Chapter 6
Advanced Models and Simulation Tools to Address Electric Vehicle Power System Integration (Steady-State and Dynamic Behavior)

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6.1 Introduction

This chapter is intended to identify grid operational management and control strategies that should be available to deal with a large-scale deployment of electric plug-in vehicles (EVs). EVs are high flexible loads that can be used as mobile storage devices, thus being capable of providing several power system services [1]. In fact, EV batteries when in charging mode can behave as controllable loads, providing spinning reserves as a result of a load decrease or even providing power back to the grid under the so-called vehicle-to-grid (V2G) mode, helping peak load demand management. In this way, the growing prospects of an EV market expansion may strengthen the concepts that aim at the active grid management.

Future deployment of EV should also consider the fact that the power system of the future is facing considerable challenges due to the large-scale integration of distributed generation (DG) [2], which brought new technical, commercial, and regulatory challenges to the power systems. In the beginning, DG integration to the distribution system was made on the basis of a "fit-and-forget" policy. Consequently, while the penetration of DG was moderate, these generation units were regarded as passive elements within the power system.

In order to accommodate these changes, active management solutions were sought to deal with more DG, breaking with the conventional paradigm, being created new concepts such as those of microgrid (MG) and multi-microgrid (MMG) [3, 4]. Within this new paradigm, MG can be defined as low-voltage (LV) feeders with several microsources (such as microturbines, micro wind generators, photovoltaic panels, etc.) together with storage devices and controllable loads connected on that same feeder and managed by a hierarchical control system. EV will then become as an additional actor within these new grid concepts.

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Under this vision, the management and control architecture for the distribution networks would then follow a hierarchical control structure, with a central controller unit for each control level, one at the high voltage (HV), other at the MV, and the other at the LV. So, if properly managed, EV may integrate these concepts and create the opportunity of further DG integration expansion.

This chapter focuses on the effects and benefits of EV and EV active management on the power systems, both in steady-state and dynamic operation modes. Major synergies between utilities and EV owners are envisioned through means of cost reduction for both parties. By adopting adequate strategies, several benefits for the environment, quality of life, and social welfare may be achieved.

This chapter addresses the following issues:

- *Definition of a specific EV integration framework*: Moving from a "fit-and-forget" policy to the active EV management and control implies the creation of a conceptual framework. This framework should be able to deal with the technical aspects of electricity grid operation, with market operation. This will require an advanced communication infrastructure to link all the involved players. The technical operation layer considered under this framework is supposed to be managed by the distribution system operator (DSO) and expands the concepts of MG and MMG to establish a hierarchical control structure, from the central distribution management system (DMS) down to specific EV controllers to be housed in EV charging points. For the market layer, a new player will have to be considered for aggregating EV and represent them in the electricity and reserve markets. This layer should have a similar hierarchical structure to the technical layer, in order to be able to share the communication path and control entities.
- *Development of an approach to create different load scenarios to evaluate EV grid impacts*: This approach will include a stochastic model to simulate the EV movement in a geographic region, as well as their owners' behaviors, and a Monte Carlo simulation method to create the different scenarios of EV load in a given network. The analysis of a large number of scenarios generated with the Monte Carlo simulation method is of utmost importance for an accurate evaluation of the grid impacts provoked by EV presence, namely in what concerns branches' overload, voltage profiles, and networks' energy losses.
- *Development of charging management strategies, involving the exploitation of the EV high controllability*: These new strategies can be used in real-time applications to solve the technical problems identified and to maximize the number of EV that can be safely integrated in the system, without performing any network reinforcements. These management strategies should, however, take into account the drivers' requests concerning the foreseen use of the vehicles, assuming for that purpose the existence of some smart grid functionalities, like smart-metering and a reliable and efficient communication platform.
- *Development of an approach to identify the maximum number of EV that can be integrated in a given network without provoking violations of its components'*

technical limits: This approach will be developed taking into consideration both uncontrolled and controlled EV charging modes.

- *Participation of EV in primary frequency control*: In isolated systems, load/generation imbalances may lead to large frequency deviations. If EVs, when connected to grid, are capable of adjusting their charging rates or even to inject power into the grid as a response to frequency changes, increased robustness of operation will be achieved. Such a control approach should be able to allow further integration of intermittent RES in these systems.
- *Participation of EV in the Automatic Generation Control (AGC)*: EV may be integrated in the AGC operation, providing secondary frequency control and reducing the dependency on the conventional secondary reserves, which may also lead to an increase in variable renewable power sources into the electrical system.

6.2 Models for Studies of Electric Vehicle Integration in the Electrical Power System

6.2.1 Charging Methods

EV batteries are loads with unique characteristics, medium-to-high power consumption over a given period of time and with some degree of predictability. Such features can either be disregarded, and EVs are faced as regular loads, or they can be exploited and then specific EV charging strategies might be defined to take advantage of these unique characteristics.

There are several types of charging solutions being currently adopted [5], which involve distinct power levels:

- *Level 1*: Around 3 kW charging power that can be obtained through common domestic outlets.
- *Level 2*: 10–20 kW charging power that can be obtained only through dedicated charging outlet and wiring.
- *Level 3*: More than 40 kW charging power that can be obtained only through dedicated charging outlet and wiring and using a dedicated off-board charger for DC fast charging.

The charging type commonly classified as slow charging refers to level 1, whereas the fast charging refers to level 3. Level 2 is an intermediary level that can be considered either as a slow or a fast charging type. Slow charging is assumed to correspond to level 1, while fast charging includes both level 2 and 3.

Depending on the type of application, EV controllability may vary, and, therefore, several control schemes may be adopted. There are different solutions, which may arise according to EV owners' needs, namely the following:

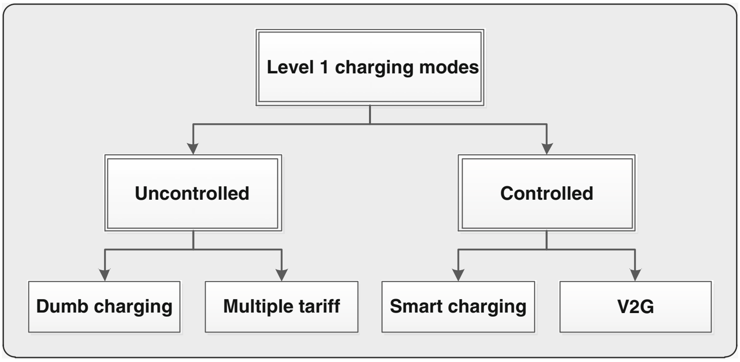


Fig. 6.1 Level 1 charging modes

- *Domestic or public individual charging points for slow charging*: This solution is the most suited for controlled charging, as EV parked in these places will remain there for longer periods (overnight stays if it is a residential area or during working period while in industrial/commercial areas). These charging points are expected to use level 1 charging rates.
- *Charging stations dedicated to fleets of EV*: This solution presents high controllability potential if EV can be charged in level 1 charging mode, as fleets of vehicles (such as buses or trucks) typically have well-known mobility patterns. When level 2 or 3 charging is required, charging management cannot be performed.
- *Public individual charging points for medium charging rates*: This solution is not suited for controlled charging, as EV parked in these places will remain there for relatively short periods (in public parking lots or in commercial areas like malls). These charging points are expected to use level-2 charging rates.
- *Battery swapping stations*: For this solution, controlled charging procedures may be defined depending on the existing battery stock on the station. Both slow (level 1) and fast (level 2 or 3) charging methods can be used depending on the specific demand patterns and on the available stock per station.
- *Fast charging stations*: As dedicated fast charging stations, this solution is not suitable for control actions due to the need of having a full charge in the minimum time span possible. The fast charging stations are expected to use level-3 charging rates.

In the solutions involving fast charging (level 2 or 3), a full charge might take <1 h [5]. Due to the urgent needs from the user of these types of services, especially level-3 clients, no controllability is envisaged. On the other hand, depending on the EV battery state of charge (SOC) and capacity, full charge solutions involving level 1 might take up to 12 h [5]. Within this charging alternative, it is assumed that EV owners can choose between a set of four charging options, two passive or uncontrolled (dumb charging and multiple tariff) and two active or controlled (smart charging and V2G), as shown in Fig. 6.1.

6.2.1.1 Dumb Charging

This is an uncontrolled charging mode where EV can be freely operated having no restrictions or incentives to modulate their charging. Therefore, EVs are regarded as normal loads, like any other appliance. In dumb charging mode, it is then assumed that EV owners are completely free to connect and charge their vehicles whenever they want.

The charging starts automatically when EVs plug in and lasts until its battery is fully charged or charge is interrupted by the EV owner.

In addition, electricity price for these EV users is assumed to be constant along the day, what means that no economic incentives are provided in order to encourage them to put their vehicles charging during the valley hour when the grid operating conditions are more favorable to an increment in the energy consumption.

For scenarios of large EV deployment with a considerable number of dumb charging adherents, it is very likely that EV load provokes several technical problems on the grid (potential large voltage drops and branches overloading).

The only way to tackle the foreseen problems is then to reinforce the existing generation system and grid infrastructures and plan new networks in such way that they can fully handle EV grid integration. Yet this is a somewhat expensive solution that will require high investments in network infrastructures and generation facilities.

6.2.1.2 Multiple Tariff

As in the previous approach, the dual tariff policy assumes that EV owners are completely free to charge their vehicles whenever they want.

However, electricity price is assumed not to be constant along the day for EV users, existing some periods where its cost is lower.

This method is based on the already existing approach where, during valley hours (normally during the night), electricity price is lower. However, as this is not an active management strategy, the success of this method depends on the EV owner willingness to take advantage of this policy. In this case only part of the EV load eventually would shift toward valley hours.

This solution could have been included in the controlled EV charging/ discharging approaches, but as this type of control is not directly imposed to EV, it is considered an uncontrolled charging approach.

It should be taken into account that the economic signals provided to EV owners with the multiple tariff policy might have a perverse effect in scenarios characterized by a high integration level of EV.

It might happen that a big number of EV connect simultaneously in the beginning of the periods when the electricity cost is lower, making the grid reach its technical limits.

6.2.1.3 Smart Charging

The smart charging strategy envisions an active management system where there exists a hierarchical control structure headed by an EV aggregating entity that is used to control the EV charging rates.

However, as it will be explained later on this chapter, EV will only be exclusively managed and controlled by the EV aggregators when the grid is operating in normal conditions.

The EV aggregators' main functionality will be grouping EV to exploit business opportunities in the electricity markets, always taking into account the EV owners' charging requests. They will monitor all the EV under their domain, providing power or requesting from them the services that they need to cope with what was previously defined in the markets' negotiations.

As electricity markets are not usually present in small isolated systems, like the ones from small islands, the existence of EV aggregators is not required. In these situations, the smart charging should be controlled by the DSO.

This type of EV charging management is likely to provide the most efficient usage of the resources available at each moment, since EV aggregators will naturally try to buy electricity during valley hours in order to provide energy at a lower cost to their clients. Therefore, the EV aggregators' market actions are likely to naturally enable overload prevention and excessive voltage drops, avoiding the need to invest largely in network reinforcements.

This charging approach also enables EV to provide several ancillary services, like reserves, since they can increase/decrease their charging rates in order to deliver upward/downward reserves. EV aggregators are thus capable of also negotiating reserve provision in the respective electricity markets.

6.2.1.4 Vehicle-to-Grid

This approach is an extension of the previous one where, besides the charging, the EV aggregators control also the power that EV might inject into the grid.

In the V2G mode of operation, both EV load controllability and storage capability are exploited. From the grid perspective, this is the most interesting way of using EV capabilities given that besides helping managing branches' overloading and voltage-related problems in some problematic spots of the grid, EV have also the capability of providing peak power in order to make the energy demand more uniform along the day.

Nevertheless, there are also some drawbacks related to the batteries' degradation that need to be accounted for. Batteries have a finite number of charge/discharge cycles, and its usage in a V2G mode might represent an aggressive operation regime due to frequent shifts from injecting to absorbing modes. Thus, the economic incentives to be provided to EV owners must be even higher than that in the smart charging approach, so that they cover the battery damages owed to its extensive use.

As in the smart charging, EVs that adhere to the V2G mode are also capable of providing several ancillary services to the system. As besides adjusting their charging rates, EVs are also capable of injecting power into the grid. This operating mode provides then more flexibility to the EV aggregators regarding reserve provision negotiations in the market, namely in what concerns downward reserves.

6.2.2 Structure of Control

6.2.2.1 Electric Vehicle Integration in Interconnected Systems

The technical management of an electric power system having a large-scale deployment of EV will require, for their battery charging, a combination of a centralized hierarchical management/control structure with a local control located at the EV grid interface.

The simple use of a smart device interfacing the EV with the grid does not solve all the problems arising from EV integration in distribution networks. These interfaces can be rather effective when dealing with the likely occurrence of voltage drops that may be caused by EV charging, by locally decreasing charging rates through a voltage droop control approach. However, this local solution fails to address issues that require a higher control level, such as managing branches' congestion levels or enabling EV to participate in the electricity markets. For these cases, coordinated control is required, and so a hierarchical management and control structure responsible for the entire grid operation, including EV management, must be available. Therefore, the efficient operation of such a system depends on the combination/coordination of local and centralized control modes. The latter control approach relies on the creation of an adequate communication infrastructure capable of handling all the information that needs to be exchanged between EV and the central control entities organized in a hierarchical structure.

When operating the grid in normal conditions, EVs will be managed and controlled by a new (central) entity—the aggregator—whose main functionality will be grouping EV, according to their owners' willingness, to exploit business opportunities in electricity markets [6, 7]. If EV would enter this market individually, their visibility would be small and, due to their stochastic behavior, rather unreliable. Nonetheless, if an aggregating entity exists, with the purpose of grouping EV to enter in the market negotiations, then the services provided would be more significant and the confidence on its availability much more accurate.

