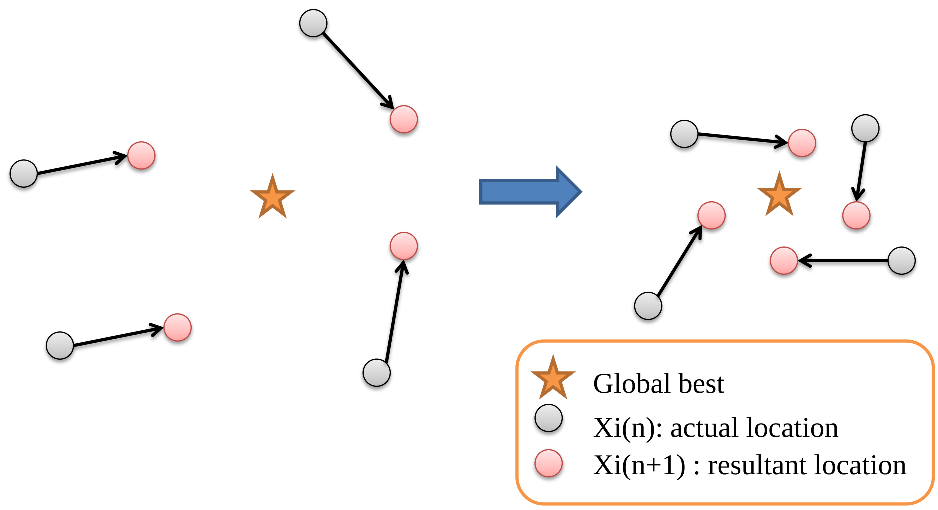

Figure 4.8: Particles random two iteration movement toward the global best.

and one numbers and produces a real number as output which is equal to the sum of all one numbers in input. This real number indicates the objective function value of the given candidate solution. Based on the model PSO parameters definitions are:

- Particles in this model are the index of buses. Each bus has one particle. So the total particles number is bus number in the grid. Each particle is known with the index of related bus. So each bus is related to a particle that has the index equal to the bus number. S is equal to total bus numbers.
- $f : \mathbb{R}_n \rightarrow \mathbb{R}$: objective function with a vector of zero and one in input.
- x_i: list of the buses including bus i(particle index) in which stations are installed. This list is modeled with a vector of zero and one numbers. For the buses with station, index of vector is one and others are zero. For index i, the vector value is one.
- p_i: list of the buses including busi in which stations are installed. This list is a local best for x_i. The case with maximum ST_n is saved in this vector of zero and ones. This configuration of stations in the region should have a $success_index$ equal to one to be presented as best local.
- g: list of the buses in which stations are installed. This list is the best case found and saved during movements of particles.

- $success_index$: is an index of success for Monte Carlo Simulation results. After running the power flow analysis of the specified configuration of stations in the region, this configuration is tested with random allocation of variables like EV charging characters, power demand, DG, number of EVs at stations and SOC of EVs at arrival time to station. Results could cross the power system constraints in some random allocations. The percentage of total iteration in which constraints are not crossed gives $success_index$. If this percentage is higher than 99%, $success_index$ is one, otherwise it would be zero.

- V_i is defined based on this formula:

  $$v_{i,d} \leftarrow \omega v_{i,d} + \varphi_p r_p (p_{i,d} - x_{i,d}) + \varphi_g r_g (g_d - x_{i,d})$$

  r_p and r_g are random integer numbers on the ST_n difference between $p_i - x_i$ and $g - x_i$ respectively. φ_p is supposed to be 2/6 or 33%, ω is 1/6 and φ_g is 3/6 or 50%. This values are selected in the way to increase the movement toward g and p_i.

All particles vectors together make a matrix with size of $(Bus_N O, Bus_N O)$, this matrix is shown in a simplified schematic in Figure4.9.

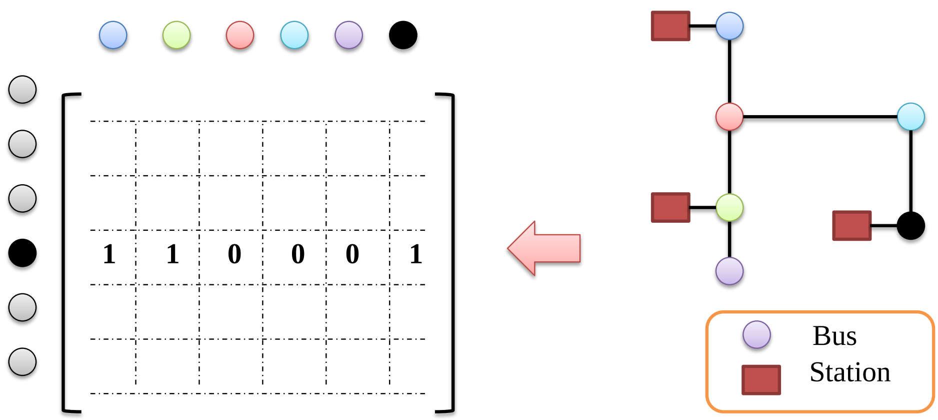

Figure 4.9: simplified schematic of particle matrix extraction.

Figure Figure 4.10 illustrates the flowchart algorithm of proposed optimization method.

4.3.7 Simulation results and method Comparison

Simulation results are shown in Figure 4.11. Maximum STn result is 22 stations for this simulations.

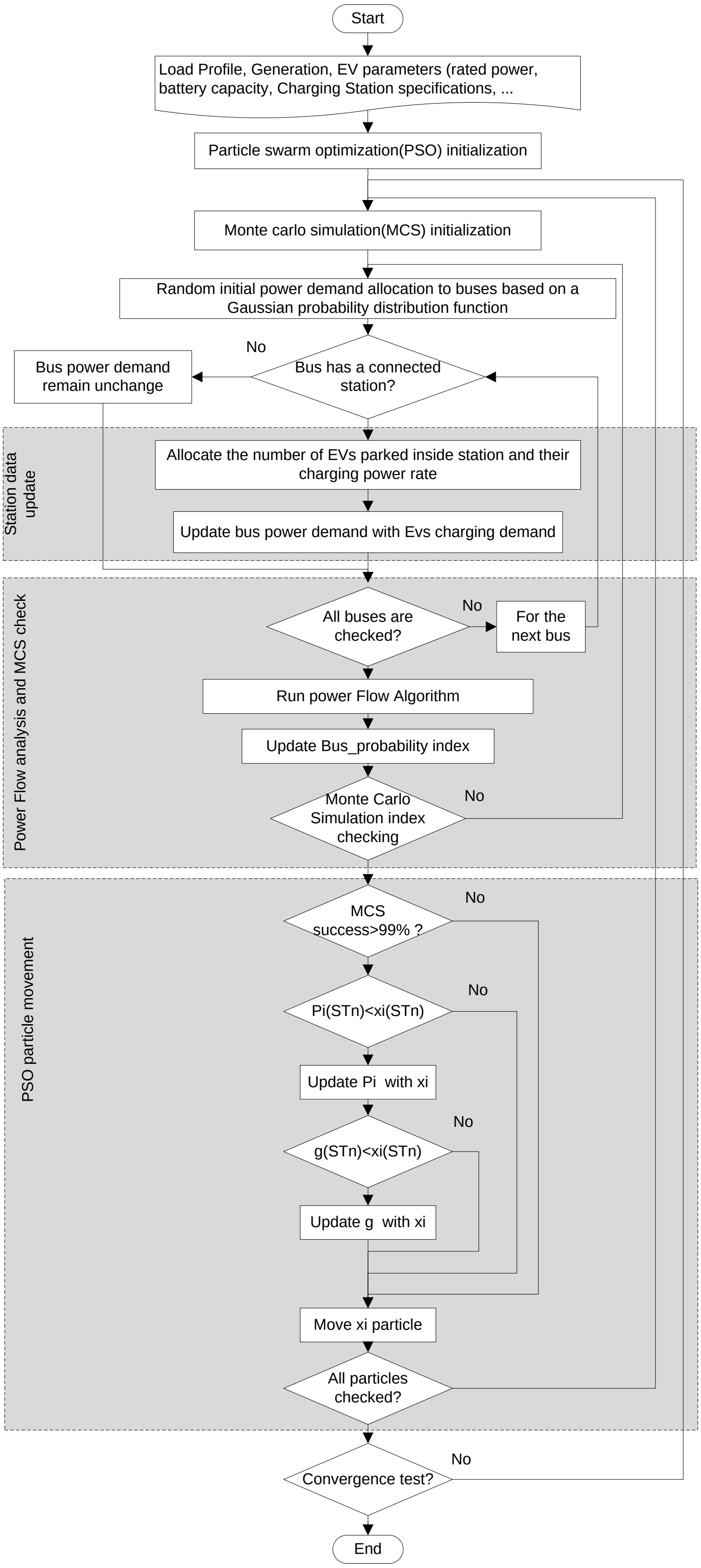

Figure 4.10: Flowchart algorithm of proposed method to find optimal maximum number of station using MCS and PSO .

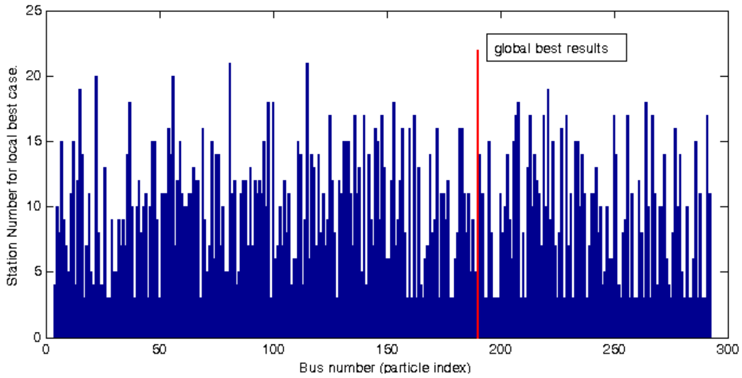

Figure 4.11: particles local best and global best results.

4.4 Placement of fast charging station considering geographic data of the region

In order to consider geographic data including road networks data, we added the geographic data to the existing model in this section. In this scenario some buses are supposed to be with a constraint such as being away from the roads or special substations with limits on connecting charging stations to them. In fact we supposed a list of substation as black list in which all buses have no capacity to install fast charging station in their related geographical region. The proposed algorithm has the same bus selection process. Bus selection process is based on a random selection from buses which are not in black list. In PSO step of algorithm, particles position x_i, cannot move in the direction with buses from black list. It should be mentioned that in power flow analysis step, EVs in normal charging mode, are considered at the black list buses and only fast charging at station is not possible at these buses.

In the first sections of this chapter, all scenarios of study are based on a model with no geographic data assumption. All other data including power system data and driver behaviour information are two main axes in created model. These two axes are applied as two separate layers in related model. In this section another independent layer is applied, the geographic layer. These three different layers are simplified in the schematic design in Figure Figure4.12. The created model based on this plan includes a superposition of all these three layers.

4.4.1 Parameters and hypothesis of the method

Road network data of the region in which power system data are applied as case study should be used in geographic model of the region. Road network

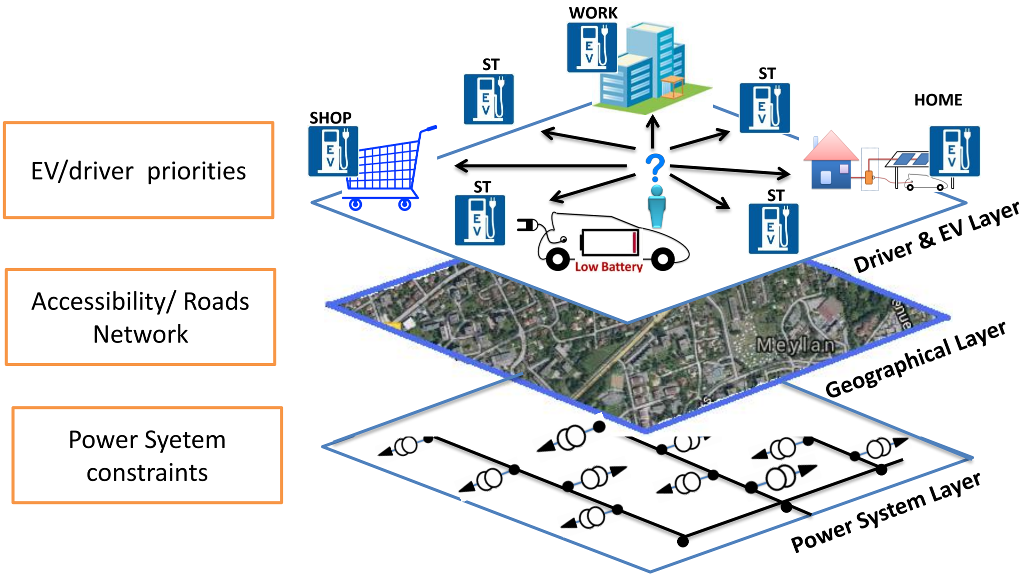

Figure 4.12: Simplified schematic design of three different layers in geographic based model.

data including road type (street, boulevard,), road length and road sections of the region should be extracted from the map of the region. For an EV in a given location, the distance to nearest charging station is important in driver decision. Road type indicates the frequency of EV passage in a given section of road. This frequency is equivalent to the probability of presence of EV the section. The larger road has higher frequency of passage and higher probability of presence of EV. For example large boulevards have a larger probability of EV presence than small streets.