Nevertheless, even considering the EV aggregators' activities, a still high degree of uncertainty will exist related to when and where EV will charge, namely in LV grids. Due to these uncertainties and assuming that networks will evolve toward a decentralized generation paradigm, the existence of a grid monitoring structure, such as the one developed for MG and MMG, will be expected. This structure will be controlled by the DSO and should be capable of acting over EV charging in

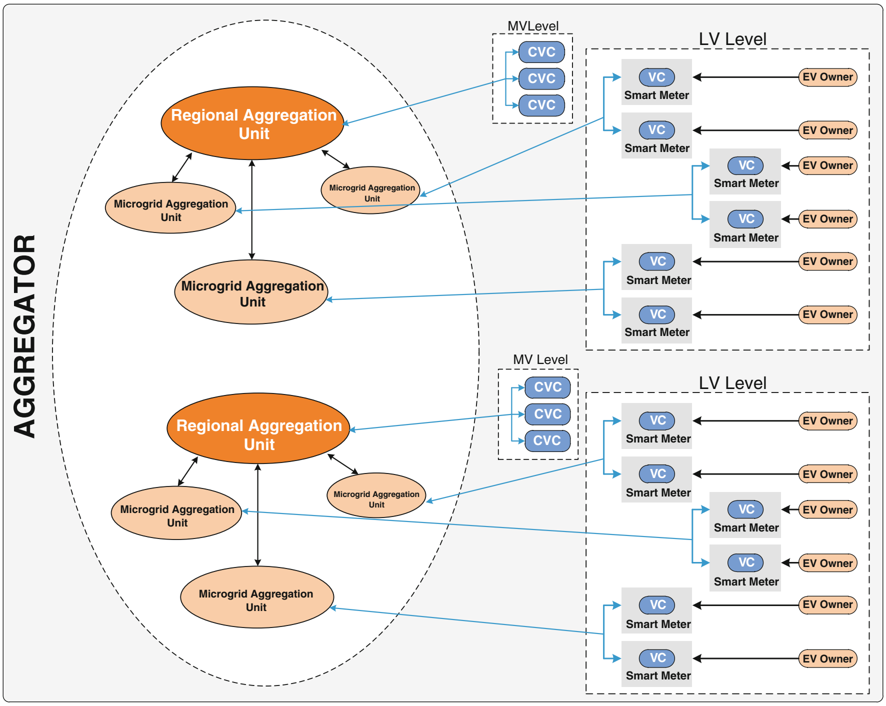


Fig. 6.2 Aggregators' hierarchical management structure

abnormal operating conditions, i.e., when the grid is being operated near its technical limits, or in emergency operating modes, e.g., islanded operation [8].

Normal System Operation

In order to manage a large amount of EV parked in a large geographical area, where MV and LV grids exist, the existence of aggregators will be necessary, in order to serve as an interface between EV and electricity markets. These aggregators will have the capability of grouping EV so that together they represent a load/storage device with the adequate size to participate in electricity markets, in a similar way as described in [6]. It is important to stress that the aggregator will always take into account the drivers requests, which will provide information about power demand and connection period via the smart meter. In the same regional area, several aggregators might coexist and compete to gather as much clients as possible. This competition will be beneficial for the EV owner who will be able to choose for his aggregator the company that better fits his needs.

Given the complexity of the information that an aggregator needs to collect and process, a hierarchical management structure, independent of the DSO, is suggested (Fig. 6.2).

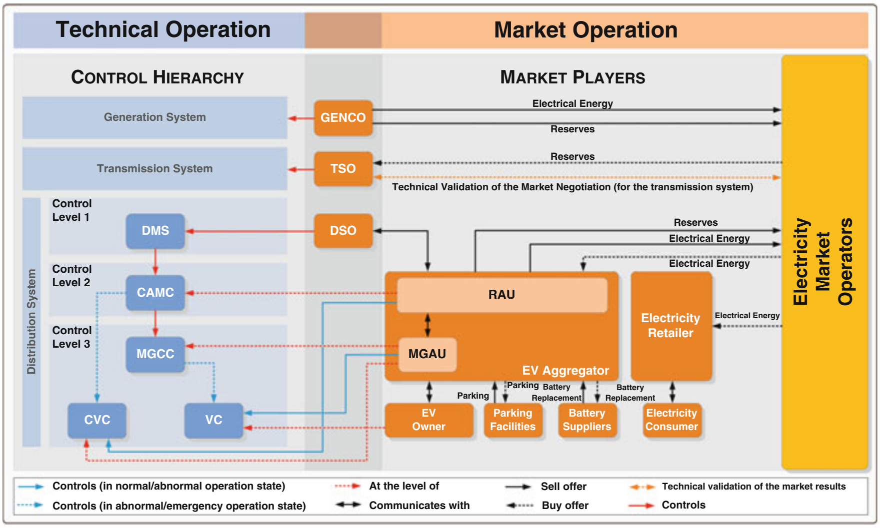


Fig. 6.3 Technical management and market operation framework for EV integration in interconnected systems

Since each aggregator develops its activities along a large geographical area, e.g., a country, it will be composed of two different entities: the regional aggregation unit (RAU) and the micro-grid aggregation unit (MGAU). The RAU is considered to be located at the HV/MV substation level, communicating with several downstream MGAU, which, by their turn, will be located at the MV/LV substation level. The RAU and the MGAU were created in order to decrease communication and computational burden that a real implementation of the concept would require. This will provide the aggregator preprocessed information regarding groups of EV located in the LV and MV grids. Each EV must have a specific interface unit—the vehicle controller (VC)—to enable bidirectional communication between the EV and the upstream aggregator. The VC may be located in the smart meter to which EV will be connected and the smart metering communication infrastructure should be used to support this architecture. In addition to the VC, there is a new type of element, the cluster of vehicles controller (CVC), designed to control the charging of large parking lots (e.g., shopping centers), and fed directly from the MV network. Individual controllers of EV under a CVC management do not need to have an active VC communicating with higher hierarchical controllers. During normal operation, the VC will interact with the MGAU and the CVC directly with the RAU [7].

The market operation column in the right-hand side of Fig. 6.3 presents an overview of the aggregators' market activities.

Based in historical data, the aggregators will forecast the market behavior for the next day and will prepare their buy/sell bids. Having this defined, a prior negotiation with the DSO might exist to prevent the occurrence of severe congestion and voltage problems in the distribution networks. The aggregators will thus present their day-ahead proposal to the DSO, which will analyze it to evaluate its technical feasibility. If valid, the aggregator can proceed to the market negotiation. If not, the DSO will ask the aggregator to make the changes needed to guarantee a safe operation of the distribution grid in the next day. It is foreseeable that in this case, the DSO will have to compensate the aggregator for this service.

If market prices of electricity are cost reflective (i.e., include the cost of electricity generation, transmission, and distribution), a direct consequence of the hourly energy prices variation will be the flattening of the daily load diagram. As response to the energy prices, aggregators will naturally perform load shifting in order to provide energy at a lower cost to their clients. They will buy electricity from the market mainly during the night, at lower prices, to charge their clients' EV, and they may sell it during the day, at peak hours, taking advantage of their clients' EV storage capability. Aggregators will then compete directly with electricity retailers for energy acquisition and with Generation Companies (GENCO) for selling energy.

Taking advantage of EV capability to provide reserves, EV might also offer in the electricity markets these systems' services to the transmission system operators (TSO), competing once again with the GENCO. Also with this approach, it will be possible to have EV participating in secondary frequency control, through the link TSO → aggregator. After market closure, the TSO proceeds to the evaluation of the load/generation schedules, and if problems on the transmission system are foreseen, it requests modifications to these schedules until feasible operating conditions are attained. Everyday the aggregator will manage the EV under its domain, according to what was previously defined in the market negotiations and validated by the TSO, by sending set points to VC or CVC related to rates of charge or requests for provision of ancillary services. To accomplish such a complex task successfully, it is required that every fixed period (likely to be defined around 15 min), the SOC of each EV battery is communicated to the aggregator, to assure that, at the end of the charging period, batteries will be charged according to EV owners' requests [7].

Additionally, the aggregators can also negotiate with other entities parking and battery supplying services for EV, as mentioned in [6] and included in Fig. 6.3. Yet these parallel negotiations will not be addressed in this chapter.

For secondary control, the AGC operation is the centerpiece in the control hierarchy. The TSO, who is responsible for the AGC, will acquire in the electricity markets the secondary reserves that it needs from GENCO and aggregators. Then, in accordance with the secondary reserve services negotiated in the market with the TSO, the aggregator will receive requests from the AGC to participate in secondary control. Each aggregator will receive a given set point value of regulation up/down, split this participation value by EV willing to provide this service, and send set points to these EV. The set points EV will receive from the aggregator will lead to a load charging adaptation or to the injection of stored power into the network for the period of time the AGC requires this service.

Abnormal System Operation or Emergency Mode

When grid-normal technical operation is compromised, market management can be overridden by the DSO, through the technical operation control hierarchy, described in the left-hand side column of Fig. 6.3. For these abnormal or emergency conditions, it makes sense to adapt the MG and MMG concepts [3, 4]. In fact, as referred in Sect. 6.1 of this chapter, the MG and MMG already contemplate the existence of a hierarchical monitoring and management solution that includes a suitable communication infrastructure, capable of managing the presence of EV, either individually connected at the LV level or as a cluster of EV (fleet charging station or fast charging station cases) connected at the MV level. Within an LV MG, a micro-grid central controller (MGCC) may control EV batteries through the VC. As depicted in the "Technical Operation" column of Fig. 6.3, within an MMG environment, the elements of the MV grid, including MG and CVC, can be technically managed by a control entity, named Central Autonomous Management Controller (CAMC), to be installed in the HV/MV substation. All the CAMC will be under the supervision of a single DMS, which is directly controlled by the DSO. It is important to stress that, in abnormal system operation conditions or in emergency modes, all the technical management and control tasks are a responsibility of the DSO, being performed by a main control entity, the DMS, and by the other distributed entities, CAMC and MGCC [3].

6.2.2.2 Grid Control Architecture for Isolated Systems

In small isolated systems, the framework presented in the previous section may not be applicable, as no real market participation is possible. For these cases, the electricity supply chain remains vertically integrated. Yet these systems have evolved by integrating whenever possible intermittent RES in their generation mix. RES potential is, however, not usually fully explored in order to assure enough security of operation.

The integration of EV in such systems is a natural occurrence as fossil fuel scarcity, and environmental concerns are present in both interconnected and isolated systems. Being low resilience electricity grids, the greatest beneficial and adverse effects are expected from the integration of these new loads. When EVs are regarded as common loads, then these systems may get even more fragile. Conversely, if properly controlled, these systems could even benefit from further integration of RES.

The next two sections present the necessary adaptations of the previously exposed concepts, in order to manage EV in isolated grids. On the one hand, the MG and MMG concepts will still be required for these systems. On the other hand, some of the functionalities that were shared among aggregators must now be assured by the sole energy provider in the island, which typically is also the DSO.

Normal System Operation

As previously mentioned, small isolated systems are vertically integrated. Therefore, system operators are responsible for its management at the generation, transmission, and distribution levels.

Therefore, only the existence of the hierarchical control structure presented in the Technical Operation column (left hand side) of Fig. 6.3 is necessary. As it is observable, the complexity of the control structure is smaller than that in interconnected grids due to the inexistence of market players.

In normal system operation, VC and CVC are controlled by the system operator's sub-entities, MGCC and CAMC. Depending on the type of contract established with EV owners, the system operator may be allowed to control EV charging rate through those sub-entities. Day ahead, the system operator will run a smart charging algorithm using forecasted data on load (both typical consumption and EV) and generation profiles. During the day, it will update this solution, eventually by providing real-time pricing, so that consumers shift EV charging for cheaper electricity periods harmonizing the load/generation diagram.

In some cases, regulation may make EV response to the system operator's request mandatory, in order to not jeopardize the system operation and, eventually, allow increased intermittent RES penetration. In these cases, the local government or the system operator may have to be the co-owner of the EV batteries or provide a large incentive on EV purchase.

All the ancillary services presented for interconnected systems may also be provided by EV in isolated grids, provided that EV owners are granted sufficient incentives. The system operator control structure will be responsible for managing the provision of these ancillary services.

Abnormal System Operation or Emergency Mode

When grid-normal technical operation is compromised, the system will be controlled in the same way as described for interconnected systems. The main difference is that the system operator does not need to override market operation, as it does not exist.

6.2.3 Modeling EV for Steady-State Studies

The process of modeling EV for steady-state studies can be divided into three main categories: EV modeling for LV, for MV, and for HV/VHV network studies.

In what regards LV networks, as EV will charge in the majority of the situations at level 1 power rates (~3 kW), they are very likely to be connected to the LV grids using single-phase connections. For this reason, aiming at representing EV as realistic as possible, they should be modeled as single-phase loads. The addition of these new single-phase loads to the conventional loads that already exist in LV grids, which are typically three-phase unbalanced systems, will probably aggravate the load and voltage imbalances in these networks.

Conversely, for MV network studies, the loads resulting from EV batteries charging at level 2 and 3, directly connected to the MV grids, should be modeled as three-phase balanced loads, as the power levels involved in these charging modes (*c.a.* 12 and 40 kW, respectively) will probably require three-phase connections in the majority of the situations. Concerning the load of EV charging at level 1, in the LV grids downstream the MV network under analysis, they should be aggregated and represented as a single load value, per LV grid, at the MV bus of the respective MV/LV substation. This approximation is needed for MV network studies, as in this type of analysis, the detailed modeling of the LV grids downstream the MV/LV substations is not usually considered.

Regarding HV networks, the approach described for MV grids can be used to compute the EV load in the system downstream a given HV network and generate EV load profiles that can then be allocated to the respective node of the HV network. This process is similar to the one described for MV grids in what concerns the modeling of the load of EV charging at level 1 in LV grids. The full analysis of the HV network under study can then be performed by adding, bus by bus, the respective EV load profile to the conventional load profile. This procedure can also be used to compute the EV load and perform impact studies in VHV networks.

In what concerns the modeling of the EV batteries, it was assumed that their charging is performed always at a constant power rate for a given set point, as the detailed modeling of the battery charging cycle and of the battery ageing due to the charging/discharging cycles are not relevant for network impact studies.

6.2.4 Modeling EV for Dynamic Behavior Studies

In Europe, frequency regulation involves three layers of control: primary, secondary, and tertiary reserve provision. Primary frequency control is based on a decentralized proportional control performed on turbine governors, while secondary frequency control, performed through an AGC (AGC), requires the calculation of the integral of the area control error (ACE). Tertiary control is usually activated manually by the TSO and can only provide upward reserve in case of observed or expected sustained activation of secondary control [9]. This coordination depends on an appropriate communication infrastructure through which frequency and power measurements are obtained and set points are sent to the generation units that participate in these services. The ultimate goal of the load-frequency coordinated control is to stabilize frequency in the nominal value and keep inter-area power flows as defined in the daily market negotiations.