In real case, several criteria are considered in final selection of charging station by the driver. Total cost for a given EV is modeled in the minimum distance to the charging station. Smaller distance is one criteria but not the only that should be considered. A driver can select station A with larger distance from instance location of EV instead of station B with smaller distance. One reason could be the final destination after charging in station A or B.

In this section, a model is studied based on geographical data of the region with these parameters and hypothesis:

- Geographic data of the road network is extracted based on a supposed network for the region in which power system data are applied as case study. Power system data are real data from the case study of the previous chapters but geographic data are based on a supposed model of the road network for the region.

- *Section point*: In the geographic model,sections are simplified to a point which represents the related section. For example in the street sections, the middle point of the section is selected as the point section. This section point can represent several small section which are modeled in one point to simplify modeling the smaller roads with smaller probability of EV passage.

- *Priority list*: For each section point a priority list of stations is extracted before starting the algorithm. This list is based on the distance of the section point to all stations. The first station in the list is the nearest station to the section point. This list represents the driver's priorities. In the next steps, this priority list is applied to select the charging station for the EV in the given section point. To avoid the minimum local in the algorithm, the selection is based on a probability function with higher probability to the station in the top of the priority list. Next station in the list has a probability equal to the half of the station in the top of the list and so on.

- *Station investment factor* : In some cases, stations could be too away from the roads or EVs locations, so the total EV number connected is less than the station charging capacity. Investment in these stations couldn't be efficient from the economic point of view because of the initial investment costs of the station. A limit of 50% of station capacity is supposed as the investment cost limit. For stations with the average number of EVs connected to them at a given MCS iteration,if the half capacity of the station is used, the station investment factor (ST_{IF}) is 1, otherwise it's 0.

- EV_{pr} in the region is fixed to 10%.

- Number of stations in the region or ST_n is fixed to 20 station.

- EV charging at charging station is possible only in fast charging mode.

- Charging capacity in stations or EV_n is fixed to 20 EV.

- SOC% of batteries for EVs is supposed to be between 15% and 85% and EVs with SOC% less than 25%, are supposed to need recharging at stations.

Other assumptions in the previous chapters and applied case study are used in this section.

4.4.2 Mathematical modeling and algorithm

In this section the problem is mathematically defined. Problem is selecting the optimal location for charging stations in the region considering the geographical data of the road network and power system constraints. This problem is a NP-complete problem. To solve this problem, an optimization method based on PSO algorithm is proposed in this section.

For a given case study with specified number of EVs in the region(EV_n), the problem is finding the optimal location for installing ST_n as fixed number of stations in the region. This optimal location should be accessible by all EVs with the minimum possible distance from all the sections of the geographical network. This minimum distance is representing the minimum cost for EVs charging at stations in the region. For a given time t with ST_n and EV_n vehicles;

$$dist_{tot}(t) = \sum_{j=1}^{ST_n} \sum_{i=1}^{EV_n} dist_{EV(t)}(i,j)$$

With

$dist_{tot}(l)$: Total distance between EVs and stations for the given time t. In MCS algorithm, t represents the index of iteration.
$dist_{EV(t)}(i,j)$: Distance between EV(i) and the selected station ST(j) at which EV(i) is recharged for the given time l.

In fact the optimal location for installing charging station is the objective but it should be noticed that a location should be suitable for installing a station. Therefore, all the candidate locations for installing charging stations are extracted and listed as $[STC_1, STC_2, \dots STC_k]$ with $STC_1, STC_2, \dots$ being the list of candidate stations for installing ST_n charging station. This list is mentioned as $StationCandidateList$ or SCL.

Figure 4.13 shows a schematic figure of network road, candidate stations for installing stations and power system substation zones.

In order to the effect of traffic in different sections, Road Factor (RF) is defined. RF determines the traffic factor for each section. Two factors are used in this study; Highway or main road and Normal road. RF for Highway or main road is larger that the RF in Normal roads. RF specification could be done based on the real traffic data. In the applied case study, RF is for Highway and Normal roads is supposed to be two constant value for all sections.

The problem is finding :

$$Min\ (dist_{tot}) \quad | \quad UV_{bus} = 0, \quad OV_{bus} = 0, \quad OL_{branches} = 0$$

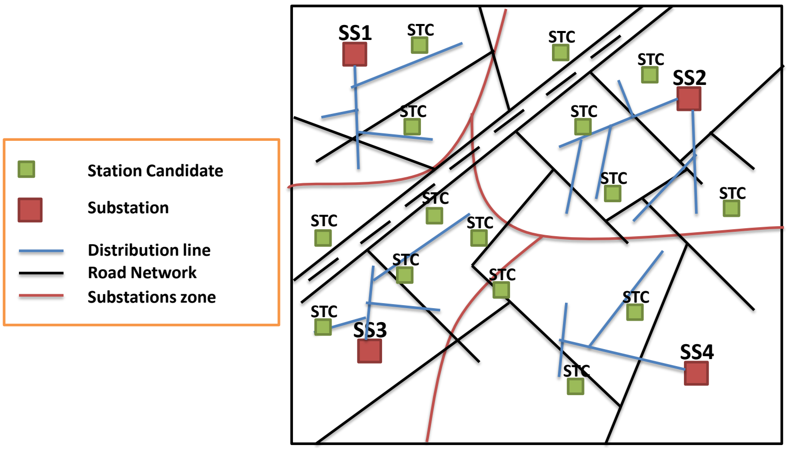

Figure 4.13: Schematic figure of network road, candidate stations for installing stations and power system substation zones.

With

ST_n =constant value

$dist_{tot}$: Total distance between EVs and stations.
ST_n: The number of objective charging stations in the region.
EV_n: The maximum EVs possible to charge in the station at the same time.
UV_{bus}: Number of under voltage buses with ST_n connected station to buses.
OV_{bus}: Number of over voltage buses with ST_n connected station to buses.
$OL_{branches}$: Number of over load branches with ST_n connected station to buses.

Solution is: $[ST_1, ST_2, \ldots ST_n]$
with $ST_1, ST_2, \ldots$ being the list of optimal selected stations. The proposed algorithm is shown in Figure 4.14. This algorithm is based on the optimization method of PSO algorithm.

Based on the proposed model, PSO parameters definitions are:

1. Particles in this model are the index of station candidates (STC). The number of particles is the number of $STCs$ in the other words, each STC has one particle. Each particle is known with the index of related STC. So each STC is related to a particle that has the index equal to the STC number. S is equal to total bus numbers.

2. $f : \mathbb{R}_n \to \mathbb{R}$: objective function with a vector of zero and one in input.

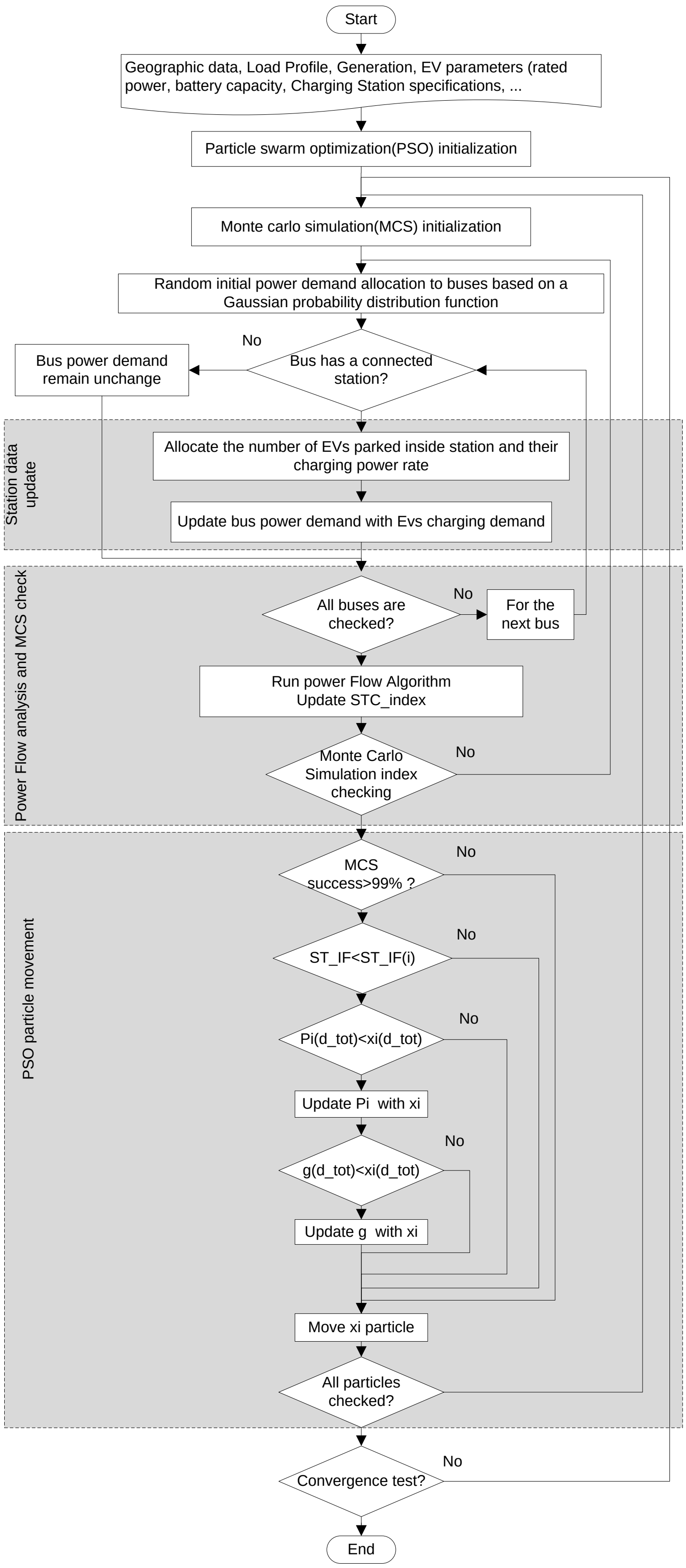

Figure 4.14: Proposed flowchart algorithm for finding the optimal ST between k the number of STC station based on PSO and MCS methods using geographic data of the region.

3. x_i: Particles in this model are list of station candidates. Each list has ST_n member. List of the $STCs$ includes i(particle index) of the selected location in which stations are going to be installed. This list is modeled with a vector of zero and one numbers. For the STC in the particle station list of particle i, index of vector is one and others are zero. For index i, the vector value is one.

4. p_i: list of the STC including STC i which is the index of particle candidate station. This list is a local best for x_i. The case with minimum $dist_{tot}$ is saved in this vector of zero and ones. This configuration of stations in the region should have a $success_index$ equal to one to be presented as best local.

5. g: list of the STC with the number of ST_n. This list is the best case found and saved during movements of particles.

   Figure Figure 4.15 represents four main parameters of PSO algorithm for one particle including x_i, P_i, g and V_i. Each one has a set of ST_n member of STC. Some $STCs$ could be common between these four parameters. For the given PSO iteration n, in the phase of movement, these four parameters are applied to move the particle toward the next position. V_i is selected randomly from S or the list of all STCs. This set represents the movement of article in all directions in the S. As mentioned before, the next position is a set of ST_n number of STCs. This list of STCs is selected from the four sets of x_i, P_i, g and V_i based on the allocated coefficient for each one. In this study all coefficients are configured so that all sets have the same impact on the result set or $x_i(n+1)$. So the final set is selected from each one by a coefficient of 25% of probability. Common STCs between sets are considered with higher probability.

6. $success_{index}$: is an index of success for Monte Carlo Simulation results. After running the power flow analysis of the specified configuration of stations in the region, this configuration is tested with random allocation of variables like EV charging characters, power demand, DG, number of EVs at stations and SOC of EVs at arrival time to station.

   Results could cross the power system constraints in some random allocations. The percentage of total iteration in which constraints are not crossed gives $success_index$. If this percentage is higher than 99%, $success_index$ is one, otherwise it would be zero.