When EVs are considered active participants in reserve provision, the currently existing system should be adapted to include aggregators and EV, as depicted in Fig. 6.4. Similar to the governors of the conventional generation units, the power

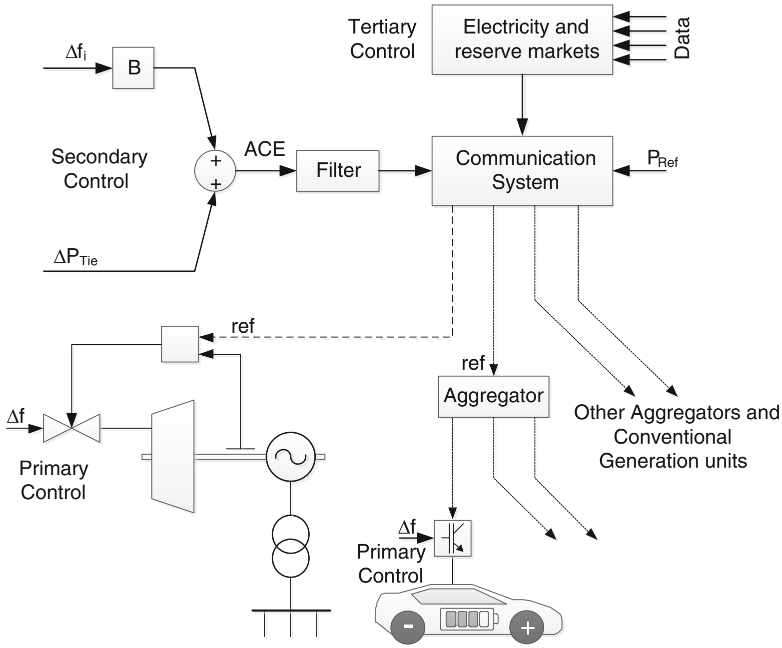


Fig. 6.4 Load-frequency control levels with EV

electronic interfaces of individual EV may react to frequency deviations to participate in primary control. Regarding secondary control, the AGC communicates the participation value to the conventional generators and aggregators. The latter must then divide and redistribute the participation value by the EV under its domain.

6.2.4.1 Electric Vehicles Participation in Primary Frequency Control

The control scheme for EV participation on primary frequency control may have two loops:

- The droop control that mimics the governors of conventional generators.
- The inertial control that also emulates the behavior of conventional generator so that EV can provide inertia to the system.

For both control loops, frequency must be read locally and the reaction to frequency deviations is performed autonomously. This reaction should consist of providing new set points for the electronic power converter that interfaces EV batteries and the grid. The control scheme should be installed on every VC, which is located next to the vehicle charger and has access to the smart grid communication infrastructure. The latter enables the upstream controllers to be logged about the activity of the VC concerning primary control provision and if needed redefine the droop control parameters or the settings for the inertial emulation.

So apart from the set point imposed by the aggregator or the charging control, the load value of the EV may be influenced by one of or both the control loops. Equation (6.1) presents the active power change requirement for the EV due to the influence of the droop. The load will change by an amount that is obtained by multiplying a proportional gain by the actual frequency change. The proportional droop is characterized for being a measure of the sensitivity of the controller to frequency deviations, expressed in units of power per unit of frequency. While a frequency error is sustained, the proportional controller will always impose a change in the load of the EV.

$$\Delta P_{\mathrm{Droop}} = k_P \bullet \Delta f, \tag{6.1}$$

where $\Delta P_{\mathrm{Droop}}$ is the load change provoked by the droop control; k_P is the proportional gain; Δf is the frequency deviation.

Equation (6.2) provides the amount of active power change, in case of a load/generation imbalance, that results from the inertial emulation implementation in the controllers of EV. In this case, the load will change by an amount equal to the product of a gain by the derivative of frequency change in respect to time. The derivative gain is a measure of the sensitivity of the controller to the rate of change of frequency, expressed in units of power per units of frequency per unit of time. The influence of this type of control is bigger for periods when frequency is changing fast and will be null when frequency stabilizes, independently of how big the absolute frequency error may be. Thus, the action of this control loop is predominantly noticeable in the initial moments succeeding a disturbance.

$$\Delta P_{\mathrm{Inertial\,Emulation}} = k_{in} \bullet \frac{\mathrm{d}}{\mathrm{d}t}\Delta f, \tag{6.2}$$

where k_{in} is the derivative gain of the controller.

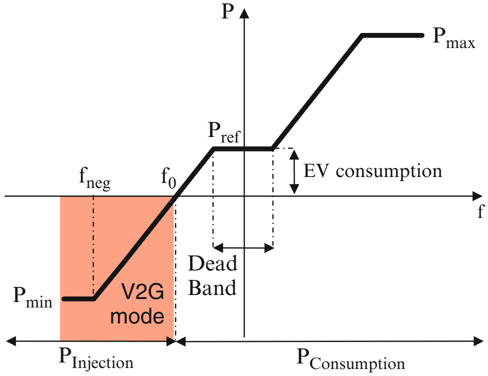
Considering that k_P and k_{in} are real positive values and that the frequency error is calculated by $\Delta f = f_0 - f$ (where f_0 is the nominal system frequency), being a real positive value for underfrequency events and real negative value for overfrequency events, the load value of an EV if both control loops are active is given by (6.3):

$$P^{\mathrm{EV}}_{\mathrm{Load}} = P^{\mathrm{EV}}_{\mathrm{Set-point}} - \Delta P_{\mathrm{Droop}} - \Delta P_{\mathrm{Inertial\,Emulation}}, \tag{6.3}$$

where$P^{\mathrm{EV}}_{\mathrm{Load}}$ is the load of the EV; $P^{\mathrm{EV}}_{\mathrm{Set-point}}$ is the required EV load value defined by the aggregator as a set point.

Yet EV should not react to every small mismatch in power, and so some extra controls must be added to limit the participation of EV to the cases that really matter. Figure 6.5 shows schematically a droop configuration that could be implemented for enabling the EV grid interface control strategy. The plugged-in

Fig. 6.5 Generic droop control for VC



EV providing primary control in steady-state conditions is charging at a given power rating, with a maximum value equal to its nominal charging power. It may occur that the EV is not charging in steady state, but is still plugged-in ready to provide primary control, if power delivery from the EV batteries to the grid is allowed. The charging reference power, P_{ref}, may be defined in two different ways:

- Set point from the aggregator or the DSO for EVs that adhere to smart charging schemes
- Local decision of EV owners who do not adhere to smart charging

The charging reference power may change as a function of the set points sent by the aggregator or the DSO, depending on the strategies for minimizing charging costs and the occurrence of possible grids technical violations.

A margin between the actual power rating and the maximum power rating may be imposed to EV participating in primary frequency control, in order to allow the participation in regulation down.

The maximum power rating, P_{max}, is the nominal charging power of the EV, whereas the minimum power rating, P_{min}, is the nominal discharging power, zero or a value between the minimum and maximum power ratings.

For frequency deviations larger than a defined dead band, the EV battery will respond according to one of the given slopes. If frequency suffers a negative deviation, then the battery charging will, first, reduce its power consumption, and, if frequency decreases further, it may inject power into the grid. Oppositely, if there is a positive deviation, the battery will increase the power absorbed from the grid.

A dead band, where EVs do not respond to frequency deviations, should be considered to guarantee longevity of the batteries and thus a beneficial synergy between parties, the grid operator/aggregator, and the EV owners. This dead band, as well as the slopes of the droops, should be defined according to not only the composition of the system, but also the EV owners' willingness to help with system frequency regulation and the characteristics of the EV battery.

As to the inertial emulation loop, the implementation may be performed in different ways in order to restrain the possible actions of EV. A dead band similar to the one implemented is also a possibility, but less interesting as the inertial behavior should be mobilized very fast. So the dead band should be reduced, at least for negative frequency values, as the most severe events are linked to the loss of generation capacity, due to either variability of primary resource or tripping of generation units. In this sense, it may be wise to introduce a saturation following the derivative of the frequency deviation to block positive rates of change and consequently prevent the action of the inertial emulation loop for periods where generation exceeds load.

In addition to the control techniques discussed so far, it is still possible to introduce further control laws, such as voltage control loops. Dealing with frequency and voltage at the same time might end with conflicting signals that may result in worsening of the operating conditions. Therefore, in case of adoption of the voltage and frequency controls simultaneously, a merit order should be established. The frequency control should override the voltage control in case of conflict.

For EV to participate in primary frequency control, a proper electronic interface control should be adopted, different from a simple diode bridge usually adopted for charging purposes. Being the system frequency an instantaneous indication of the power balance in a grid, the active power charging/discharging levels of the EV batteries must be adaptable by being capable of receiving set points. In this way, a smart EV grid interface, capable of responding locally to frequency changes, should be adopted, instead of a passive battery charging solution.

Active and reactive power set points may be sent to the power electronic converter interfacing EV and the electricity grid. To allow this, a current-controlled voltage source, a PQ inverter, is suggested [10], as depicted in Fig. 6.6.

This method computes the instantaneous active and reactive components of the inverter current: the active component is in phase with the voltage and the reactive component with a 90° (lagging) phase shift, being both limited in the interval $[-1, 1]$, as described in [4].

The active component is used to control the DC link voltage and, consequently, the inverter active power output, in order to balance the EV battery and inverter active power output. The reactive component controls the inverter's reactive power output. Power variations in EV battery lead to a variation of the DC link voltage, which is corrected via both proportional–integral regulators (PI-1 and PI-2), by adjusting the active power output. The frequency control droop present on the VC will adjust the active power set point of the PQ EV inverter interfaces (P_{ref}).

To perform dynamic simulations, the model for EV participation on primary frequency control might be easily implemented in any software that allows using block diagrams.

Figure 6.7 presents the complete model implemented to provide local primary frequency control and inertial emulation. In the droop control block diagram, the frequency deviation signal, Δf, goes through a dead band block to prevent EV charging from being disturbed by minor frequency changes and gets multiplied by the proportional gain, k_P, to determine the contribution of the EV droop for primary frequency control, $\Delta P_{\mathrm{Droop}}$. In the block diagram of the inertial emulation loop, the derivative of the input signal, the frequency deviation, Δf, is calculated, then the

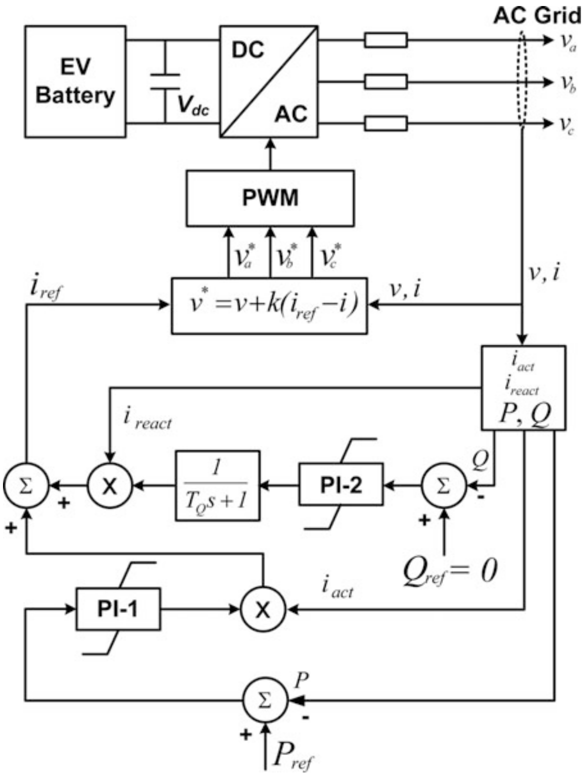


Fig. 6.6 PQ inverter control type

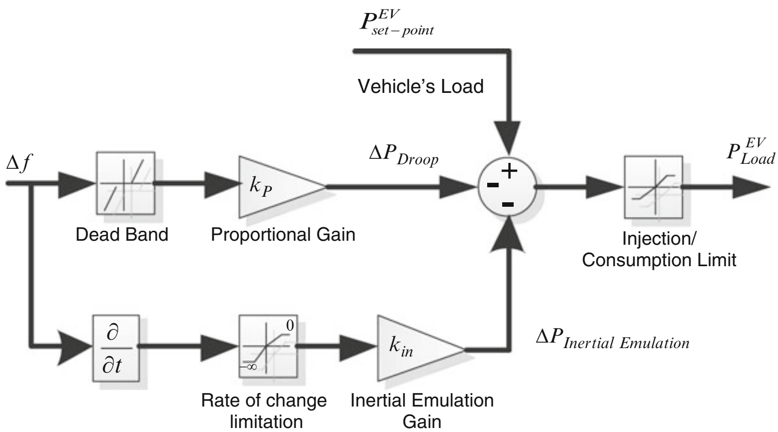


Fig. 6.7 Active power set point control for the power injector

result goes through a saturation block to limit the rates of change and the derivative gain is applied, k_{in}, to determine the contribution of the EV for primary control due to the action of the inertial emulation, $\Delta P_{\text{Inertial Emulation}}$. Finally, the contribution of both droop control and inertial emulation is added to the EV load set point, $P^{\text{EV}}_{\text{Set-point}}$, and a new saturation block assures that the request power for the EV is within its operation limits. These limits in a real implementation would depend on the contract established between EV owners and aggregators, being possible to block V2G capability. The resulting signal will be the new active power set point value for the power injector that represents the EV—$P^{\text{EV}}_{\text{Load}}$.

There are some simplifications made to implement this model:

- The SOC of the EV battery is assumed to be neither fully discharged nor fully charged, thus allowing neglecting SOC considerations for the implementation of the model.
- The EV batteries are expected to react to new set points without delays.
- The state of health of the batteries was not accounted for in this model. It is assumed that the batteries do not suffer significant damage from providing primary frequency control.
- As the time periods being studied are of the order of a few seconds, these storage elements can be modeled as constant DC voltage sources using power electronic interfaces, DC/AC inverters, to couple them to the grid. These devices act as controllable AC voltage sources (with very fast output characteristics) to face sudden system frequency changes.

6.2.4.2 Automatic Generation Control with Electric Vehicles

In secondary frequency control, the AGC operation is the centerpiece in the control hierarchy. In a scenario characterized by large-scale EV deployment, the TSO, who is responsible for the AGC, will acquire in the electricity markets the secondary reserves that it needs from GENCO and/or aggregators.

If a sudden loss of generation or load increase takes place in a control area, the AGC exploits the available secondary reserves, guaranteed by the reserve market negotiations, by sending set points to the participants in the secondary frequency regulation service. If EV aggregators are participating in this service, the AGC will send set points to aggregators that afterward will distribute their participation among the EV providing this service by sending individual set points to these EV. The set points EV will receive from the aggregators will lead to a load charging adaptation for the period of time the AGC requires this service.

To perform AGC operation with EV, some modifications as presented in Fig. 6.8, need to be introduced in conventional AGC systems in order to make the regulation of EV power consumption/output possible in response to deviations of system frequency, f_i, in relation to its reference, f_{ref}, and of the tie-lines active power flow, Pif_i, in relation to the interchanges scheduling, Pif_{ref}. As in the conventional AGC, B is the frequency bias that measures the importance of

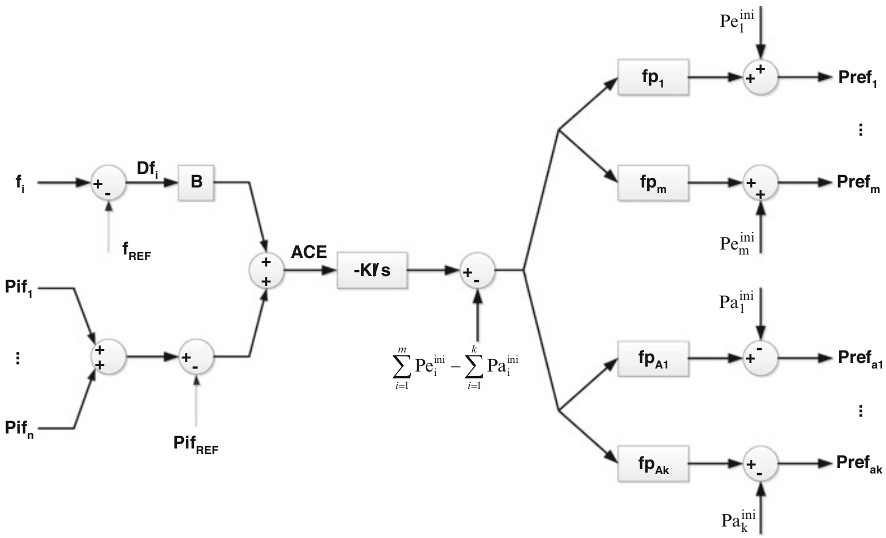


Fig. 6.8 AGC operation in the presence of EV aggregators

correcting the frequency error, when compared with the correction of the interchange power error; k_I is the gain of the integral controller; Pe_m^{ini} is the current dispatch for machine m, fp_m its participation factor; and $P_{\mathrm{ref}\,m}$ is its new active power set point value. Pa_k^{ini} is the current load of EV aggregator k (entity whose importance will be further developed in this section) and fp_{Ak} and $P_{\mathrm{ref}\,ak}$ are the aggregator k participation factor and new active power set point, respectively.

It should also be considered that the AGC with EV operation has a delay similar to the conventional AGC, within the 5 s period available for the controller cycle [9]. Yet it may happen that once the aggregators receive the set points from the AGC unit, there will be another delay to send the final set points to EV, and each EV will then take some more time before outputting the required value. The former should assume a value that should not exceed the controller cycle time of the AGC. Both actions are nearly identical, and the computational burden that the aggregator endures, distributing its set point among the participating EV possibly already predetermined once the signal is received, is likely to be lower than that of the AGC controller, integrating the error signals and distributing the set points according to the participation factors of the controlled units. The delay on the action of the individual EV is of the order of magnitude of utmost a 100 ms, being caused by the electronic interface. This delay should be negligible in the context of the AGC operation, whose deployment period starts 30 s after the disturbance and lasts for 15 min. As a matter of fact, the delay caused to the machine response by their inertia overthrows the full extra delay caused by the binomial aggregator and EV.

For the purpose of dynamic simulation, EV charging can be modeled, as any load, as constant power load, constant current load, constant admittance load, or a combination of those. The following equations present the mathematical formulation of such a modeling [11]:

$$P = P_0[p_1\bar{V}^2 + p_2\bar{V} + p_3], \tag{6.4}$$

$$Q = Q_0[q_1\bar{V}^2 + q_2\bar{V} + q_3], \tag{6.5}$$

where P is the active power; Q is the reactive power; p_1 to p_3 and q_1 to q_3 are coefficients that define the proportion of each component.

In addition to this dependency on voltage, loads may suffer the influence of frequency and so (6.4) and (6.5) may be written as follows:

$$P = P_0[p_1\bar{V}^2 + p_2\bar{V} + p_3](1 + k_{pf}\Delta f), \tag{6.6}$$

$$Q = Q_0[q_1\bar{V}^2 + q_2\bar{V} + q_3](1 + k_{qf}\Delta f), \tag{6.7}$$

where Δf is the frequency deviation; k_{pf} and k_{qf} are coefficients that reflect the dependency of the load value to Δf.

Typically, in dynamic simulation, a simplification is done and all loads are considered to be of constant admittance type. This occurs due to the fact that is virtually impossible to achieve perfect knowledge on the loads distributed through the network that is being studied. Some particular cases, such as networks representative of industrial areas, may consider certain portions of the load to have specific behaviors, and consequently specific models are adopted to study their influence. This happens in the case where large induction motors or air-conditioning devices have a large presence, which requires additional load modeling.

In this particular case, EVs are assumed to be a known proportion of the total load and so EV load was distinguished from the conventional load. Being interfaced with the electricity grid by power electronics, EV charging is controlled following well-known patterns. The constant current, constant voltage charging process of a lithium-ion battery cell [12], is depicted in Fig. 6.9.

It is observable that current is constant during most of the time, while voltage slowly varies over time, except for very low values of SOC. When SOC reaches a high value, then voltage is kept constant and current decreases tending to zero.

AGC operation regards time periods of 15 min. For these small periods of time, one can assume a constant power load for the EV battery charging process, also because variations of voltage at EV terminals are quite small during the large majority of this period of time and can therefore be neglected.

When advanced management strategies are considered, to the adopted model, extra control loops have to be added to EV loads, enabling them to respond to the following:

- Frequency, when participating in primary frequency control
- Upstream active power set points, when participating in AGC operation

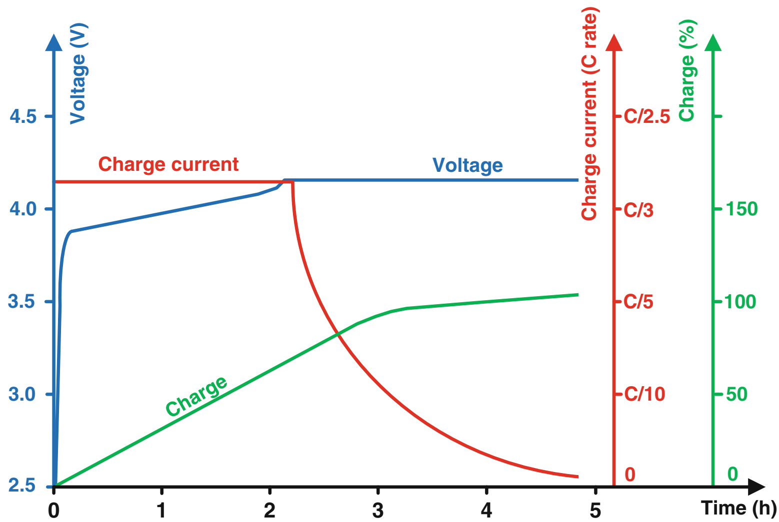


Fig. 6.9 Constant current, constant voltage charging, based on [13]

6.3 Steady-State Studies of Electric Vehicles Integration in Distribution Networks

The foreseen deployment of EV will considerably affect the way distribution grids will be managed and operated. The extra amount of power they will demand from the grid will oblige DSO to understand the impacts resulting from EV connection into distribution networks. Several approaches to this problem have been pursued. As an example, the works published in [14] and [15] present two strategies for assessing EV grid integration impacts. The work presented in [14] follows a deterministic strategy to locate EV along the network buses and, consequently, determine EV loads during an entire day. Conversely, the work presented in [15] introduced a probabilistic method for determining EV load. Both options proved to be interesting approaches, though they were able to reveal only the effects of a possible scenario for a given period. To overcome this limitation, it is important to develop tools that allow exploring different scenarios in a coordinated way, enabling the analysis of both average scenarios and extreme case scenarios that may appear when EVs start being integrated in the networks. Such tools can be used to enhance the current planning techniques of DSO, allowing them to obtain additional knowledge on the impacts of a new type of load, so far unknown or negligible to the electrical power systems, the EV battery charging. Given the fact that EVs are mobile loads that may appear in almost any bus of a given electricity network, voltage profiles, lines loading, peak power, and the variations of the energy losses in the network need to be properly evaluated for the planning exercise.

In this sense, two approaches are presented in this section, henceforth referred to as Methodology 1 and Methodology 2, aiming at performing a steady-state evaluation of the EV impacts in distribution networks, both LV and MV networks. In both methodologies, the EVs are modeled as described in Sect. 6.2.3. As it will be discussed in the following sections, charging at levels 2 and 3 was only considered in Methodology 2.

The first approach, Methodology 1, follows a deterministic method to distribute EV along the network buses and determine EV loads during an entire day. Three charging strategies are used to evaluate the EV impacts in the networks, one for each charging strategy addressed: dumb charging, multiple tariff, and smart charging.[1] An algorithm based in this methodology is also presented, for which main characteristics are described further ahead in this chapter.

The second approach, Methodology 2, uses a Markov chain to simulate the expected movement of EV during 1 week and a Monte Carlo simulation method that allows exploring different scenarios in what regards the EV locations in the grid and their power requirements [16]. This approach includes a set of management and control strategies that may be used by DSO and aggregators to manage the EV charging in real time, which allow attaining the following objectives:

- Minimizing the deviations between the energy bought in the markets by the aggregators and the energy sold to EV owners
- Minimizing the renewable energy wasted in systems with a large integration of intermittent RES
- Flattening, as far as possible, the load diagram of a given network
- Solving technical problems related to voltages outside the allowable limits and branches' overloading that might appear in the networks due to EV charging

An algorithm based in Methodology 2 is also presented further ahead in this chapter.

6.3.1 Identification of EV Integration Limits: Methodology 1

This approach assumes that the load inherent to EV charging will appear in the grid nodes proportionally to the residential power installed in each node. It allows evaluating the maximum number of EV that can be safely integrated in a given distribution network when the different charging strategies are implemented.

[1] As the V2G mode of operation (described in Sect. 6.2.1) is the most aggressive mode for charging EV, due to possible implications with EV batteries' life cycle, this option is not likely to be a reality neither in the short run nor in the medium term. Only in the very long term, when battery technology has reached a high maturation stage, this strategy may be adopted. For this reason, the V2G mode of operation was neither considered in the development of Methodologies 1 and 2 nor in the implementation of these approaches in the steady-state algorithms presented.

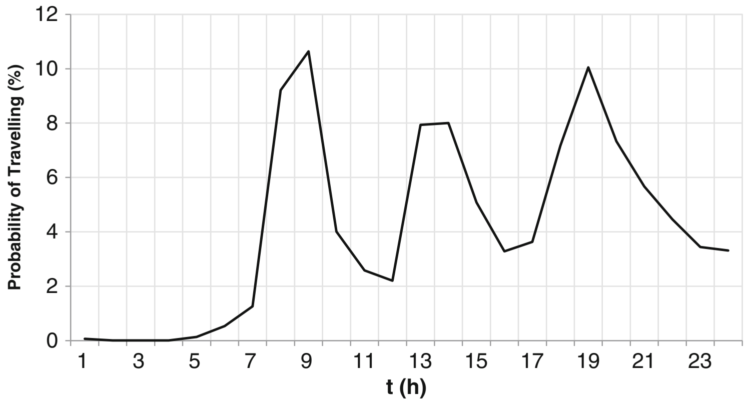


Fig. 6.10 Probability distribution used to define the EV daily journeys

The methods proposed for the dumb charging and multiple tariff are based on a simple set of rules, whereas the smart charging methodology involves an optimization problem with the objective of managing the EV load in order to minimize the networks' peak load.

It should be noted that in this methodology, the EV batteries charging was assumed to be performed always at a constant power rate of 3 kW in all the charging strategies addressed (at level 1 charging rate, as described in Sect. 6.2.1).

As in this approach it was not taken into account the real amount of energy spent by EV during their daily journeys, being impossible to know their battery SOC in the moment they plug in to the grid to recharge, an average charging time of 4 h was assumed for all the EV. This means that all EV absorb 12 kWh from the grid during the day under analysis. Assuming an energy consumption of 0.2 kWh/km [17], the daily energy absorbed would be enough for traveling 60 km without needing to recharge.

6.3.1.1 Formulation of the Approach

The formulation of this approach is essentially focused on the determination of the locations and time periods during which EV will be plugged in to the grid for charging purposes, when the three different charging strategies are adopted.

Thus, its first step is defining the period during which each EV will be connected to the grid. For that, it is assumed that EVs make only two journeys per day and that they are plugged in only in the periods between the last journey of 1 day and the first journey of the next day. The two moments when EVs make their daily journeys are drawn using the probability distribution presented in Fig. 6.10.

This procedure is constrained by the fact of the charging time being assumed to be 4 h for all EV. Thus, it is always assured that the time period between the last and the first journey of the day is at least 4 h.

The probability distribution in Fig. 6.10 was obtained from a statistical study of which the main goal was the characterization of the common traffic patterns in a region in the north of Portugal, covering the city of Porto and other smaller surrounding cities [18].

The following step of the approach is defining the periods during which EV will effectively absorb power from the grid. These periods will vary in accordance with the charging strategy under consideration.

When dumb charging is considered, it is assumed that EV owners are completely free to connect and charge their vehicles whenever they want. Thus, the charging starts automatically when EVs are plugged in, right after home arrival, and, as previously referred, lasts for the following 4 h.