7. V_i is defined based on this formula:

$$v_{i,d} \leftarrow \omega v_{i,d} + \varphi_p r_p (p_{i,d} - x_{i,d}) + \varphi_g r_g (g_d - x_{i,d})$$

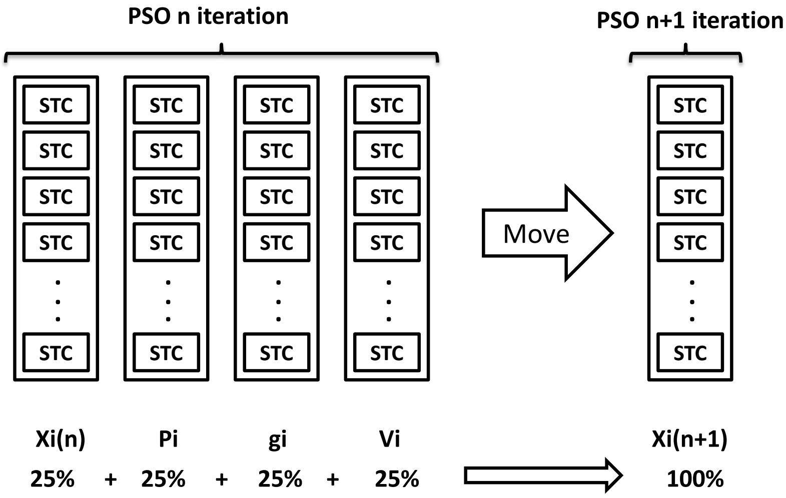

Figure 4.15: Particles movement in PSO for iteration n.

r_p and r_g are random integer numbers on the ST_n difference between $p_i - x_i$ and $g - x_i$ respectively. φ_p, ω and φ_g are supposed to be 1/3 or 33%.

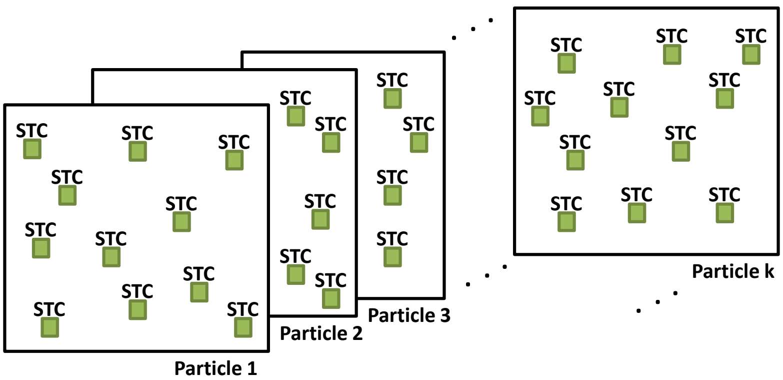

Figure 4.16: Particles station list with the number of ST_n for each particle.

Some other definitions in the used algorithm are;
STC_{index}: The index of candidate station in the station list.
d_{tot}: $dist_{tot}$ in mathematical model.
$ParticleStationList$: or PSL is the list of selected candidate with the number of ST_n station from station candidate list for each particle.
$StationCandidateList$: or STL is the list of candidate locations for installing the optimal charging station.

In Figure 4.16 particle station list of each particle is illustrated. In this Figure, the ST_n for the target solution is supposed to be 11 stations. The PSL is different for each particle.

Figure 4.17 shows the x_i particle movement step from Figure 4.14. Particle movement and update is done by removing or adding one STC from/to the particle station list. firstly the investment factor limit is checked to see if at least one STC from the particle station list has lower EV number than the ST_{IF} percentage. If the answer is yes, the STC with lower ST_{IF} ratio is removed from particle station list. Otherwise the STC with higher average $dist_{tot}$ is removed from the particle station list.

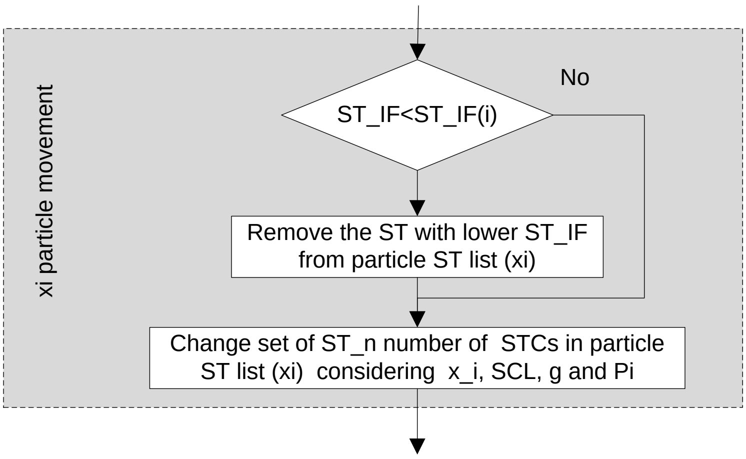

Figure 4.17: Particle movement in PSO algorithm

In the next step, the removed STC should be replaced by a new STC from the SCL. STC selection is the main part of the PSO algorithm which is the particle movement. For a given particle x_i, the selection is done between three list of $STCs$; the PSL or the x_i, the p_i list and the g list with a different probability of selection for each one. These probabilities are the same as the mentioned values and coefficients for PSO parameteres definition.

4.4.3 Results and method comparison

In order to evaluate the proposed method, the power system case study of the previous chapters is applied. After running the algorithm with the mentioned initial setting values in Table 4.4 for parameters, results are analyzed.

Using these parameters with values in Table 4.4, simulation results for the proposed method are extracted. These results are illustrated in Figure 4.18. In this figure, variation of the total distance between EVs and stations in PSO

Parameter description	Value	Unite
Electric Vehicles penetration rate (EV_{pr})	10	%
Target Station Number (ST_n)	20	#
Substation Investment Factor(ST_{IF})	50	%
The number of substations in the black list	30	#
The number of candidate locations for installing station(STC)	200	#
Monte Carlo Simulation iteration number	200	#
Particle Swarm Optimization maximum iteration number to stop simulation	5000	#
Particle Swarm Optimization stop iteration if unchanged result after convergence	600	#
Road Factor for Highway or main road sections	2	
Road Factor for normal road sections	1	

Table 4.4: Supposed values for different parameters.

iterations is shown. The global best total distance, represented in black curve, has the minimum value for all iterations. Two other curves in red and blue, are representing variation of two particles, numbers 50 and 100. These curves show the particles movement in different directions based on the PSO coefficients and sets for each particles. In some cases, movements caused increase in the total distance which means that selected $STCs$ are not exactly in the direction of the global best and could be in other directions too.

After about 2800 iterations, results of the simulation converge to the optimal result. For this case study, the total distance is decreased to 31% of its initial value. Simulations stopped when results remained unchanged after 600 iteration. Small variations in two particles numbers 50 and 100 after converging the global best, is caused by the V_i vector which represents movement of particles in all directions in S.

In order to evaluate the impact of different parameters on the the final results, the first three parameters are studied. Other parameters are taken basically from geographic data or the topologies of the road network which are not variable generally and are considered as constant values. Therefor the first three variable parameters including EV_{pr}, ST_n and ST_{IF} are studied.

Results show that simulations do not converge for some values of these three parameters. In fact the optimization could sensitive to special range of values for these three parameters.These special ranges are;

- For cases with very small EV_{pr}, the ST_{IF} value could not be very high.

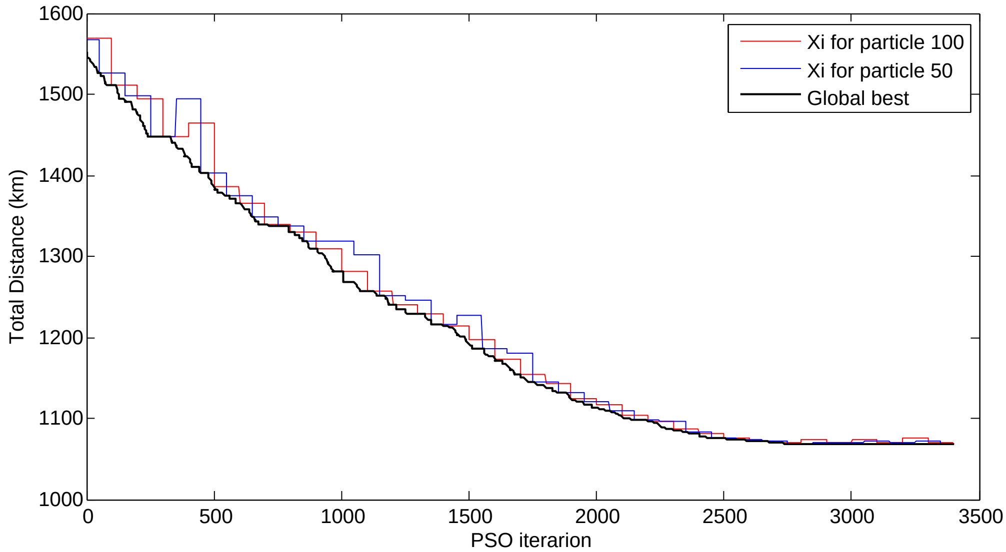

Figure 4.18: Convergence of particle 50 and 100 toward the global best position.

In cases with small EV_{pr}, the total number of EV in the region is not enough to fulfill conditions of investing in installation of charging stations. Stations will have free charging capacity in these cases. For the applied case study, with the mentioned above initial conditions, simulations didnt converge with EV_{pr}s lower than 3%. In order to solve this problem, two solutions are proposed. First one is decreasing the number of stations or ST_n and the second one is to decrease the investment factor or ST_{IF}. Both these two solutions could be applied together.

- For cases with very high level of EV_{pr}, the number of ST_n can not be larger than a limit. This limit is 13% of EV_{pr} for the applied case study. High level of EV_{pr} causes the problems in the constraints of power system. In this case with limited ST_n the problem is not solved but it could be managed automatically. In fact, EVs recharge at stations only up to the certain numbers depending on the capacity of the stations. Other EV remain uncharged. As mentioned, this is not a solution for the large EV_{pr}. For cases with high level of EV_{pr}, by increasing the ST_n number, power system constraints cause lower level of MCS_{index} and the OPS model will not converge.

These ranges could be defined for each case study. Means that the proposed method could be applied independently from the case study. However before doing the optimization on the location for the charging station, we can achieve the suitable range, by running some initializations on the parameters.

In another analysis, results of the proposed method based on the PSO algorithm are compared with the results of MCS method with the same initial conditions. In the MCS based model, for each iteration, a random selection of ST_n number of stations from STL is performed. If power system constraints are not passed, total distance for STC is registered. At the end of MCS iterations, the average of total distances for all STCs is compared and a list of the ST_n number of STCs with lower total distance is selected as the final solution. This list is compared with the global best final list of the proposed PSO method. Table 4.5 results of two cases are shown. The number of MCS iteration in this case is 5000 iterations.

description	MCS	PSO Method
Total distance between EVs and stations (km)	1325.3	1076.8
Success index for final stations list (%)	99.6	99.9

Table 4.5: Comparing results of PSO method with MCS method

4.5 Conclusion

This comprehensive method is based on an optimization method and includes traffic data, geographic data, EV characters, drivers behaviors and power system uncertainties in one model. The proposed PSO method has advantages in comparing with other methods described in the first section in terms of the number of uncertainties which are taken into account. Power system constraints and minimum distance to charging station are considered in finding the optimal location for installing fast charging stations. This approach and proposed model can be used to find the maximum number of charging stations as well as their locations for other urban region cases.

Chapter 5

Reciprocal impact of electric vehicles and distributed generation of energy simultaneously integration into power system

5.1 Renewable energies in smart grid

In this section two main sources of distributed generation in the power system are presented: photovoltaic and wind energy. For each one, the power generation model is discussed and various parameters effect on final power generated is determined.

5.1.1 Photovoltaic energy characterization

Photovoltaic systems have been studied widely as a renewable energy source because they are not only environmentally friendly, but also have infinite energy available from the sun. Although the PV system has the above-mentioned advantages, its study involves precise management of factors such as solar irradiation and surface temperature of the PV cell [YGC01]. The PV cells typically show varying $v-i$ characteristics depending on the factors mentioned above. Figure 5.1 shows the output characteristics of a PV cell with changing levels of illumination.

As is clear from Figure 5.1, the current level increases with increase in the irradiation level. Figure 5.2 shows the $v-i$ curves with varying cell temperatures.

As depicted in Figure 5.2, the output curves for varying cell temperatures

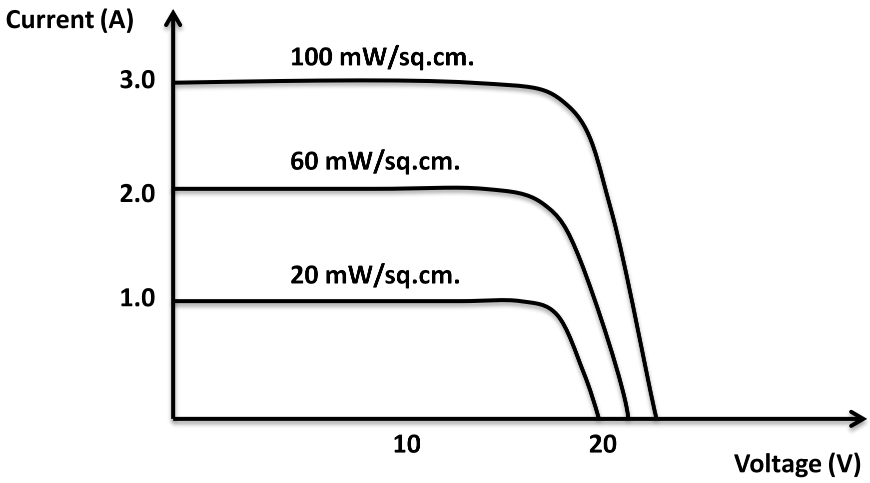

Figure 5.1: Typical $v-i$ characteristics of PV cell with varying illumination levels.[EEM04]

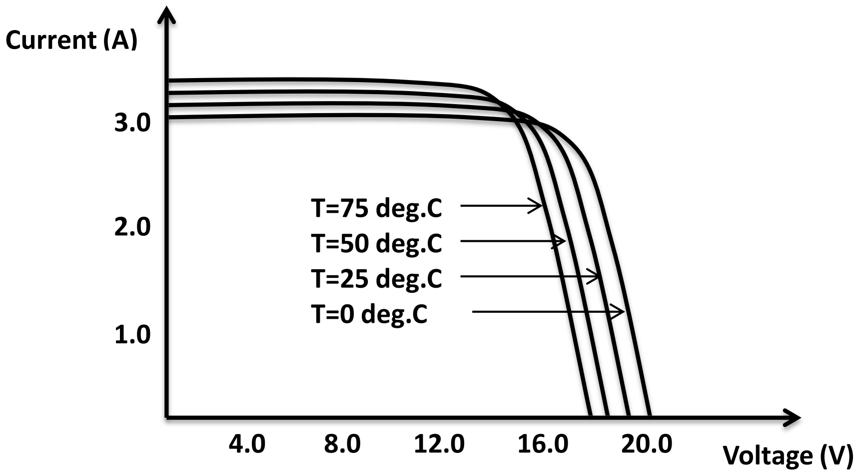

Figure 5.2: Typical $v-i$ characteristics of PV cell with varying cell temperatures [EEM04].

show higher voltage level as the cell temperature increases. Therefore, while modeling the PV cell, adequate consideration must be given to these two characteristics in particular. Keeping the above-mentioned factors in mind, the electrical equivalent circuit modeling approach is proposed here. This model is basically a non-linear distributed circuit in which the circuit elements consist of the familiar semiconductor device parameters. Eventually, running a suitable computer simulation can easily simulate this model. The PV cell can basically be considered as a current source with the output voltage primarily dependent on the load connected to its terminals [VMS91]. The equivalent circuit model of a typical PV cell is as shown in Figure 5.3. As is clear from Figure 5.3, there are various parameters involved in the modeling of a typical PV cell. These parameters are:

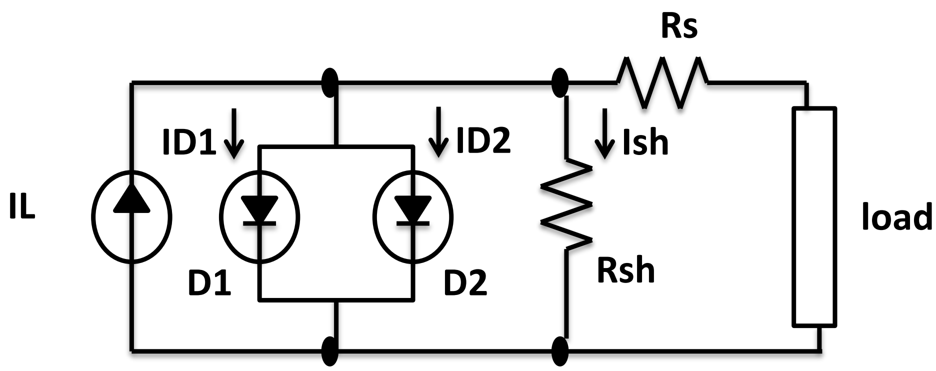

Figure 5.3: Schematic of equivalent circuit model of a PV cell.[EEM04]

I_l: light generated current (A),
I_{D1} : diode saturation current (A),
I_{D2} : additional current due to diode quality constant (A),
I_{sh} : shunt current (A),
R_s : cell series resistance (Ω),
R_{sh} : cell shunt resistance (Ω), and
I : cell generated current (A).

The model depicted in Figure 5.3 examines all the characteristic measurements of the $p-n$ junction cell type. From the above circuit, the following equation for cell current can be obtained:

$$J = JL - Jo1\left\{e^{\frac{q(V+J.R_s)}{kT}} - 1\right\} - Jon\left\{e^{\frac{q(V+J.R_s)}{A.kT}} - 1\right\} - G_{sh}(V + J.R_s) \quad (5.1)$$

Here, q and k are electron charge and Boltzmans constant, respectively. The voltage at the terminals of the diodes in Figure 5.3 can be expressed as follows:

$$V = V_{oc} - IR_s + \frac{1}{\Delta}\log_n\left\{\frac{\beta(I_{sc}-I)-\frac{V}{R_s}}{\beta.I_{sc}-\frac{V_{oc}}{R_s}} + e^{\Delta(I_{sc}.R_s-V_{oc})}\right\} \quad (5.2)$$

Here, β is the voltage change temperature coefficient (V/°C).

For the PV cell model of Figure 5.3, R_s and R_{sh} are usually estimated when the cell is not illuminated. Thus, these values can be approximated from the dark characteristic curve of the cell. The generated light current (I_L) is calculated by the collective probability of free electrons and holes. It can be expressed as follows:

$$I_L = q.N \left[\sum f_c(x_N) + f_c(x_P) + 2l\right] \tag{5.3}$$

Here, $f(x)$ is the probability distribution function and N is the rhythm of generated electrons and holes.

Once the equation of the cell model are formulated, the efficiency of the PV cell can be obtained as :

$$Efficiency = \frac{P_{out}}{P_{in}} = \frac{f.I_{sc}.V_{oc}}{P_{in}} \tag{5.4}$$

A distinct advantage of such a computer model is the fact that, with a very few number of changes, it can receive data from different kinds of PV cells, maintaining satisfactory results [VMS91]. 8 [VMS91] [VMS91] [YGC01]

5.1.2 Wind power modeling

For power system simulations involving grid disturbances, it is a reasonable approximation to assume that wind speed remains uniform for the 5 to 30 seconds typical of such cases. However, the mechanical power delivered to the shaft is complex function of wind speed, blade pitch angle and shaft speed. Further, with wind generation, the impact of wind power fluctuations on the output of the machines is of interest. The turbine model depends on the wind power model to provide this mapping. The function of the wind power module is to compute the wind turbine mechanical power (shaft power) from the energy contained in the wind, using the following formula [MPSG03]:

$$P = \frac{\rho}{2} A_r V_W^3 C_p(\lambda, \theta) \tag{5.5}$$

P is the mechanical power extracted from the wind, ρ is the air density in kg/m^3 , A_r is the area swept by the rotor blades in m^2, vw is the wind speed in m/sec, and C_p is the power coefficient, which is a function of λ and θ. λ is the ratio of the rotor blade tip speed and the wind speed (v_{tip}/v_w), θ is the blade pitch angle in degrees. For the rigid shaft representation used in this model, the relationship between blade tip speed and generator rotor speed, ω, is a fixed constant, K_b. The calculation of λ becomes:

$$\lambda = k_b(\frac{\omega}{V_m}) \tag{5.6}$$

C_p is a characteristic of the wind turbine and is usually provided as a set of curves relating C_p to λ, with θ as a parameter. The C_p curves for the GE wind turbine are shown in Figure 5.4. Curve fitting was performed to obtain the mathematical representation of the C_p curves used in the model:

$$C_p(c, \lambda) \sum_{i=1}^{4} \sum_{j=1}^{4} = \alpha_{i,j} \theta i \lambda_j \tag{5.7}$$

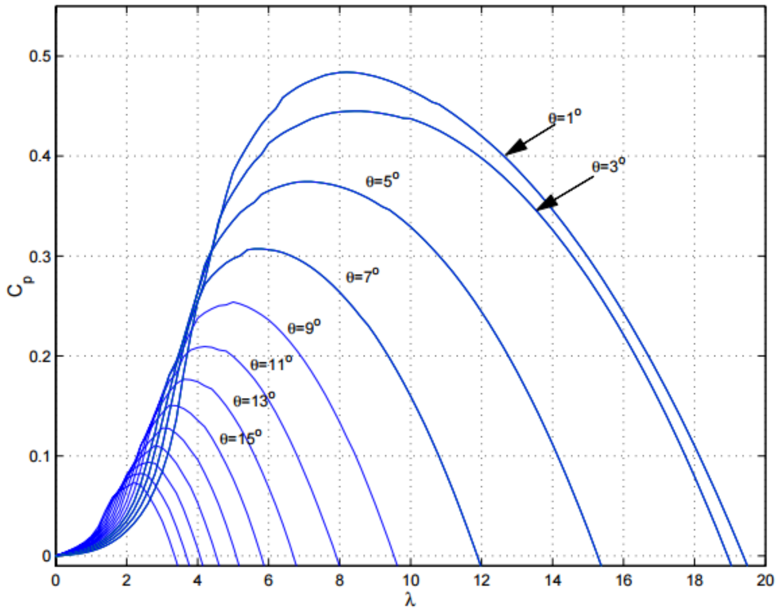

Figure 5.4: Wind Power C_p Curves [MPSG03]

Initialization of the wind power model recognizes two distinct states: initial electrical power (from the loadflow) is less than rated, or initial electrical power equal to rated. In either case, $P_{mech} = P_{elec}$ is known from the loadflow and $\omega = \omega_{ref}$ is set at the corresponding value ($1.2pu$ if $P > 0.75pu$). Then, using the C_p curve fit equation, the wind speed v_w required to produce P_{mech} with $\theta = \theta_{min}$ is determined.

5.2 EVs and DG integration into power system reciprocal impact study

In all studied cases in the previous chapter, the actual connected Distributed Generation (DG) is applied. This DG power generation values are exerted as the generation in the modelling. In this way, DG power is assumed as the basis of the allocated values to the generation in each bus. The maximum power generation in the PV plants is exerted to do a random allocation. Random allocated value is applied in power flow analysis. According to this assumptions, the EV penetration rate is assessed.

In this section, EVs and DG integration into power system reciprocal impact is studied. In the other words, with an increase in one side, the impact of this increase in other side is assessed. This section includes two parts.

In the first part of this study, EV_{pr} for different DG_{pl} is assessed. In the second part, the DG_{pl} is evaluated for two cases with different EV_{pr}.

5.2.1 Impact of DGs increase on maximum allowed EV_{pr}

The problem is to find the maximum allowed Electric Vehicles Penetration Rate (EV_{pr}) with some fixed values for DG_{pl}. The solution is taking into account power system constraints. That means we are looking for the limit value of allowed EVs to be integrated into power system for a given DG_{pl}. This value is a percentage of total vehicles in the region. The proposed model is working based on the Monte Carlo Simulation (MCS) algorithm. In fact the power system constraints are evaluated by a Monte Carlo Simulation Success/Fail index.

The mathematical problem is :

Finding

$$
\begin{gathered}
Max \quad EV_{pr} \\
With: \qquad UV_{bus} = 0, \quad OV_{bus} = 0, \quad OL_{branches} = 0 \\
and \\
DG_{pl} = fixed \quad value \\
Considering: \\
\begin{cases}
\text{Large-Scale EVs integration} \\
\text{Traffic Data} \\
\text{Drivers Behavieurs} \\
\text{Power System uncertainities}
\end{cases}
\end{gathered}
\tag{5.8}
$$

Parameters are:
EV_{pr}: Electric Vehicles Penetration Rate (%).
DG_{pl}: Distribution Generation Penetration Level (%).
UV_{bus}: Number of under voltage buses.

OV_{bus}: Number of over voltage buses.
$OL_{branches}$: Number of over load branches.

Solution is a percentage value which determines the percentage of total vehicles in the region which are electric vehicle type.

To assess the impact of DGs increase on the maximum allowed EV_{pr}, the comprehensive model of the previeus chapter is applied. Figure 5.5 shows the results with no DG and 5% for DG_{pl}. Figure shows that EV_{pr} for the initial case with no DGs is augmented by 5% increase in DG_{pl}.