When considering the multiple tariff, it is supposed that the economic incentives provided with this policy are enough to make the EV owners changing their charging to the cheaper electricity period.[2] Therefore, EV will preferably charge in the period between 22 and 8 h. They will charge only outside it if they are not plugged in the required 4 h in the period between 22 and 8 h.

Regarding smart charging, it is assumed the existence of an EV charging management system that controls the EV charging in order to avoid, as far as possible, increasing the networks' peak load. This system provides high flexibility to the EV charging, and thus it is possible to shift the EV load from the peak to the valley periods. Following this assumption, the smart charging was formulated as an optimization problem, as shown below, for which the main objective is the minimization of the networks' peak load.

$$\min\left\lfloor \max_{t=1:24\,\mathrm{h}}\left(\sum_{j=1}^{m} CL_t^j + \sum_{i=1}^{n}\left(EVC_t^i\right)\times 3\right)\right\rfloor, \tag{6.8}$$

subject to

$$\sum_{t=1}^{24} EVC_t^i = 4, \quad \begin{cases} i \in [1,n] \\ t \in [1,24] \end{cases}, \tag{6.9}$$

$$EVP_t^i \geq EVC_t^i, \quad \begin{cases} i \in [1,n] \\ t \in [1,24] \end{cases}, \tag{6.10}$$

where $\left\lfloor \max\left(CL_t^j + \sum_{i=1}^{n}\left(EVC_t^i\right)\times 3\right)\right\rfloor$ represents the network's peak power, in kW, given by the maximum value registered along the 24 h of the sum of the network conventional load and the EV load; CL_t^j is the conventional load in bus j,

[2] The lower electricity price period assumed was that of the dual tariff policy currently implemented in Portugal: 22–8 h. More information can be found in http://www.edpsu.pt/pt/particulares/tarifasehorarios/ (in Portuguese).

in kW, in time step t; EVC_t^i is used to define the periods t when EV i will charge; if $EVC_t^i = 1$, the EV i will charge in moment t, else if $EVC_t^i = 0$, the EV will not charge; the $n \times 24$ binary variables EVC_t^i are the decision variables of the optimization problem; t is the time step index; i is the EV index; n is the number of EV assumed to be within the network's geographical area; j is the bus index; m is the number of buses in the network; EVP_t^i is used to define the periods t when EV i is parked and plugged in to the grid; if $EVP_t^i = 1$, the EV i is plugged in in moment t, else if $EVP_t^i = 0$, the EV is neither plugged in nor available for charging; the $n \times 24$ binary values EVP_t^i are parameters of the optimization problem.

The equality constraint presented in (6.9) assures that all EV will charge exactly 4 h along the day, whereas the condition implemented in (6.10) assures that EV will only charge when they are plugged in to the grid. The number 3 presented in (6.8) is referred to the charging rate, in kW, assumed for all the EV.

The problem formulated for the smart charging strategy is a pure integer problem, as all the decision variables are restricted to be integers.

After determining the periods when EV will charge, in accordance with the charging strategy addressed, the network buses where EVs plug in for charging are calculated taking into account the proportion of residential power installed in each node, as presented in (6.11).

$$Nr.EV_j = \frac{\mathrm{Load}_j^R}{\sum_{j=1}^{m} \mathrm{Load}_j^R} \times n, \quad j \in [1, m], \tag{6.11}$$

where $Nr.EV_j$ is the number of EV allocated to bus j; Load_j^R is the residential load, in kW, installed in bus j; $\sum_{j=1}^{m} \mathrm{Load}_j^R$ is the total residential load, in kW, in the network.

A consequence of (6.11) is that buses with a higher residential load will have allocated a higher number of EV. Following the results obtained with this equation, all the EVs are tagged with a bus number, indicating the bus where they plug in for charging. This procedure allows computing the EV load in the system, node by node and for each time step.

Finally, the total load in the network with the three charging strategies is calculated by adding the conventional load to the respective EV load, as follows:

$$TL_j^t = CL_t^j + \sum_{k=1}^{Nr.EV_j} EVC_t^k \times 3, \quad \begin{cases} j \in [1, m] \\ k \in \left[1, Nr.EV_j\right] \\ t \in [1, 24] \end{cases}, \tag{6.12}$$

where TL_j^t is the total load in bus j, in kW, in time instant t; EVC_t^k is the EV charging vector composed of 24 binary variables used to define the periods t when EV k will charge; if $EVC_t^k = 1$, the EV k will charge in moment t, else if $EVC_t^k = 0$, the EV will not charge; k is the index used for the EV allocated to bus j.

6.3.1.2 Development of the Approach

An algorithm based in the approach proposed can be developed, with the objective of characterizing the impacts provoked by a given EV integration level in a distribution network or quantifying the maximum number of EV that can be integrated in a given network, without violating its components' technical limits.

The algorithm should include the following steps:

1. Definition of the type of study to be performed (evaluate the impacts of a given level of EV integration or quantify the maximum number of EVs that can be safely integrated in a given network).
2. Evaluation of the initial operating conditions of the network (power flow analysis[3]), without considering the presence of EV (for comparison purposes).
3. Definition of the number of EVs assumed to be enclosed in the geographical area covered by the network.
4. Definition of the periods during which each EV will be plugged in.
5. Definition, in accordance with the specificities of the charging strategy being addressed, of the periods during which EV will effectively absorb power from the grid (the analysis of the smart charging strategy demands the resolution of the pure integer optimization problem formulated in (6.8)–(6.10)[4]).
6. Distribution of the EVs through the network nodes.
7. Calculation of the total load in the network, node by node and for each time step, by adding the conventional load to the EV load.
8. Evaluation of the new grid operating conditions (power flow analysis).
9. If no technical violations are registered, increase the number of EVs and repeat steps 4–9 (this step is only performed if the type of study selected in step 1 is "quantify the maximum number of EVs that can be safely integrated in a given network").
10. Store all the relevant data.

The flowchart of the algorithm is presented in Fig. 6.11.

6.3.2 Spatial–Temporal EV Simulation Tool: Methodology 2

Methodology 2 is an improved version of Methodology 1. It fully copes with the conceptual framework described in Sect. 6.2.2, namely in what regards the smart charging, which was addressed assuming the possibility of adjusting the EV

[3] All the required power flows were run using the *PSS/E* software.

[4] The optimization problem was solved using LINGO 13.0, which is an optimization modeling software that includes a set of built-in solvers for linear, nonlinear, quadratic, quadratically constrained, second-order cone, stochastic, and integer optimization. More information can be found in http://www.lindo.com/index.php?option=com_content&view=article&id=2&Itemid=10

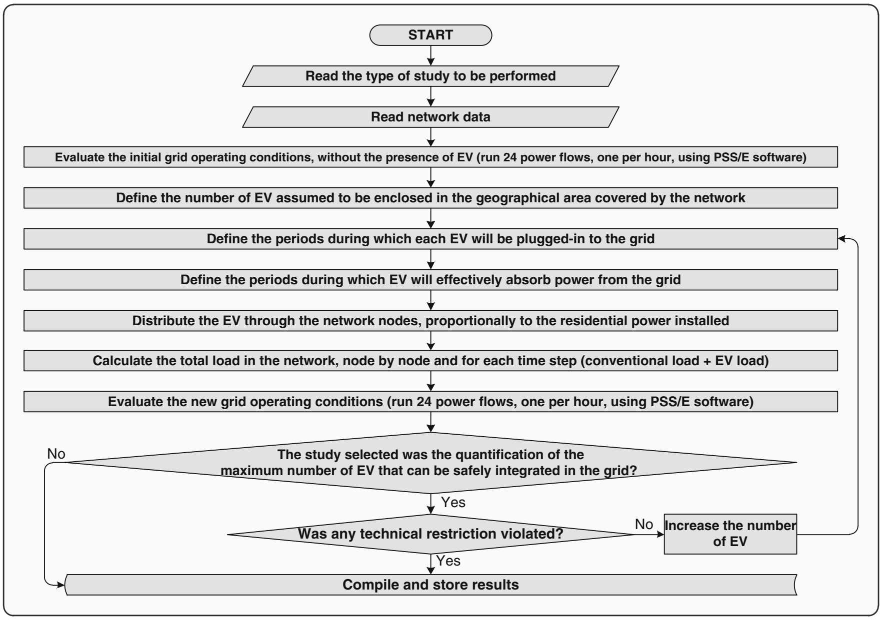


Fig. 6.11 Flowchart of the algorithm based in Methodology 1

charging rates between zero and the maximum power rate of the charging point where a given EV is plugged in (3 kW for level 1, 12 kW for level 2, and 40 kW for level 3 charging infrastructures, as described in Sect. 6.2.1). This methodology uses a Markov chain to simulate the expected movement of EV during 1 week and a Monte Carlo simulation method that allows exploring, in a coordinated way, different scenarios in what regards the EV locations in the grid and their power requirements.

Different from Methodology 1, where the period of only 1 day was considered, with time steps of 1 h, the time horizon of 1 week was considered in Methodology 2, with time steps of ½ h. This improvement allows not only evaluating the EV impacts taking into account the load variations that usually occur between week and weekend days, but also quantifying the EV impacts in time steps shorter than 1 h, as 1 h is a very long period of time during which the network operating conditions can change considerably. It should be mentioned that the formulation of this methodology can be easily adapted to analyze the EV impacts during different periods of time, like 1 year, if the objective is evaluating other seasonal load variations, like load changes between seasons.

As it will be described later on, this approach also includes a set of management and control strategies that may be used by DSO and aggregators to manage the EV charging in real time.

6.3.2.1 Mathematical Formulations

This section covers the mathematical formulation of the Markov chain used to simulate the expected movement of the EV during 1 week in the geographical area covered by a given network, as well as of the set of procedures created to manage the EV charging in real time.

Electric Vehicle Motion Simulation

The EV movement during 1 week is simulated using a discrete-state and discrete-time Markov chain [19–21], to define the states of all the EVs at each time step of 30 min. In this Markov chain, it was assumed that, at every unit of time, one and only one event from a set of a finite number of events can occur to a given EV: E_M, E_R, E_C, and E_I. When the event $E_k(k = M, R, C, I)$ occurs, it is said that the EV passes into the state E_k:

- E_M—The EV passes into the state "in movement"
- E_R—The EV passes into the state "parked in a residential area"
- E_C—The EV passes into the state "parked in a commercial area"
- E_I—The EV passes into the state "parked in an industrial area"

As the time terminology will be used, i.e., it is considered that one trial is performed at every unit of time, when the event E_k occurs at the moment t, it is represented by E_k^t. Besides this, it is assumed that at the initial moment $t = 0$. Therefore, E_k^0 denotes that the initial state of the EV was E_k.

This method is classified as a discrete-time process, given that t is finite and can be enumerated [19]. As the objective is to simulate EV movement along 1 week (7 days), 337 time steps of ½ h will be considered. Thus, $t \in [0, 336]$.

One trial is performed initially to define every EV state when $t = 0$. In this trial, an EV may be in the state E_k with probability $P(E_k)$.

The conditional probability that at the moment t, for $t \in [1, 336]$, a given EV passes into the state E_k is denoted by $p_{j\to k}^t$ provided that at $t - 1$ it was in the state $E_j(j = M, R, C, I)$:

$$p_{j\to k}^t = P(E_k^t | E_j^{t-1}). \tag{6.13}$$

As mentioned above, this sequence of trials forms a Markov chain, given that for any j and k and for any $t \in [1, 336]$, the equalities

$$p_{j\to k}^t = P(E_k^t | E_j^{t-1}) = P(E_k^t | E_j^{t-1} \bullet E_j^{t-2} \bullet \ldots \bullet E_j^1 \bullet E_j^0), \tag{6.14}$$

are satisfied for arbitrary $E_j^{t-2}, \ldots, E_j^1, E_j^0$.

This Markov Chain is periodically stationary, or cyclostationary [22], as the transition probabilities are periodically repeated. The period of this cycle is 1 week and will be represented by τ. As time steps of ½ h are being considered, $\tau = 7 \times 48 = 336$. If the purpose of the study was evaluating the EV impacts during one complete year (365 days), τ would have to be repeated ≈ 52.14 times.

$$p_{j \to k}^{t} = p_{j \to k}^{t+\tau}. \tag{6.15}$$

One transition matrix can be created with the transition probabilities $p_{j \to k}^{t}$ for each moment t, where $t \in [1, 336]$. This matrix is denoted by M_t, and given the cyclostationary properties of this Markov chain, it will be periodically repeated every τ time steps, in accordance with (6.16):

$$M_t = M_{t+\tau}. \tag{6.16}$$

For a given moment t, the transition matrix assumes the following form:

$$M_t = \begin{bmatrix} p_{M \to M}^{t} & p_{M \to R}^{t} & p_{M \to C}^{t} & p_{M \to I}^{t} \\ p_{R \to M}^{t} & p_{R \to R}^{t} & p_{R \to C}^{t} & p_{R \to I}^{t} \\ p_{C \to M}^{t} & p_{C \to R}^{t} & p_{C \to C}^{t} & p_{C \to I}^{t} \\ p_{I \to M}^{t} & p_{I \to R}^{t} & p_{I \to C}^{t} & p_{I \to I}^{t} \end{bmatrix}, \tag{6.17}$$

where the indexes M, R, C, and I stand for "in movement," "parked in a residential area," "parked in a commercial area," and "parked in an industrial area," respectively.

Logically, all the elements $p_{j \to k}$ of the matrix, being probabilities, are nonnegative.

Supposing that an EV is in the state E_j, the event where, as a result of one trial, the EV remains in the state E_j or passes to any of the states E_k, where $j \neq k$ is the sure event. Since the events E_k are mutually exclusive, for $k = M, R, C, I$, the following equation can be obtained:

$$P[\sum_k E_k^t | E_j^{t-1}] = \sum_k p_{j \to k}^{t} = 1. \tag{6.18}$$

Thus, the sum of the terms in each row of the matrix M_t equals one. However, the sum of the terms in a column might be different from one.

Figure 6.12 presents an overview of the Markov chain developed.

As denoted in Fig. 6.12, there are some restrictions when defining the EV states for each time instant. While EV in movement can keep their state or change for one of the others, parked EV can only remain in the same state or change to in movement.

As mentioned previously, the Markov chain developed is cyclostationary and the period of one complete cycle, τ, is 1 week. This cycle is, in fact, a composition of two sub-cycles with the duration of 1 day: one for the weekdays (repeated five times in a row) and the other for the weekend days (repeated twice consecutively).