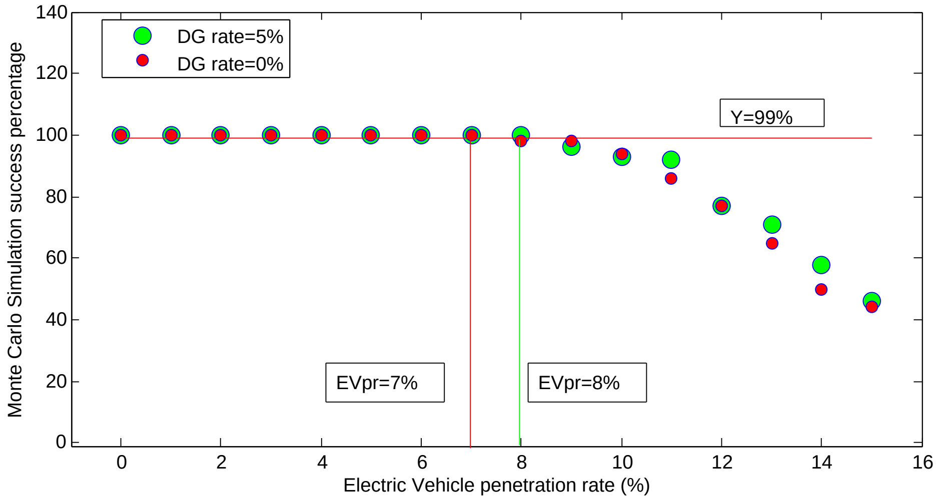

Figure 5.5: Impact of DGs increase on maximum allowed EV_{pr}.

5.2.2 Impact of EVs increase on maximum allowed DG_{pl}

To study the effect of DGs and EVs integration into power system, in next step we study the effect of increase in EV_{pr} on the maximum allowed DG_{pl} in the power system. EV_{pr} is assumed to be constant in this part of study. Two constant values of EV_{pr} are tested.

The problem is to find the maximum allowed (DG_{pl}) with some fixed values for EV_{pr}. The solution is taking into account power system constraints. That means we are looking for the limit value of allowed DGs to be integrated into power system for a given EV_{pr}. This value is a percentage of total generation in the power system. The proposed model is working based on the Monte Carlo Simulation (MCS) algorithm. In fact the power system constraints are evaluated by a Monte Carlo Simulation Success/Fail index.

The mathematical problem is :

Finding

$$Max \quad DG_{pl}$$

$$With: \qquad UV_{bus} = 0, \quad OV_{bus} = 0, \quad OL_{branches} = 0$$

$$and \qquad EV_{pr} = fixed \quad value$$

$$Considering: \quad \begin{cases} \text{Large-Scale EVs integration} \\ \text{Traffic Data} \\ \text{Drivers Behavieurs} \\ \text{Power System uncertainties} \end{cases} \tag{5.9}$$

Parameters are:
EV_{pr}: Electric Vehicles Penetration Rate (%).
DG_{pl}: Distribution Generation Penetration Level (%).
UV_{bus}: Number of under voltage buses.
OV_{bus}: Number of over voltage buses.
$OL_{branches}$: Number of over load branches.

Solution is a percentage value which determines the percentage of DGs power ratio to the total power generation in the power system .

In order to evaluate the impact of DG in a general case, EV charging is done in normal plan. Charging conditions are the same as the previous chapter. The comprehensive model of EVs connection to the grid is applied. So power system uncertainties and EVs SOC probability distribution function and drivers behavieurs is exerted.To evaluate the conditions of the model in the worst case, dumb charging scenario is applied for EVs charging. Hence EVs could be charged in a dumb charging scenario with normal charging at home and work and fast charging only at station in shopping centers.

Figure 5.6 shows the results with no EVs and 5% for $DG_{pl}EV_{pr}$. Figure shows that DG_{pl} for the initial case with no EVs is augmented by 5% increase in DG_{pl}.

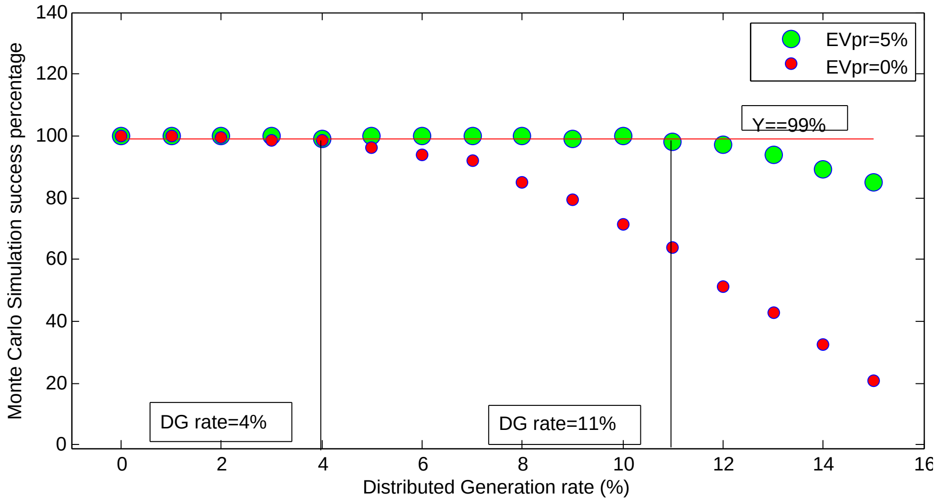

Figure 5.6: Impact of EVs increase on maximum allowed DG_{pl}.

5.2.3 Results comparison

Table 5.1 summarized results of applying scenarios on the case study.

Description	With fixed DG_{pl}		With fixed EV_{pr}	
DG_{pl}	0%	5%	4%	11%
EV_{pr}	7%	8%	0%	5%

Table 5.1: DG_{pl} and EV_{pr} scenarios comparison

5.3 Heuristic strategies in mathematics

5.3.1 Heuristic strategies

Heuristic strategies in mathematics have a long history almost from the beginning of the classic mathematics but modern heuristic is revived by Polya in 1945. A full 35 year s after the declaration of heuristic intentions, the National Council of teachers and Mathematics (NCTM) in USA published an agenda for action saying that problem solving must be the focus of school mathematics in the 1980s. Polyas work Idea to solving problems was based on four-stage guide and the first was How to solve it. His work on problem solving is held in high regard by both mathematicians. Heuristic, or the mental operation typically useful for the solution of the problems have been the focus of most problem-solving in mathematics education and the foundation for most problem-solving research in mathematics education and foundation for most development efforts in problem solving [A.H85].

5.3.2 Two general heuristic strategies

Two general heuristic strategies are examining special cases and exploiting subgoals. The analysis reveals that such heuristic strategies are not, as in generally assumed, coherent problem-solving approaches that are used the same way across-the-board. Rather, each general heuristic can be seen as a loose collection of somewhat related substrategies. Heuristic in science and engineering:

1. Strategy S:
   To better understand an unfamiliar problem, you may wish to exemplify the problem by considering various special cases. This may suggest the direction of, or perhaps the plausibility of, a solution.

2. Strategy H:
   if you cannot solve the given problem, establish subgolas (the partial fulfillment of the desired conditions). Having attained them, build upon them to solve the original problem.

The general heuristic strategies are so broadly defined that their definition are far to vague so serve as a guide to their implementation. The successful use of such strategies calls for identifying and characterizing the major component substrategies in substantial detail and giving as much attention to those as one would any other complex subject matter. One cannot expect too much of heuristic strategies. Ones success in any domain is based on a foundation of ones resources in that domain, and even a mastery of heuristics cannot be expected to replace shaky mastery of subject matter.

5.3.3 Heuristic strategies and engineering

The increase in artificial intelligence in recent years has resulted in an increased interest in the area of heuristic. The word heuristic is often used to mean a science, method or technique of discovery. The importance of heuristics lies in the fact that heuristic solutions are necessary in problems where the conventional sequential or analytical methods are regarded as unable, or very difficult in a practical sense, to produce a correct solution. The area of heuristic will be of increasing importance as engineers and scientist more and more attempt understand and model complicated, large-scale systems [Wom74].

Heuristic have long been associated with education. What is discovered is not as important as the act of discovery itself, the underlying philosophy of this approach to education being that it is important for the pupil to learn to think for himself in an age of rapid progress. In a heuristic method of education, therefore, the method of discovery is not a means to an end, discovery, but is, in fact, the end itself. The same statement cannot be made about the application of heuristics to the fields of science and engineering. In engineering, the emphasis is on the discovery, which is a discovery in the narrow sense of the word, in that the discovery is constrained to be of a certain type. In particular, heuristics are used to arrive at a solution of a problem. In the area of education a heuristic method has intrinsic value independent of the discovery arrived at but in the area of science and engineering a heuristic method has value only in relation to its ability to arrive at a good solution to a particular problem.

Heuristic method are used to solving the types of problem for which during the process of arriving at a solution, certain decisions must be made from among large number of alternatives. If the number of alternatives is large enough, a complete enumeration of the consequences of each alternative would be, if not impossible, then certainly impractical. For example in writing a computer program to play chess, where a strategy of considering one by one all possible consequences of all possible moves would simply be infeasible. [KF74].

5.3.4 Heuristic strategies and Experimental Mathematics

Experimental Mathematics is that branch of mathematics that concerns itself ultimately with the codification and transmission of insights within the mathematical community through the use of experimental exploration of conjectures and more informal beliefs and a careful analysis of the data acquired in this pursuit. Mathematics is frequently distinguished from the physical sciences by Philosophers. Computer has begun to change the constraints and pictures in the sciences via experimentation to the real world. The computer has given us the ability to look at new and unimaginably vast worlds. It has created mathematical worlds that would have remained inaccessible to the unaided human mind. The computers of tomorrow promise even stranger worlds to explore. Today, however, most of these explorations into the mathematical wilderness remain isolated illustrations. Heuristic conventions, pictures and diagrams developing in one sub-field often have little content for another. In each sub-field unproven results proliferate but remain conjectures, strongly held beliefs or perhaps mere curiosities passed like folk tales across the Internet. The computer has provided extremely powerful computational and conceptual resources in solving mathematical problems.[JBP14]

5.3.5 Heuristic strategies in computer science

Heuristic strategies are generally effective techniques and approaches for accomplishing tasks that might be regarded as "tricks of the trade"; they don't always work, but when they do, they are quite helpful. Most heuristics are tacitly acquired by experts through the practice of solving problems; however, there have been noteworthy attempts to address heuristic learning explicitly [A.H85]. For example, a standard heuristic for writing is to plan to rewrite the introduction and, therefore, to spend relatively little time crafting it in the first draft. In mathematics, a heuristic for solving problems is to try to find a solution for simple cases and see if the solution generalizes [AC91].

Learning strategies are another domain of using heuristic strategies. Learning strategies are strategies for learning any of the other kinds of content described above. Knowledge about how to learn ranges from general strategies for exploring a new domain to more specific strategies for extending or reconfiguring knowledge in solving problems or carrying out complex tasks. For example, if students want to learn to solve problems better, they need to learn how to relate each step in the example problems worked in textbooks to the principles discussed in the text [Chi89] , [AC91].

5.4 Finding the maximum simultaneously DG and EVs penetration rate

Following the second section, a method is proposed in this section to find the case with simultaneously maximum DG_{pl} and EV_{pr} percentages. In fact we are searching for the optimal case in which both EV_{pr} and DG_{pl} are in the maximum possible. Power system constraints should be considered in this case.

5.4.1 Modelling and complexity

The problem is to find the maximum allowed DG_{pl} and EV_{pr} simultaneously. The solution is taking into account power system constraints. That means we are looking for the limit value of allowed DG_{pl} and EV_{pr} to be integrated into power system for a given. The proposed model is working based on the Monte Carlo Simulation (MCS) algorithm. In fact the power system constraints are evaluated by a Monte Carlo Simulation Success/Fail index.

The mathematical problem is :

Finding

$$Max \quad DG_{pl} \quad \text{and} \quad Max \quad EV_{pr}$$

$$With: \qquad UV_{bus} = 0, \quad OV_{bus} = 0, \quad OL_{branches} = 0$$

$$Considering:$$

$$\begin{cases} \text{Large-Scale EVs integration} \\ \text{Traffic Data} \\ \text{Drivers Behavieurs} \\ \text{Power System uncertainties} \end{cases} \tag{5.10}$$

Parameters are:
EV_{pr}: Electric Vehicles Penetration Rate (%).
DG_{pl}: Distribution Generation Penetration Level (%).
UV_{bus}: Number of under voltage buses.
OV_{bus}: Number of over voltage buses.
$OL_{branches}$: Number of over load branches.