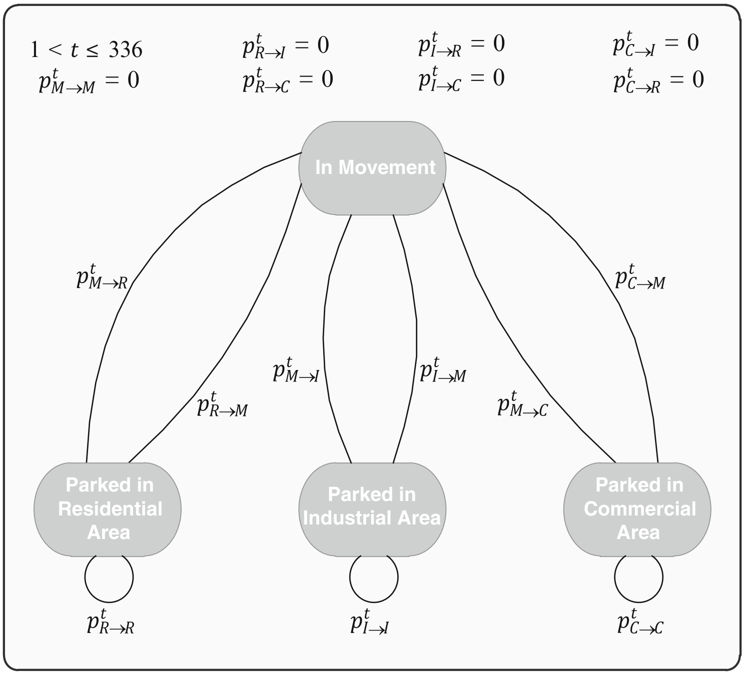


Fig. 6.12 Discrete-state and discrete-time Markov chain

Therefore, to have the Markov chain completely characterized, it is only needed to define the initial probabilities, for $t = 0$, and the state transition probabilities, for $t \in [1, 48]$, of these to sub-cycles, as shown in (6.19) and (6.20), and then repeat them to compose the full weekly cycle.

Initial probabilities:

$$P(E^t_k) \quad \text{for} \begin{cases} t = 0 \\ k = M, R, C, I \end{cases}. \tag{6.19}$$

Transition probabilities:

$$p^t_{j\to k} = P\left(E^t_k \mid E^{t-1}_j\right) \quad \text{for} \begin{cases} t \in [1, 48] \\ k = M, R, C, I \\ j = M, R, C, I \end{cases}. \tag{6.20}$$

The required probabilities were determined by analyzing the results of the same statistical study referred previously, of which the main goal was the characterization of the common traffic patterns in a region in the north of Portugal [18].

The values obtained from the study presented in [18], for the EV initial-state probabilities ($t = 0$), were 0.89 for "parked in a residential area," 0.04 for "parked

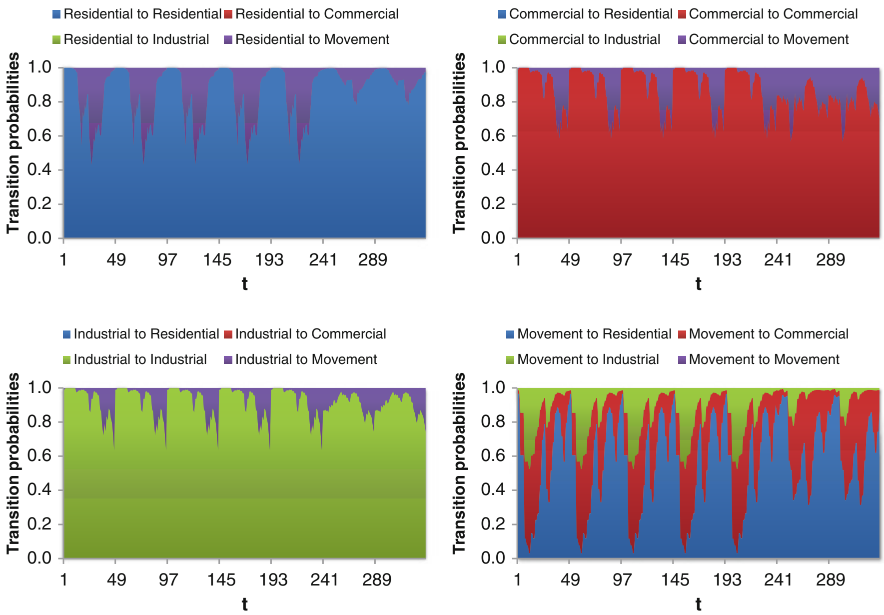


Fig. 6.13 EV state transition probabilities: full weekly cycle (Monday to Sunday)

in a commercial area," 0.02 for "parked in an industrial area," and 0.05 for "in movement."

Regarding the state transition probabilities, the values obtained for the full weekly cycle, which already includes the results of the weekday and weekend day sub-cycles, are presented in Fig. 6.13.

Procedures to Define Which "Flexible EV[5]" Should Charge at Each Time Step

Taking into consideration the characteristics of the problem to be analyzed, two procedures to define which of the "flexible EVs" should charge at each time step are presented along the current section. These procedures were specifically developed to accomplish the EV charging management performed by the aggregator for interconnected systems or by the system operator for isolated systems.

Procedure 1

The main objective of Procedure 1 is to define which "flexible EV" should charge at each time step, in order to minimize the deviations between the energy bought in the market by the aggregators and the energy consumed by EV. It should be stressed that it was assumed that the charging rate for level 1, in what regards smart charging adherents, could vary between 0 and 3 kW.

[5] "Flexible EVs" are the EVs whose owners adhered to the smart charging scheme.

To achieve the intended objective, it is required to find a set of n load values, being n the number of "flexible EV," which can be defined as optimal in the sense that they allow minimizing the deviations between the energy bought by the aggregators and the energy consumed by EV.

This problem can be formulated as an optimization problem, as shown below:

$$\min \left| EBA_t - TIEVL_t - \sum_{i=1}^{n} FEVL_t^i \right|, \tag{6.21}$$

subject to

$$0 \le SOCR_{td}^i - SOC_t^i \le \frac{(FEVL_t^i + (td - (t+1)) \times 3) \times 1/2 \times EV_{ce}}{EV_i^{bc}} \times 100, \tag{6.22}$$

$$0 \le FEVL_t^i \le 3, \tag{6.23}$$

$$0 \le SOCR_{td}^i \le 100, \tag{6.24}$$

$$0 \le SOC_t^i \le 100, \tag{6.25}$$

$$t + 1 \le td, \tag{6.26}$$

where i represents the "flexible EV" index; t represents the time index; n is the No. of "flexible EV" under the aggregator control; EBA_t represents the average power along ½ h, in kW, related to the energy bought in the day-ahead market by the aggregator for time period between t and t + 1; $EBA_t(\mathrm{kW}) = (\text{energy bought}_{t \to t+1}(\mathrm{kWh}))/(1/2\,\mathrm{h})$, which is a parameter of the optimization problem; $TIEVL_t$ represents the total "inflexible EV[6]" load, in kW, in time step t, which is a parameter of the optimization problem; $FEVL_t^i$ represents the power absorbed by "flexible EV" i, in kW, in time step t; the $n\,FEVL_t^i$ are the decision variables of the optimization problem, which can assume continuous values in the interval $[0, 3]$; td represents the time step at which a given "flexible EV" disconnects from the grid; SOC_t^i represents the battery SOC of EV i, in percentage, in time step t; the SOC_t^i values are parameters of the problem; $SOCR_{td}^i$ represents the battery SOC required by the owner of EV i, in percentage, in time step td; the $SOCR_{td}^i$ values are parameters of the optimization problem; EV_i^{bc} represents the battery capacity, in kWh, of EV i; the $n\,EV_i^{bc}$ values are parameters of the optimization problem; EV_{ce} is the efficiency of the EV charging process, which is a parameter of the optimization problem.

[6] "Inflexible EVs" are the EVs whose owners adhered to the dumb charging or multiple tariff schemes.

Equation (6.22) is used to assure that the EV battery SOC required by the EV owners at the moment of disconnection is possible to attain when considering a maximum charging rate of 3 kW. The condition implemented in (6.23) assures that only charging rates between $[0, 3]$ kW will be attributed to “flexible EV,” as it was assumed that a “flexible EV” is a smart charging adherent that is charging either in a residential or in an industrial area at level 1. Equations (6.24) and (6.25) are used to guarantee that the required EV battery SOC and EV battery SOC in the time step t are always within the interval $[0, 100]$ %. Equation (6.26) assures that the time of disconnection is always posterior to time step $t + 1$.

The objective of this optimization problem is to minimize the sum of the absolute value of the deviations, as there can be positive deviations (energy bought by the aggregators higher than energy consumed by “flexible EVs” and “inflexible EVs”) and negative deviations (energy consumed higher than energy bought).

The problem formulated is a linear optimization problem, which is suitable for real-time applications since it does not require any type of forecasted data. It is only necessary to know, for the current time step (t), the energy bought by the aggregators, the power consumed by the “inflexible EV,” the moment of disconnection of the “flexible EV” that are currently plugged in, and the amount of energy required by their owners during the period they will stay connected to the grid.

It should be noted that the approach presented in this section can be easily adapted for other cases, like the minimization of the renewable energy wasted in systems characterized by a large integration of intermittent RES (e.g., wind). Under these circumstances, the renewable power generated by intermittent RES that is in risk of being wasted would be treated as parameters of the problem.

Procedure 2

The main objective of Procedure 2 is defining which “flexible EV” should charge at each time step and with which charging rate, in order to flatten the network load diagram as much as possible. As described next, this objective can be accomplished in two distinct stages.

During the first stage, an optimization technique is used to find a set of 336 “flexible EV” load values, which can be defined as optimal in the sense that they allow obtaining a load diagram as flat as possible for a given network. The value 336 is referred to the number of time steps of ½ h that compose 1 week.

The formulation of the optimization problem is shown below.

$$\min \sum_{t=1}^{336} (FL_t + IL_t)^2, \tag{6.27}$$

subject to

$$FL_t \geq 0, \tag{6.28}$$

$$\sum_{t=1}^{336} FL_t = TFL, \tag{6.29}$$

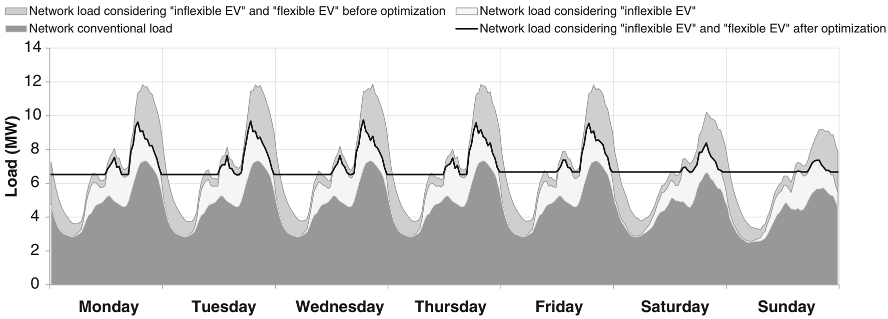


Fig. 6.14 Results obtained with the optimization problem presented in (6.27)

where t is the time step index; FL_t represents the "flexible EV" load, in kW, in time step t; the 336 FL_t values are the decision variables of the optimization problem; IL_t represents the "mandatory load[7]" in the network, in kW, in time step t; the 336 IL_t values are parameters of the optimization problem; TFL is the load consumed by the "flexible EV," in kW, during the 336 time steps considered and it is a parameter of the problem.

In order to solve the formulated problem, there are some data that need to be available, like IL_t and TFL. In practical applications, and since the optimization problem should be solved by the DSO, these data should be obtained using forecasting techniques to predict the "mandatory load" and the "flexible EV" load for the next week (the problem can also be formulated in a daily basis).

Figure 6.14 illustrates the type of results that can be obtained with the optimization problem (considering the formulation for 1 week).

The second stage of Procedure 2 is dedicated to put the results obtained with the optimization problem into practice. For this purpose, during this stage, a problem analogous to that presented in (6.21) is formulated, as shown next:

$$\min \left| FL_t - \sum_{i=1}^{n} FEVL_t^i \right|, \tag{6.30}$$

where i represents the "flexible EV" index; n is the No. of "flexible EV" assumed to be under the DSO control; FL_t represents the optimal "flexible EV" load, in kW, in time step t; the 336 FL_t values are parameters of the optimization problem; $FEVL_t^i$ represents the power absorbed by "flexible EV" i, in kW, in time step t; the $n \times 336$ $FEVL_t^i$ are decision variables of the optimization problem, which can assume continuous values in the interval $[0, 3]$.

[7] "Mandatory load" is the conventional load of the network plus the load from the EV whose owners adhered to the dumb charging or multiple tariff schemes.

This problem is subject to the same restriction of the problem presented in (6.21). Its objective is minimizing the absolute value of the deviation between the optimal amount of "flexible EV" load, determined with the optimization problem presented in (6.27), and the real amount of load consumed by the "flexible EV." The absolute value of the deviations is considered as there can be positive deviations (optimal load higher than load consumed) and negative deviations (load consumed higher than optimal load).

It should be noted that unlike in the problem presented in (6.27), where FL_t were the decision variables, in this problem, FL_t are treated as fixed parameters. The decision variables of the current problem are the power absorbed by the flexible EV for each time step—$FEVL_t^i$.

Procedures to Solve Network Operating Problems by Adjusting the EV Charging Rates

After defining which "flexible EV" should charge and with which charging rate at each time step, the network operating conditions should be analyzed to detect eventual technical problems that may appear due to the EV load. The increase in the power consumption might provoke LV or line overloading problems that demand corrective measures in order to being solved. Under these circumstances, it is necessary to define the amount of load that is required to decrease to bring voltages and lines' ratings again to the allowable limits and to define which of the "flexible EVs" should decrease their charging rates in order to attain the desired load reduction. A procedure to tackle these problems, Procedure 3, is presented in this section. This procedure is capable of tackling simultaneously multiple LV and line overloading problems, whether these problems occur in separate feeders or in the same feeder of a given network, as both these problems require the same measure: a load reduction.

It should be referred that the two problems referred above, LV and line overloading, could be solved simultaneously using an (Optimal Power Flow) OPF-like method. However, as the resolution of this type of problems is usually very time-consuming, due to its high dimension, the expeditious approach provided by Procedure 3 was chosen over the OPF-like option since the latter is rather impractical for real-time applications.

Procedure 3

To achieve the intended objective, it is required to find a set of n load values, being n the number of "flexible EV," which can be defined as optimal in the sense that they allow minimizing low bus voltages and line overloading problems detected in the network in a given time instant t.

This problem can be formulated as an optimization problem, as shown below.

$$\min NLVP_t + NLOP_t, \tag{6.31}$$

subject to

$$0 \leq SOCR_{td}^{i} - SOC_{t}^{i} \leq \frac{(FEVL_{t}^{i} + (td - (t+1)) \times 3) \times (1/2) \times EV_{ce}}{EV_{i}^{bc}} \times 100, \quad (6.32)$$

$$0 \leq FEVL_{t}^{i} \leq 3, \quad (6.33)$$

$$0 \leq SOCR_{td}^{i} \leq 100, \quad (6.34)$$

$$t + 1 \leq td, \quad (6.35)$$

where $NLVP_t$ represents the number of LV problems in time instant t; the number of LV problems is determined by counting all the situations where $V_t^j < V^{\min}$, where V_t^j is the voltage in bus j, in time step t, and $V^{\min}$ is the minimum allowable voltage; $NLOP_t$ represents the number of line overloading problems in time instant t; the number of line overloading problems is determined by counting all the situations where $S_t^b > S^{\max}$, where S_t^b is apparent power flow in branch b, in percentage, in time step t, and $S^{\max}$ is the maximum allowable apparent power flow, in percentage; i represents the "flexible EV" index; t represents the time index; n is the No. of "flexible EV" assumed to be under the DSO control; td represents the time step at which a given "flexible EV" disconnects from the grid; $FEVL_t^i$ represents the power absorbed by "flexible EV" i, in kW, at time step t; the $n\,FEVL_t^i$ are decision variables of the optimization problem; they can assume continuous values in the interval $[0, 3]$; SOC_t^i represents the battery SOC of EV i, in percentage, in time step t; the $n\,SOC_t^i$ values are parameters of the optimization problem; $SOCR_{td}^i$ is the battery SOC required by the owner of EV i, in percentage, in time step td, which is the instant when the EV disconnects from the grid; the $n\,SOCR_{td}^i$ values are parameters of the problem; EV_i^{bc} represents the battery capacity, in kWh, of EV i; the $n\,EV_i^{bc}$ values are parameters of the optimization problem; EV_{ce} is the efficiency of the EV charging process, which is a parameter of the optimization problem.

The solution of this problem demands the resolution of the power flow equations in order to check if the bus voltages and the apparent power flow in the branches are off-limits. This becomes a complex optimization problem due to the nonlinearity introduced by the power flow equations that might take a considerable amount of time to solve, namely when the number of buses and branches of the network and the number of "flexible EV" under consideration are very high.

These reasons make the optimization problem presented above rather impractical for real-time applications, as the amount of time required to solve it might not be compatible with the time available to mitigate the problems detected.

In order to overcome these limitations, an expeditious approach can be used to deal with this problem in an efficient way, which, despite not providing optimal results, allows tackling the LV and line overloading problems quickly and with very satisfactory results.

This approach is based in a heuristic that comprises two stages.

In the first stage, all the relevant network data are gathered, its topology is processed, and a power flow is run to evaluate its operating conditions. Then, a list of problematic buses is created and the buses are sequentially analyzed. A given bus is flagged as problematic if it has a voltage value below $V^{\min}$ or if it is located in the upstream end of a branch with a rating above $S^{\max}$.

For each problematic bus, the feeder that contains the bus under analysis is selected, and the amount of load that is required to decrease in each of the feeder's buses, which allows solving the problem identified, is calculated. This calculation is performed iteratively, by decreasing in steps of a fixed value, in this case assumed to be 10 %, the existing EV load in each of the feeder's buses.

In the second stage, the "flexible EVs" that should reduce their charging rates are selected, in order to decrease the amount of power calculated in the first stage that allows solving all the problems identified. The "flexible EVs" whose charging rates are decreased are selected taking into consideration their location in the grid, being only chosen "flexible EVs" that are capable of effectively contribute to solve the LV or line overloading problems identified.

It should be noted that in a first phase, this heuristic process reduces only the charging rates of "flexible EV," always taking into consideration their owners' requests in what regards the battery SOC required in the moment they will disconnect from the grid. Nevertheless, when LV and line overloading problems are so severe that the emergency operating state is triggered, this heuristic reduces the charging rates of all the EV located in the problematic areas of the grid, disregarding if they are "flexible EV" or "inflexible EV," in order to avoid jeopardizing global system security.

The implementation of this heuristic is briefly illustrated in Fig. 6.15.

After processing the network topology and running a power flow, the buses 31 and 45 are flagged as "problematic buses." Bus 31 is flagged since it is the bus in the upstream end of a branch with congestion problems, whereas bus 45 is flagged due to its voltage value, which is assumed to be below the threshold that triggers the abnormal operating state. Then, feeders 4 and 5 are flagged as "problematic feeders," as these are the feeders that contain the buses 31 and 45, respectively.

The total load that is required to decrease is then calculated (first stage), by simulating that the EV load in the buses that belong to feeders 4 and 5 is decreased by 10 %. Afterward, a power flow is run to verify if the LV and line overloading problems were solved.

If so, the total amount of load that is required to decrease in the buses that belong to feeders 4 and 5 is computed. It should be noted that two load values are computed separately, one for feeder 4 and the other for feeder 5.

If not, the EV load in the buses that belong to feeders 4 and 5 continues to be iteratively decreased in steps of 10 %, until feasible operating conditions are attained. Then, the total amount of load that is required to decrease in the buses that belong to feeders 4 and 5 is computed.

After having knowledge of the amount of power that is required to decrease in the buses of the problematic feeders, it is defined which "flexible EV" should decrease their charging rates to achieve the desired load reduction (second stage).

In order to avoid interfering repeatedly with the same EV charging in buses 31 and 45, as branches' overloading and voltages under the allowed limits are

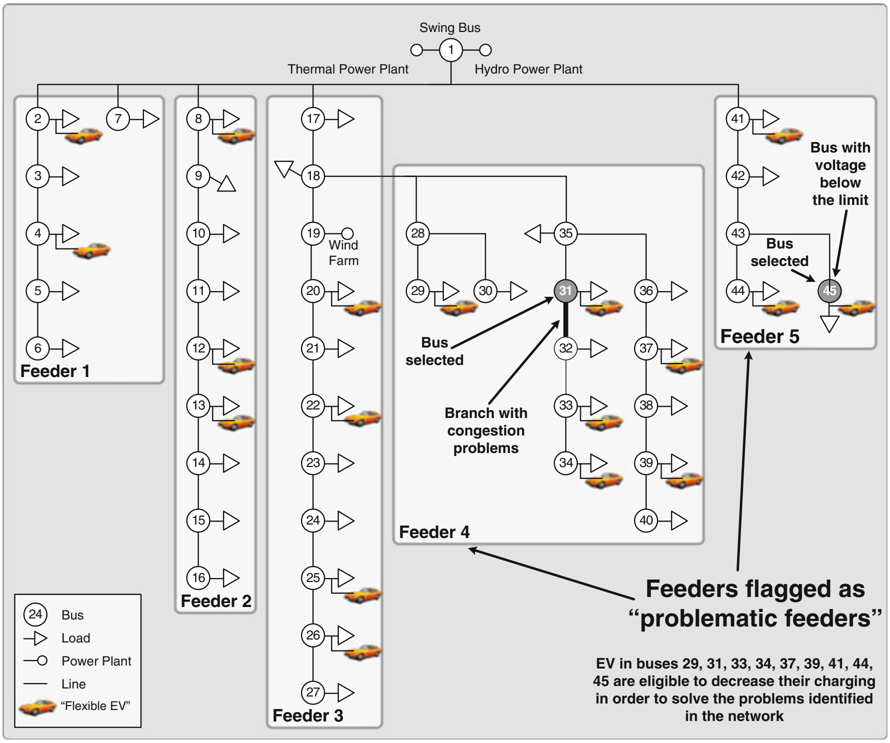


Fig. 6.15 Method used to select the EV whose charging will be decreased

problems that usually appear recurrently in the same locations of the grid, all the "flexible EVs" charging in the "problematic feeders" are considered to be eligible to decrease their charging rates in order to solve the network problems.

In the example presented in Fig. 6.16, all the "flexible EVs" charging in buses 29, 31, 33, 34, 37, 39, 41, 44, and 45 are considered to be eligible to decrease their charging rates. Thus, their charging rates are iteratively decreased in steps of 10 %, being run a power flow to evaluate the network operating conditions after each reduction, until feasible operating conditions are attained.

6.3.2.2 Development of the Approach

An algorithm based in the approach proposed can be developed, aiming to evaluate its efficiency when addressing EV impact studies. A Monte Carlo simulation method can be included in the algorithm, to iteratively generate samples of EV load in the network, terminating only when a predefined convergence criterion is met. Each sample generated provides the total amount of load in the network (conventional load plus EV load) in each time step of the week simulated,

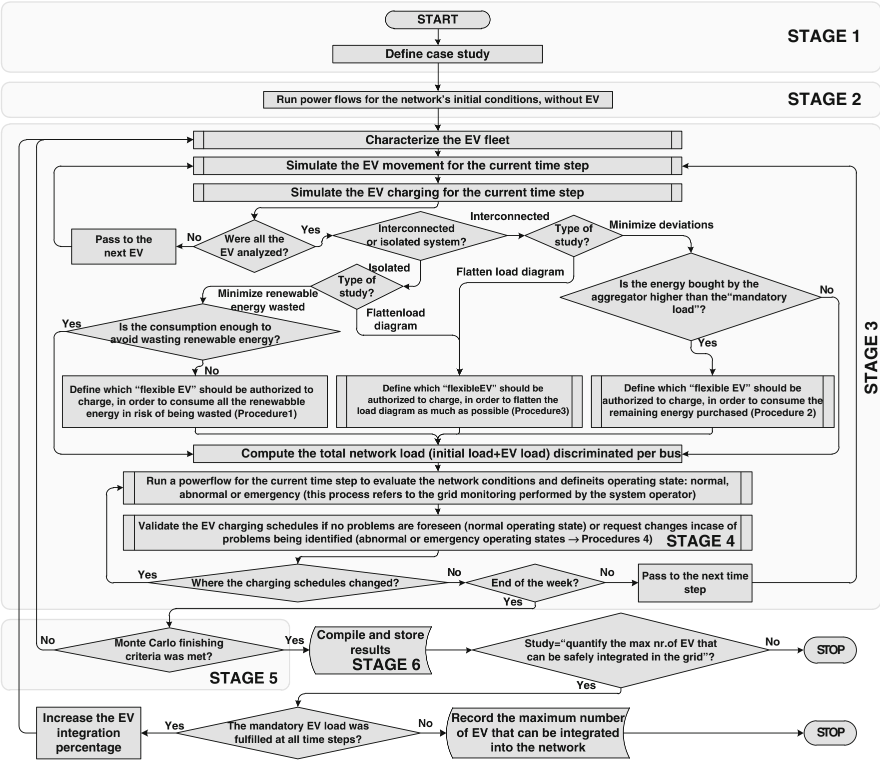


Fig. 6.16 Flowchart of the algorithm

discriminated per bus. The sample evaluation, which corresponds to the evaluation of the network operating conditions, is performed by running a power flow for each time step of the week and by analyzing the respective results. This section presents the algorithm's functionalities, as well as the most important details related to the implementation of the procedures described above.

The algorithm can be divided in six major stages, as depicted in Fig. 6.16:

1. *Study definition*: During this phase, the details related to the case study are defined, namely the type of analysis to be performed.
2. *Assessment of the initial network conditions*: After gathering all the relevant network data, the network's operating conditions, without the presence of EV, are evaluated by running consecutive power flows,[8] one per time step, until the end of the simulation period is reached. The results obtained (voltages, lines ratings, energy losses in the network, and loads) are stored and used later for comparison purposes.

[8] All the required power flows were run using the *PSS/E* software.

3. *Samples generation*: In this stage of the algorithm, the following steps are performed: (a) initial characterization of each EV in terms of battery capacity, charging power, energy consumption, and battery SOC in the beginning of the simulation [23]; (b) simulation of the EV movement and calculation of their energy requirements (using the Markov chain previously described); (c) definition of which EVs are available for charging and which will effectively charge at each time step (using Procedures 1 or 2); (d) evaluation of the grid operating conditions (by running power flows); and (e) if technical problems are detected by the DSO, the required changes in the EV charging schedules to solve them are calculated (using Procedure 3). Each sample generated provides the total load in the network (conventional load plus EV load) in each time step of the week simulated, discriminated per bus. It should be noted that the optimization problems of Procedures 1 and 2 were solved using LINGO 13.0 software.
4. *Sample evaluation*: The evaluation of the samples is made by running a power flow for each time step, being gathered information regarding loads, voltages, power flows in branches, and energy losses in the grid.
5. *Termination criteria*: To terminate the Monte Carlo simulation method, two criteria are used: (a) number of iterations; and (b) variances obtained, along the iterations of the Monte Carlo simulation method, of the aggregated grid load of each one of the 336 time instants. The second termination criterion presented means that one variance value is computed, during the iterations of the Monte Carlo simulation method, for the total network load per time instant $t, t \in [1, 336]$. The Monte Carlo simulation method is set to perform 4,000 iterations (4,000 weeks) and check, in the end, if the variation of all the 336 variances in the last five iterations is lower than $1e^{-6}$. The variance variation is calculated using the following equation:

$$\Delta\text{Variance} = \left|\text{Variance}_h^t - \text{Variance}_{h-5}^t\right| < 1 \times 10^{-6}, \qquad (6.36)$$

where t is the time instant index; h is the index used for the iterations of the Monte Carlo simulation algorithm; ΔVariance represents the variance variation of the aggregated network load, in time instant t, in the last five iterations of the Monte Carlo simulation algorithm; Variance_h^t represents the variance of the aggregated network load, in time instant t, in the hth iteration of the Monte Carlo simulation algorithm; Variance_{h-5}^t represents the variance of the aggregated network load, in time instant t, in the $(h-5)$th iteration of the Monte Carlo simulation algorithm.