Solution is a set of two percentages which determines the maximum percentage of DGs and EVs allowed to be integrated into the grid at the same time.

This problem is a np complete problem so it's not possible to find the solution with deterministic models. A methode is proposed in next sections based on MCS method and heuristic method.

5.4.2 Heuristic based method in solving problem

A heuristic based method is proposed in this section to solve the problem. Based on this method, the first step is to find the maximum EV_{pr} percentage. Next step is finding the maximum DG_{pl} related to the maximum EV_{pr} in first step. In next step we use this DG_{pl} to achieve the maximum EV_{pr} percentage. This cycle is repeated until the new achieved values for EV_{pr} percentage and DG_{pl} converge to a certain value. Figure 5.7 summarized this procedure in a simple picture. In top side simulations are initialized with maximum EV_{pr} and in the bottom of the figure, maximum DG_{pl} is the starting point of simulation.

Figure 5.8 shows the results for two scenarios. First scenario results in blue starts from the initial case with maximum EV_{pr}. Another scenario results in red is initialized in the case with maximum DG_{pl}. Results show the same convergence for both scenarios. The maximum possible EV_{pr} and DG_{pl} is for the case with 13

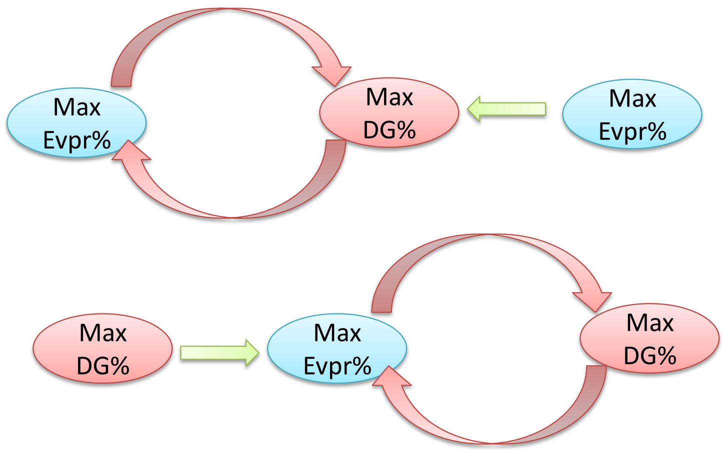

Figure 5.7: Finding the maximum case with two initialization.

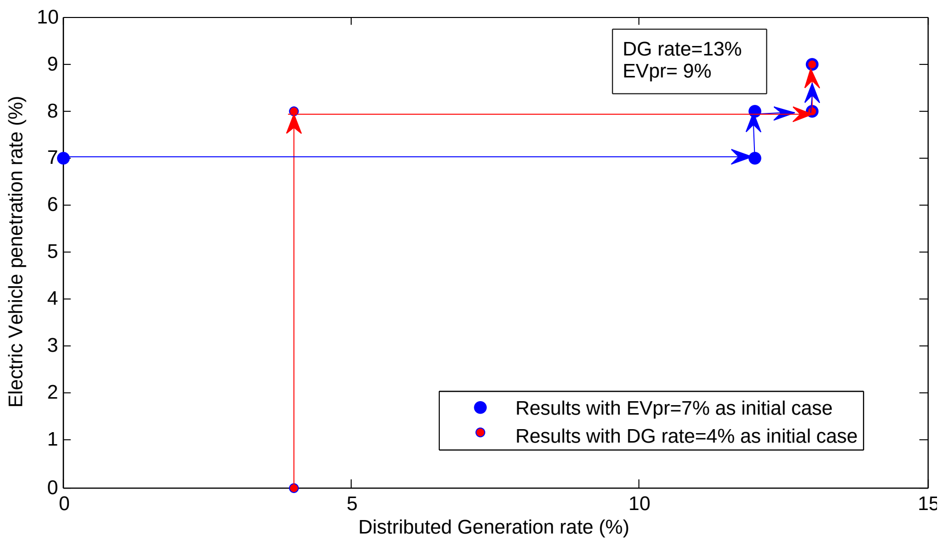

Figure 5.8: Max DG_{pl} and EV_{pr} convergence toward the optimal case.

5.5 A PSO based model

To solve the problem of simultaneously maximum DG_{pl} and EV_{pr} percentages, a method is proposed in this section based on optimization approach. In fact we are searching for the optimal case in which both EV_{pr} and DG_{pl} are in the maximum possible.

The proposed model exerts the PSO method in finding the optimal solution.

PSO parameters including global best, local best, particles position, particles movement vectors are applied from Chapter 4 definitions. The only basic differense in this model is using "multiple global best" position instead of using "single global best" in the previeus proposed model in Chapter 4. Other particles parameters definitions are presented here based on the general PSO algorithm.

5.5.1 Mathematical modeling and algorithm

In this section the problem is mathematically defined. Problem is selecting a case with maximum DG_{pl} and EV_{pr} percentages considering power system constraints. This problem is a NP-complete problem. To solve this problem, an optimization method based on PSO algorithm is proposed in this section.

For a given case study with specified power system parameters, EV_n and DG_{pl} are variant two variables. These two variables are not independent as illustrated in the first section, both variables have reciprocal impact on each other. the problem is finding the case with maximum value for both EV_n and DG_{pl} at the same time.This maximum values represent the capacity of the power network to accept increase in EV_n and DG_{pl} values. In order to create the model, first of all, the"State(i)" is defined as:

$$State(i): \quad \{DG_{pl} = DG_{pl}(i) \quad and \quad EV_n = EV_n(i)\}$$

With:
$State(i)$:State of the system where $DG_{pl} = DG_{pl}(i)$ and $EV_n = EV_n(i)$.
$DG_{pl}(i)$: DG_{pl} value of the system in case with index i.
$EV_n(i)$: EV_n value of the system in case with index i.

Therefore, all the candidate States for the optimal solution of the problem are extracted and listed as $[State_1, State_2, \dots State_k]$ with $State_1, State_2, \dots$ being the list of candidate States. This list is mentioned as $StateCandidateList$ or SCL.

The problem is the same as defined before in 5.11. Thus:
The problem is finding :

$$State(i) \quad With \quad Max \quad \{DG_{pl}(i) \quad and \quad EV_{pr}(i)\}$$

$$With: \qquad UV_{bus} = 0, \quad OV_{bus} = 0, \quad OL_{branches} = 0$$

$$Considering:$$

$$\begin{cases} \text{Large-Scale EVs integration} \\ \text{Traffic Data} \\ \text{Drivers Behavieurs} \\ \text{Power System uncertainties} \end{cases} \tag{5.11}$$

Solution is:

$[DG_{pl}(f), EV_{pr}(f)]$

with $DG_{pl}(f)$ and $EV_{pr}(f)$ being the DG_{pl} and EV_{pr} of optimal state with maximum values, called state f. It should be mentioned that the solution is not unique and problem can have multiple solutions

Based on the proposed model, PSO parameters definitions are:

1. Particles in this model are the index of state candidates (STC). The number of particles is a constant value which is determined at the beginning of the algorithm. In this model, the number of particles is fixed to 10 particles.

2. $f : \mathbb{R}_n \to \mathbb{R}$: objective function with a vector of zero and one in input.

3. x_i: Particles in this model are list of states of the system. Each list has *State* member. List of the *STCs* includes i(particle index) of the selected state of the system. This list is modeled with a vector of two variables for each state. For the STC in the particle state shows the $DG_{pl}(i)$ and $EV_{pr}(i)$ values.

4. p_i: State of STC including $DG_{pl}(i)$ and $EV_{pr}(i)$ for index i which is the index of particle candidate state. This list is a local best for x_i. The case with maximum *dist* is saved in this vector. This state should have a $success_index$ equal to one to be presented as best local.

5. g: list of the states with at least one variable ($DG_{pl}(i)$ and $EV_{pr}(i)$) with maximum value.The best case is found and saved during movements of particles.

6. $success_{index}$: is an index of success for Monte Carlo Simulation results. After running the power flow analysis of the specified configuration of stations in the region, this configuration is tested with random allocation of variables like EV charging characters, power demand, DG, number of EVs at stations and SOC of EVs at arrival time to station.

   Results could cross the power system constraints in some random allocations. The percentage of total iteration in which constraints are not crossed gives $success_index$. If this percentage is higher than 99%, $success_index$ is one, otherwise it would be zero.

7. V_i is defined based on this formula:

$$v_{i,d} \leftarrow \omega v_{i,d} + \varphi_p r_p (p_{i,d} - x_{i,d}) + \varphi_g r_g (g_d - x_{i,d})$$

r_p and r_g are random values on the $State(i)$ difference between $p_i - x_i$ and $g - x_i$ respectively. φ_p, ω and φ_g are supposed to be 1/3 or 33%.

In Figure **??** particle movement from results of a simulation on the case study from Chapter 2. In this case, particles is fixed to 10. Particle movement in PSO algorithm is depicted in this figure. Points in red are particles with $success_{index} = 0$, in black, $success_{index} = 1$ and finally in green shows global best particles. The initial case is a random allocation to particles in a determined interval of DG_{pl} and EV_{pr} variables. This interval could be selected by a heuristic approach in to reduce simulation duration. However this initialization has no effect on final results.

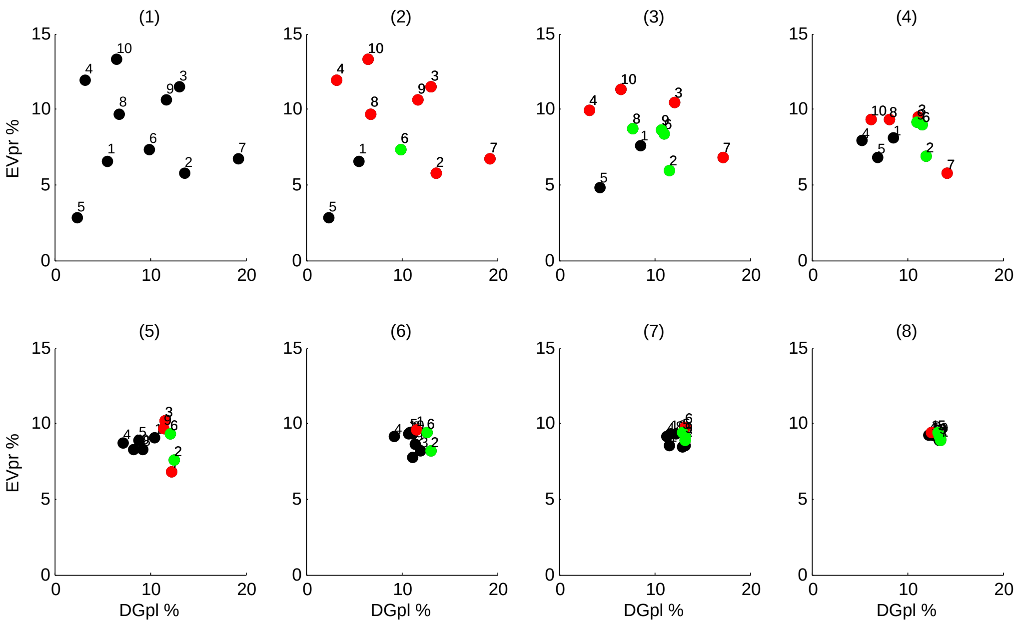

Figure 5.9: Particle movement in PSO algorithm,points in red are particles with $success_{index} = 0$, in black, $success_{index} = 1$ and finally in green shows global best particles

Figure 5.10 shows the a superposition of 8 iteration. Particles movement is illustrated in this figure.