If at least one of the 336 variances does not meet the referred convergence criterion, the process keeps running more iterations until all the variance variations are lower than the predefined value.

6. *Algorithm outputs*: The algorithm allows obtaining the EV fleet characteristics, the EV state at each time step (parked or in movement), the periods during which EVs are plugged in and available to charge, the network bus where EVs are plugged in (only for parked EV), the power absorbed by each EV at each 30 min interval (discriminated per network bus), the amount of energy provided at each

time step by the aggregators or by the DSO (depending on whether the network under analysis belongs to an interconnected or an isolated system), the total network load at each time step, the energy losses in the network at each time step, the network's voltage profiles at each time step, the network's branches ratings at each time step, among other results.

6.4 Dynamic Studies of Electric Vehicles Integration in the Power System

The implementation of the dynamic simulation models for EV may be performed differently, according to the type of application that will be analyzed. Mainly, two implementation methods can be followed, one for primary frequency control and the other for AGC operation [24].

Regarding primary frequency control, most of the commercially available software provides a module where the block diagram associated with the model that represents EV can be implemented using a graphical user interface (GUI). *Eurostag* or *Matlab* and even the very recent Graphical Module Builder add-on for *PSS/E*, among others, allow GUI implementation of dynamic simulation models, by drawing the block diagrams of the functionalities that may be required. Alternatively, these functionalities can be coded, using, for instance, *Fortran* to perform the classical implementation of the dynamic models in *PSS/E*. Being the most user-friendly option, the GUI implementation tends to be the preferred method for primary frequency control.

Concerning the modeling of AGC operation, a different strategy for implementation is followed, mainly due to the reason that AGC is a centralized control and primary control is a distributed control. This fact implies that several measurements from different points of the grid are provided to the AGC, like tie-line interconnection power flow, which computes new set points and distributes them across the generation units that participate in secondary reserve provision.

PSS/E was the adopted simulation environment for the AGC operation modeling, as it is widely used by TSO to model their networks, and so the implementation of AGC control in this software provides reassurance regarding the obtained results. In *PSS/E*, there are two approaches to the implementation of the desired control actions:

- *Conventional implementation, PSS/E focused*: Internal to the simulation procedures used by the software
- *Python script focused, interacting with PSS/E*: External to the simulation procedures used by the software

To implement the first option, it is necessary to develop a model using *Fortran*,[9] including specific *Fortran–PSS/E* routines and global variables, compile it, and declare its usage in the dynamic simulation data input file for *PSS/E*.

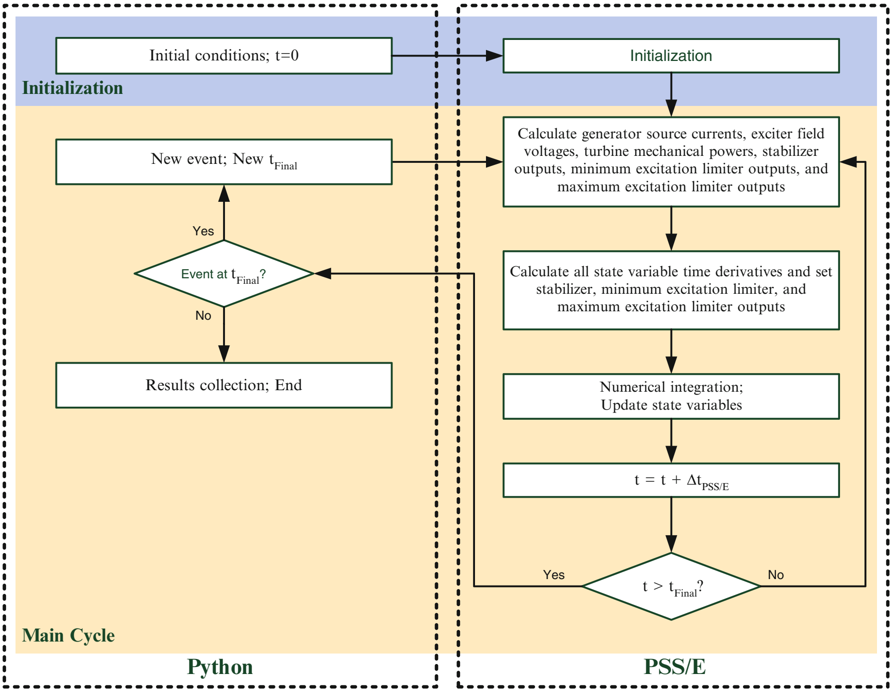


Fig. 6.17 Simulation scheme with conventional modeling, *PSS/E* focused

Following the typical implementation scheme, the developed model gets embedded in the simulation.

This alternative is robust and does not delay the simulation time. The simulation is stopped only when an event, such as load variation or bus fault, occurs. Event file is coded using *Python*.

Figure 6.17 is a flowchart of the simulation process using the conventional model implementation. On the left, the activities external to *PSS/E* operation are presented, whereas *PSS/E* simulation is depicted on the right (this part was adapted from *PSS/E* Operation Manual [25]).

To implement the second option, the dynamic data input file remains unchanged, keeping all the data related to generation.

Advanced modeling is now executed using a *Python* script. Instead of being used only to generate events, the *Python* file is also used to collect the system state evolution and manage control variables.

In opposition to what happened with the *Fortran* modeling, the data collection period, in this case, is user defined and can be as short as the integration period defined internally by *PSS/E*.

To create fast controllers using this implementation, the script must stop the simulation with time steps close to that used by *PSS/E* (using a larger time step means that a larger delay is being introduced to the response time of the controllers).

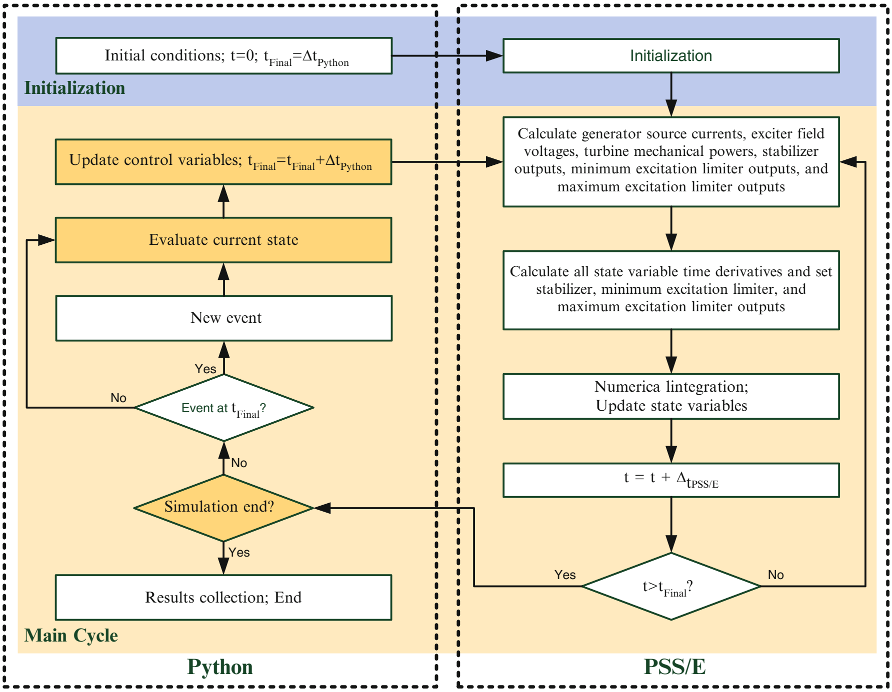


Fig. 6.18 Simulation scheme with Python script modeling, interacting with *PSS/E*

Then, the state evolution is evaluated and used to update the control variables that are passed into *PSS/E*.

Similar to Fig. 6.17, Fig. 6.18 depicts a flowchart of the simulation scheme with *Python* script modeling, interacting with *PSS/E*. The highlighted text boxes are the new functionalities necessary within this approach.

This method is as robust as the previous but more flexible regarding the control options that may be taken. However, external state evaluations and control actions may lead to an increase in simulation time that with nowadays processing capability is not a real drawback.

If EV frequency control droop would be the aim for implementation, the conventional modeling technique would likely be the easiest implementation method, due to the fact that the power electronic interface that is being emulated works in a decentralized way. It reads a local state variable and controls, locally, EV power consumption.

Nevertheless, as AGC operation is sought, a centralized control unit is needed. This unit requires the knowledge of state variables spread over the grid—interconnection power flows and the frequency of the center of inertia of the system. The implementation of such a control unit under the conventional approach is possible, by programming a subroutine of the simulation process of *PSS/E* called CONET. As previously explained, it would have to be compiled along with the rest of the models, but the outputs would have to be treated in a different way when compared with typical local models. In this case, the script included in the CONET subroutine would not deal only with global state variables that allow direct observation in the *PSS/E* post-simulation environment. Consequently, a post-processing work would be necessary within the *Python* script to collect all the data to replicate the state variables necessary to illustrate the reaction of the controller. If this activity is used to implement the controller in the *Python* environment, then there is no need to repeat it, as results get created along with the evolution of the script. Thus, *Python* script modeling, interacting with *PSS/E*, was chosen to model the AGC, and as it involved part of the variables needed to implement the EV droop control, this functionality was also implemented using the same strategy.

6.5 Conclusions

6.5.1 Steady-State Studies

The integration of EV in distribution networks is expected to impact the management and operation of distribution grids. For this reason, the DSO will have to understand the impacts that the extra amount of power consumed by EV will provoke in these systems.

In this sense, two approaches were presented in this chapter to evaluate the EV impacts in distribution networks: Methodology 1 and Methodology 2.

The deterministic approach followed in Methodology 1 to distribute EV along the network buses and determine the EV load during one entire day is appropriate to perform studies in small distribution networks. Yet it is only able to reveal the effects of a possible scenario in what regards the EV locations in the network. Even with these limitations, it allows satisfactorily evaluating the network impacts of a given integration percentage of EV and quantifying the maximum number of EVs that can be safely integrated in a given network with the three charging strategies addressed (dumb charging, multiple tariff, and smart charging).

These limitations were overcome in Methodology 2, which uses a more sophisticated and consistent approach for the same purpose. This improved approach, besides using a Markov chain tailored to simulate the EV movement, also uses a Monte Carlo simulation method that allows exploring different scenarios in what regards the EV locations in the grid and their power requirements. Moreover, this approach allows quantifying the EV impacts in time steps shorter than 1 h, as 1 h is a very long period of time during which the network operating conditions can change considerably. Furthermore, instead of only 1 day, it also allows analyzing the EV impacts in a longer time frame, like 1 week or 1 year.

The algorithm presented based in Methodology 2, besides being fitted for impact assessment studies at a regional level and for the networks' planning exercise, it also includes EV charging management modules suitable to be used in real applications. The referred modules can be used to manage the EV charging in real time by both aggregators and system operators.

From the DSO perspective, the algorithm can be used as a tool for the following purposes:

- Evaluate the impacts of a given number of EVs in a specific regional distribution network, taking into account the charging modes EVs have adhered to.
- Compute the maximum number of EVs that can be safely integrated in a particular network, also taking into consideration their charging modes.
- Detect the network components that are subject to the more demanding operating conditions and that might need to be upgraded.
- Validate the provisional bids of the aggregators.
- Perform grid monitoring and evaluate its operating conditions.
- Define the requests of load increase/decrease to mitigate voltage or line overloading problems that might appear in the network.
- Manage the EV charging in real time (when the system is in the emergency operating state).
- The algorithm might also be very helpful for the aggregators, since it allows.
- Defining the optimal bids for the day-ahead and intraday markets.
- Managing the EV charging in real time (when the system is in the normal operating state).

6.5.2 Dynamic Studies

EVs may be valuable resources in the provision of primary and secondary frequency control, either through the adjustment of their batteries' load charging rates or through the injection of active power into the grid. The activation time of such participation is shorter than that of conventional generators, due to ramping limitations. For that, EVs may be exploited as controllable loads or as storage devices.

While providing ancillary services, the EV behavior on the event of short-circuit disturbances is an important issue. Being the EV approximately constant power loads from a grid-side perspective, this leads to a worst case scenario in terms of voltage drops. As power requirements are constant to compensate for a voltage drop caused by a short circuit, EV will request more current from the grid, contributing for additional voltage drops. So in a future massive integration scenario, this issue may have to be dealt with, by creating new control rules that prevent these hazardous conditions. While EV integration is moderate, in the short to medium term, such considerations are not necessary as the systems may cope with EV load behavior. Additionally, when EVs are ancillary service providers, it is necessary to guarantee their availability to react after disturbances. It was verified that while EVs are regarded as controllable loads, the system behavior is controlled, but if the energy stored in the EV batteries is to be explored, then additional measures must be taken with the inclusion of the fault ride through capabilities.

In primary frequency control, EV in pre-disturbance environment can be charging or in idle operation mode, and when the disturbance occurs, the consumed value varies linearly with the frequency change. To perform primary frequency control, EV should mimic the reaction of the governing systems of the generators, implementing a power–frequency droop on the EV power electronic converter control. The usage of EV in primary frequency control can be particularly important in isolated systems with large amounts of RES that present great output variability or small controllability.

The operation of the AGC is the centerpiece of secondary frequency control. The AGC uses the resources that got committed with secondary reserve provision in the reserve market, and in case of a disturbance, it distributes set points among the participants. As individual EV would not be able to enter the reserve market alone, the aggregator is needed for market negotiations. Aggregator providing secondary reserves receives a set point from the AGC and splits it by the EV that established contracts with the aggregator for secondary reserve provision. To create the set points, the AGC must be constantly updated on frequency value and interconnection power deviations, integrating the error to define the set points that will fade possible steady-state deviations in relation to nominal frequency and scheduled tie-line power. The provision of secondary reserves by EV is potentially beneficial for interconnected systems with limited reserve margins due to large-scale deployment of uncontrollable RES or composed by generators with small ramping slopes.

Finally, simulation capability was described in this chapter with the development of models for EV and an algorithm for recreating AGC operation. These adaptations to existing dynamic simulation software allow testing the expected effectiveness of these control schemes exploiting EV and comparing the global system performance to the conventional approaches to the problem. In both cases, EV controllability will add to existing system controllers, contributing for the robustness and resilience of both isolated and interconnected systems.

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