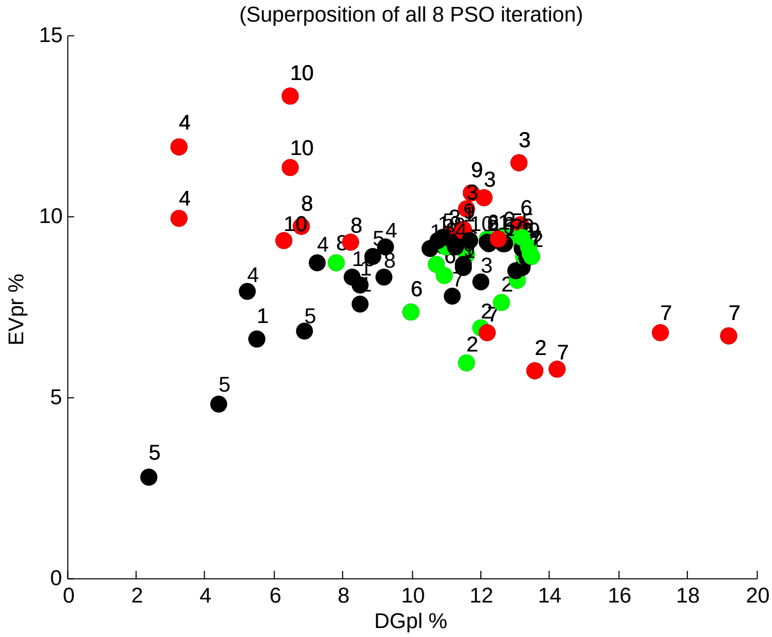

Figure 5.10: Particle movement in PSO algorithm, a superposition of 8 iterations

5.5.2 results comparison

The proposed model is tested on the case study from Chapter 2 with the mentioned settings of PSO parameters. Table 5.2 depicts $DG_{pl}(f)$ and $EV_{pr}(f)$

Description	$g_1(\%)$	$g_2(\%)$	$g_3(\%)$	$g_4(\%)$	Err
DG_{pl}	13.2	13.3	13.4	13.5	0.02
EV_{pr}	9.3	9.25	9.2	9.1	0.02

Table 5.2: DG_{pl} and EV_{pr} final states (particles)

of the final best global particles. This solution is consist of four states (or global best particles). As mentioned before, this model applies a multiple global best version of PSO algorithm. Thus all four states are true final result. It should be noticed that PSO convergence can give only one final result if the $DG_{pl}(i)$ and $EV_{pr}(i)$ were continuous variables. Knowing that changing in EV_{pr} is equivalent to adding a certain number of EVs in the model, the variation is a discrete variable. So the final result can not converge generally to a unique solution. Furthermore it is clear from the results that final solutions has a small variation in global best with 2% and 1% for $DG_{pl}(f)$ and $EV_{pr}(f)$ values respectively.

Table 5.3 compared results from two proposed model: PSO model and the heuristic method presented in previous section. As depicted in this table, error of the proposed heuristic method based model is small for this case study.

Description	PSO model	Heuristic model
DG_{pl}	13.2 - 13.5	13
EV_{pr}	9 - 9.3	9

Table 5.3: Heuristic and PSO model comparison

5.6 Conclusion

Electric vehicles and distributed generation of energy simultaneously integration into power system, can effect both of them. Simultaneous integration can increase the allowed penetration of DG an EVs compared with single integration case.

Two model for finding the maximum DG_{pl} and EV_{pr} is presented in this chapter: a Heuristic method based model and a PSO model based. Two models are evaluated by applying a power system case study and results compared. These models can be applied for other cases as a simulation tool to find the maximum values of DG_{pl} and EV_{pr} allowed by the power system.

Conclusions

Concerns for the environment and energy security are two major axes of challenge for policy makers in energy domain. From power grid point of view, Electric Vehicles (EVs) charging usually means an additional load that should be supplied by the grid. Power grid has been designed based on the normal demand of energy and can only support a limited extra demand like EV load. In case of installing charging stations, all power system constraints should be taken into account to ensure energy security in the grid.

This thesis has investigated Electric Vehicles integration into the smart grid including impact study, various challenges and their capacity to improve power system security and operational indexes. In this way, the impact of EVs charging on distribution grid is investigated and a comprehensive models are proposed in order to consider various uncertainties in the power system (i.e., load and distributed generation profiles), EVs parameters (i.e., batteries specifications, SOC% and fast/ normal charging methods) and drivers behavieurs (i.e., charging location, charging accessibility and charging duration). Proposed models in this study consists of three main subjects: EVs charging control to respect power grid constraints, fast charging station planning and optimization an finally capacity of EVs integration to improve distributed generation of energy penetration level in the power grid.

In the first step, a comprehensive model is presented in order to take into account all above mentioned uncertainties. This model is based on a stochastic method and applied the Monte Carlo Simulation (MCS) in modeling uncertainties. Results of exerting this model on two dumb and smart charging scenario, shows that with control on EVs charging the power system uncertainties crosses including over under voltage on buses and over load in branches could be improved.

In the second step, the fast charging station for EVs planning in the urban regions is investigated. The proposed method for locating the optimal location for fast charging station is presented. This model uses the Particle Swarm Optimization method in finding the best economic and technical location for installing fast charging stations.This comprehensive method includes traffic data, geographic data, drivers behavieurs and power system constraints in one model. The resulting PSO based method has been compared with the MCS method using the same initial conditions.

The third step is dedicated to the EVs capacities to increase distributed generations penetration levels in the grid. Two model are proposed in this part: a heuristic method based model and a PSO approach based model. Results of simulation of this models on a real case study demonstrates the capacity of EVs charging in increasing DGs penetration level in the grid.

In all the above mentioned models, the tools developed, tested on a case study and can be applied to the other power system cases.

Appdx A

.1 A small example of applying probability bar

A complete example shows how to make probability bar:
Probability distribution:

Description	Value				
Time index	1	2	3	4	5
Probability	0.3333	0.1667	0.2500	0.1667	0.0833

Table 4: Probability values for unique time indexes.

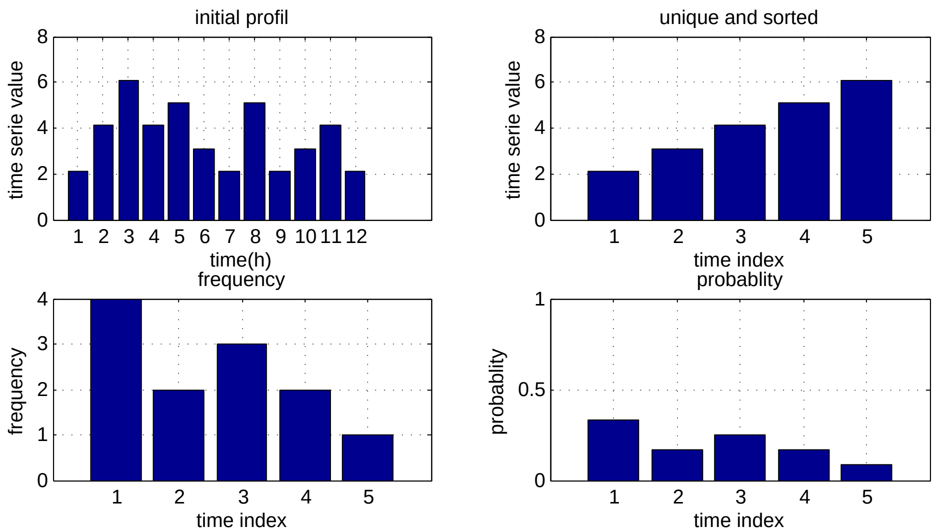

Figure 11: From initial to probability.

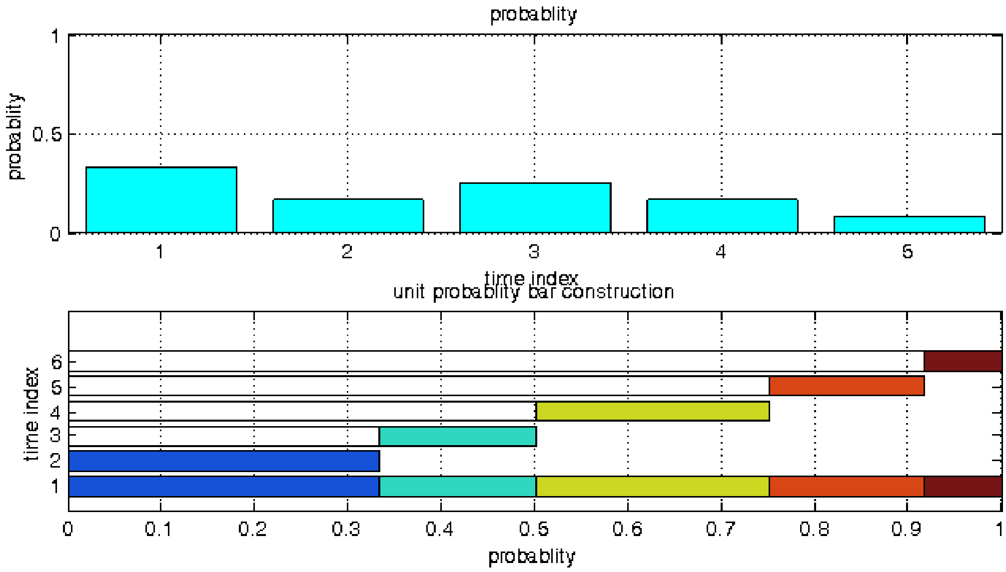

Figure 12: Unit probability bar construction.

.2 Fast charging algorithm(Simple model)

This scenario, are proposed to evaluate an extreme condition in EVs charging. Charging conditions have an image of the “worst” possible case. In this scenario EVs characters and SOC at arrival and outgoing time are supposed so that increase the power demand at buses. SOC difference for before charging and after charging process is supposed to be 70%. This percentage is the maximum possible charging rate for the battery capacity with the range between 15% and 85%. These are the maximum and minimum standard charging levels for batteries. Other assumptions are the same as average EVs charging plan. Figure [next] demonstrates total power demand and total active losses during a day with EV_{pr} = 0%, 10% and 15%. Losses has increased comparing with average plan. Regarding peak power demand increase in top side figure, we can conclude that in average and strong charging plan, dumb charging has increased peak value of power demand. Figure [next] show results of this scenario. All these figures are from the dumb charging in fast plan case.

.3 Fast charging algorithm(comprehensive model)

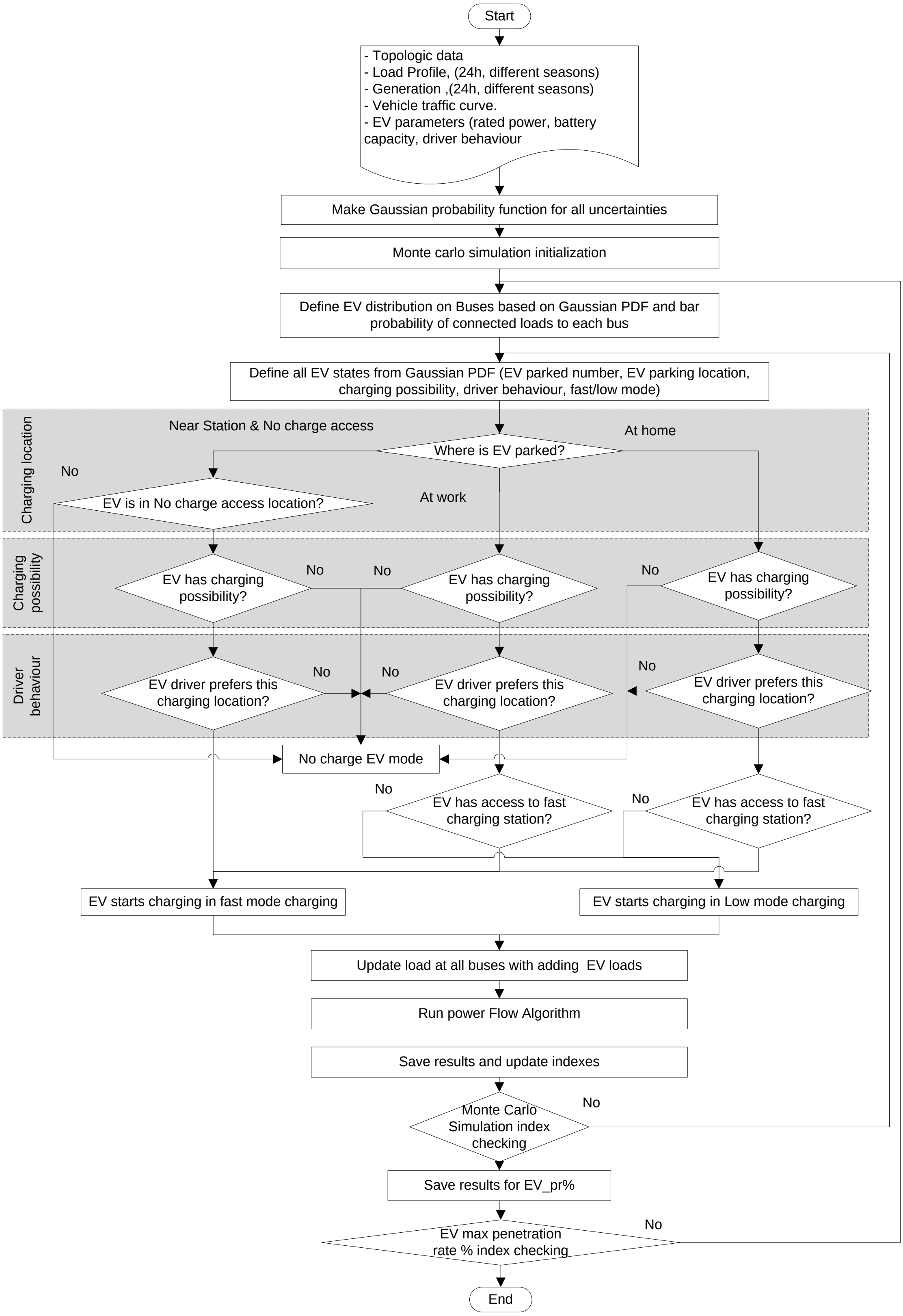

Figure 13: Fast charging plan algorithm.

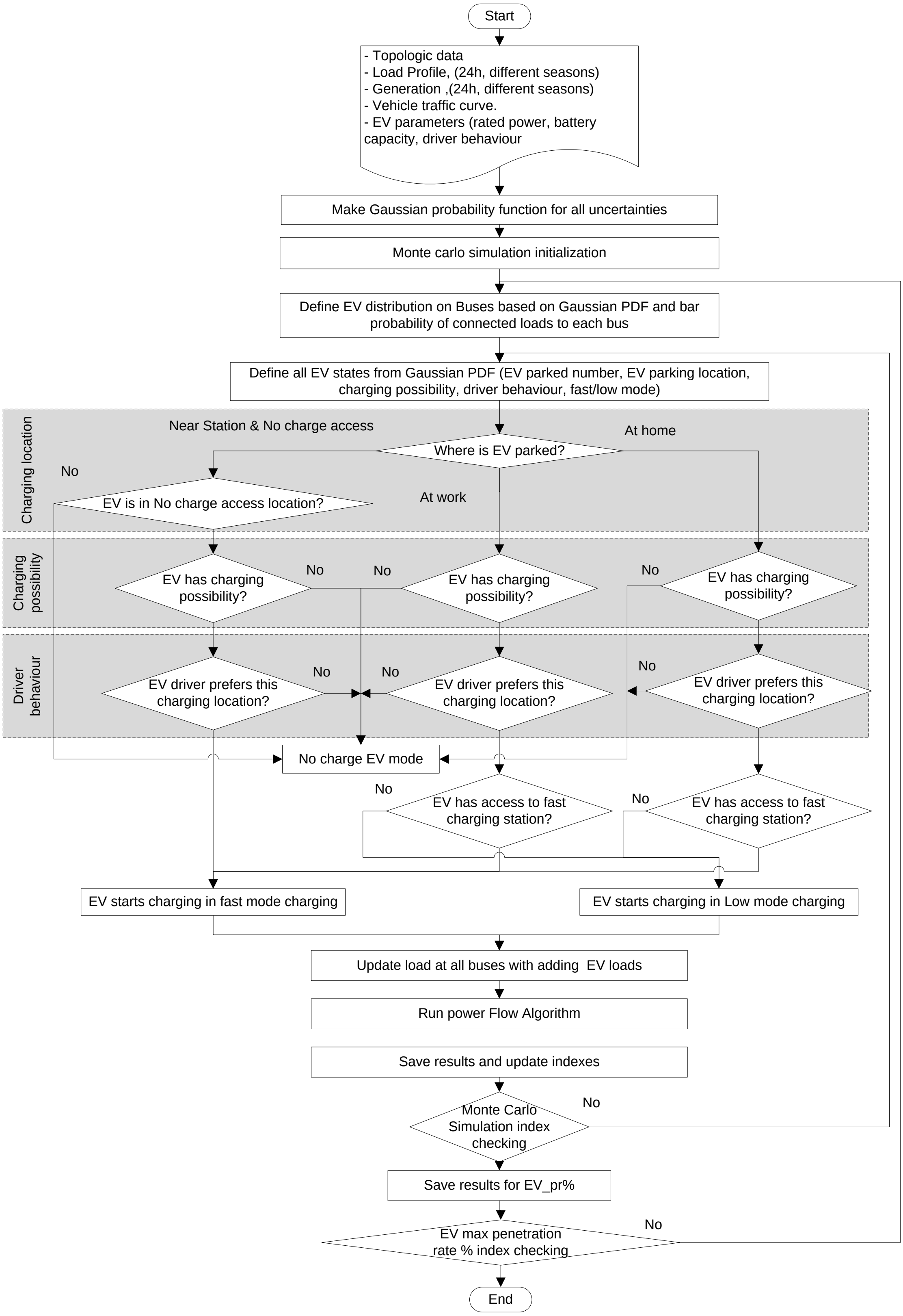

Figure 14: Fast charging plan algorithm.

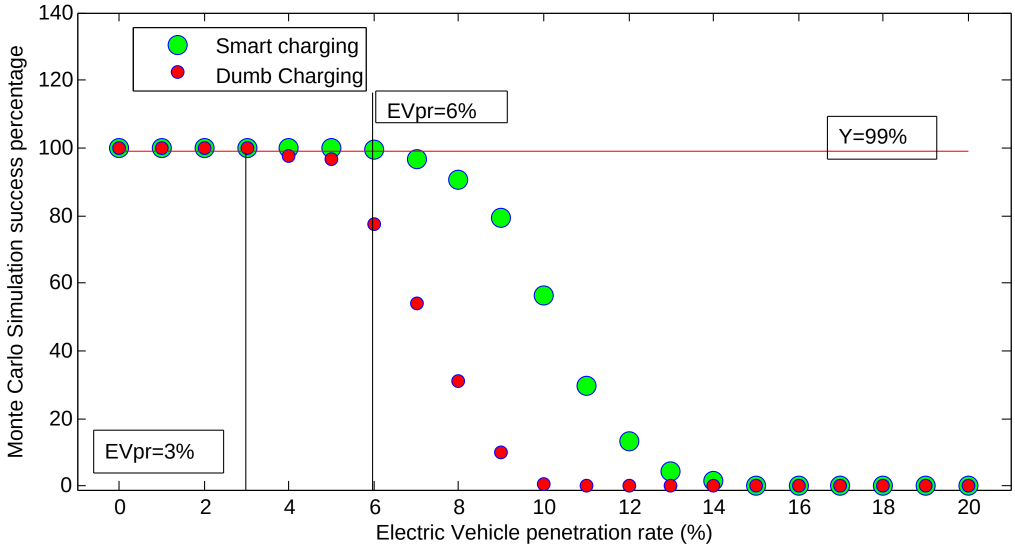

Figure 15: Bus voltage drop with decrease in EV_{pr} in fast plan.

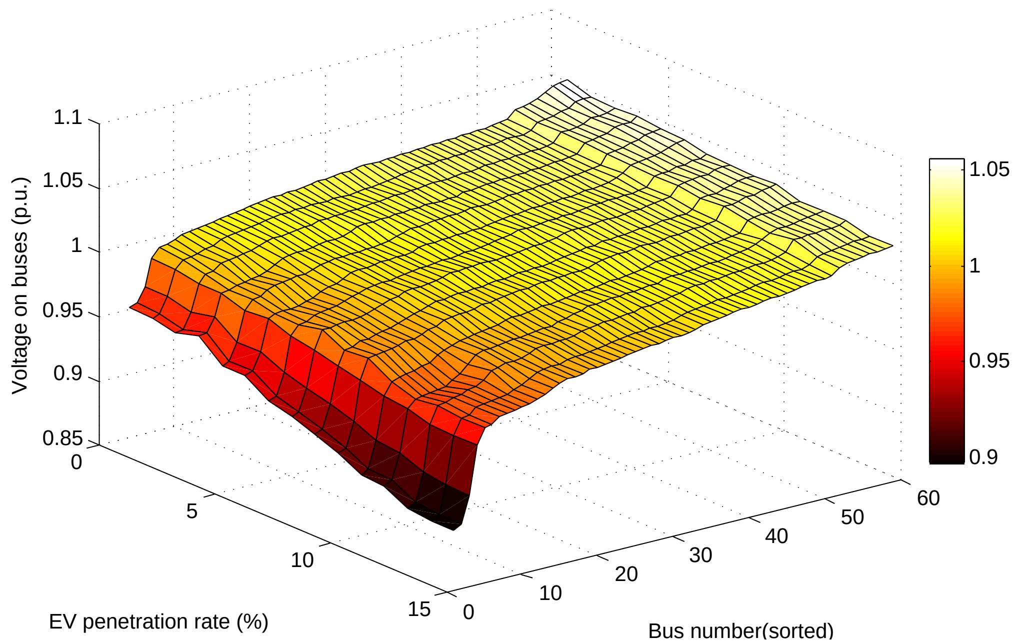

Figure 16: Smart and dumb charging scenario in fast plan, EV_{pr} comparision.

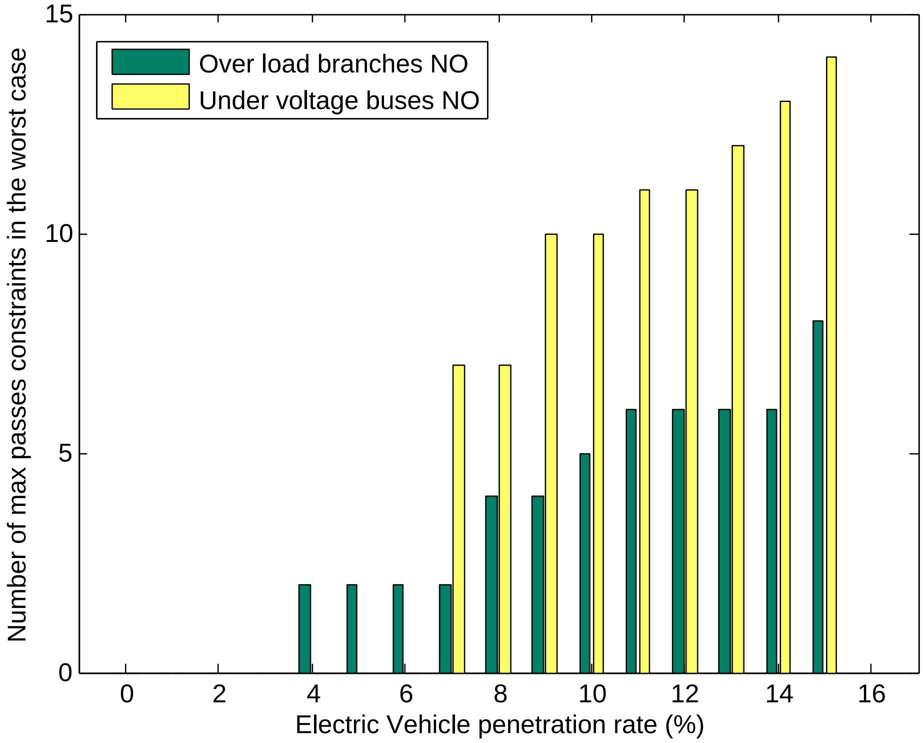

Figure 17: Power system constraints for dumb charging scenarios in fast plan.

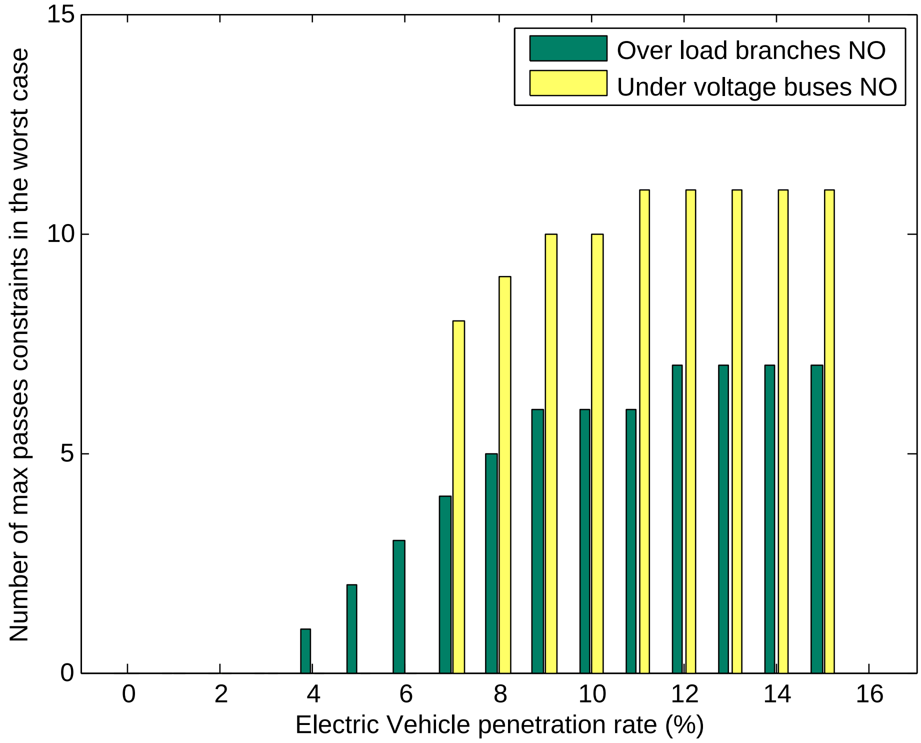

Figure 18: Power system constraints for smart charging scenarios in fast plan.

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