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Distribution Planning with Hourly Profiles for Analyzing Electric Vehicle Charging Strategies

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***Abstract*— This paper analyzes the impact of plug-in electric vehicles (PEV) on distribution networks. The Reference Network Model is used to model the grids and to carry out sensitivity analysis for several scenarios. The set of scenarios selected includes PEV penetration levels, charging strategies and location distributions. Each scenario is characterized in terms of the number of electric vehicles, the vehicles' class, technical parameters, and charging time. Five large-scale real distribution networks are modeled and analyzed. The topologies selected are intended to be representative of some typical European distribution networks. Results show that the charging strategies are critical. At least new multi-tariff schemes should be established to encourage charging at valley hours. Depending on the PEV location distribution, smart charging may also be necessary to reduce the distribution network costs further.**

***Index Terms*— Electric vehicles; power system; distribution; smart charging; load management; power system planning; model; reinforcements; impact; assessment; hourly profiles; sensitivity; scenarios; large-scale.**

1. INTRODUCTION

Electric vehicles have been the focus of a lot of research as a possible alternative to gradually replace the current transport system. The aspects to be analyzed cover many issues, including the definition of the regulatory frameworks and business models (Gómez et al., 2011). From a sustainability point of view, an appropriate generation mix is required to further reduce emissions. However, some studies also state that even CO_2 intensive scenarios could reduce emissions significantly (Kalhammer et al., 2009). Technically, storage devices are nowadays the main bottleneck for electric vehicles (EVs), and energy density is one of the major issues to be addressed. However this technology has quickly improved in the latest years (Duke et al. 2009). Local and centralized management solutions have already been proposed (Jiang and Wang, 2012, Richardson et al., 2012) in order to coordinate plug-in electric vehicle (PEV) charging. In particular, a load shifting solution has been demonstrated to improve electric vehicle uptake in residential areas from 10% in an uncontrolled charging case to 80% in a controlled charging case (Hoog et al., 2015). There can be several strategies for defining the EV charging strategy, for example, minimizing network peak loads (from a network perspective), or minimizing charging costs (from the perspective of a commercial party) (Veldman et al., 2015). This paper focuses on the network perspective point of view.

An extensive review of the impact of electric vehicles on distribution networks was recently presented in (Green et al., 2011), pointing out that only a few works have focused on the impact of PEV on distribution grids. Cost is identified as an important measurement in many models, as economic viability is one of the change drivers. It also emphasizes the importance of taking into account the exact time of electric vehicle charging. These two aspects of modelling, economic viability and charge timing are included in the analysis described in this paper.

Some analyses have focused on quantifying the technical impacts and benefits on residential distribution grids (Peças et al., 2009, Clement et al., 2010). They highlight the relevance of the charging approach, and the impact of coordinated charging on losses and voltage deviations, with case studies of Portugal and Belgium. They analyze operating magnitudes such as congestion levels and network losses in a given

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network. On the contrary, in the analysis of this paper, the networks are reinforced to accommodate more electric vehicles. Besides, in comparison to 34 node feeder (Clement et al., 2010), we analyze large-scale networks. The impact on United States' Power Grids has already been analyzed (Kintner et al., 2007), concluding that high penetration levels could be supplied using the existing infrastructure. However, in that analysis the grids were not explicitly modelled.

The research in this paper focuses on the analysis of the economic impact of PEV in distribution networks, using large-scale planning models. In general, the problem of planning networks has been extensively researched, but there are only a few studies implementing the planning of several voltage levels simultaneously (Navarro and Rudnick, 2009a,b, Ziari et al., 2011). However, Reference Network Models (RNM) deal with this problem as these models are regulatory tools designed to assess distribution costs of several voltage levels (Levi et al., 2005, Gammerlgard and Solver, 2004, Larsson, 2005, Garcia Conejo et al., 2007, Mateo et al., 2010). From a functional point of view, the models have to connect consumers and distributed generation (DG) to high voltage supply points (usually transmission substations), planning all the voltage levels within the distribution area. These models can be extended to accommodate other types of loads and devices, such as electric vehicles or storage. Although initially designed for regulatory purposes, this type of models can also be very useful for assessing the cost impact of different technologies such as distributed generation (Cossent et al., 2011).

The impact of electric vehicles have already been assessed using RNMs in (Pieltain et. al., 2011). However, this paper contributes with the adaptation of RNMs to analyze planning horizons taking into account 24 hour profiles. Moreover, the models are applied in a wide set of large-scale real distribution networks, integrating also the predicted PEV penetration scenarios and technical data from the European MERGE project (Hasset and Bower, 2011, Ball et al., 2010).

Section II gives an outline of the model and presents the methodology used to assess the impact of electric vehicles in the distribution grids. Section III describes the scenarios selected in the analysis and, subsequently, section IV shows the results obtained for each scenario. Finally, section V summarizes the main conclusions and makes some recommendations.

2. Methodology

In this section the methodology is described and the main electric vehicle parameters are identified. The methodology is based on the use of the RNM presented in (Mateo et al., 2011), that have already been used to carry out several studies of Distributed Energy Resources impact on distribution grids (Cossent et al., 2011, Pieltain et al., 2011). Although these models are already described in detail in these papers, a brief overview is presented in this section.

A. Introduction to the Reference Network Model

The Reference Network Model is a technical tool designed to assess impact cost under incentive regulation. These models have to connect network users (domestic and industrial consumers, DG or electric vehicles) to transmission substations using standard equipments. From a practical point of view, two model types can be defined. The greenfield model type builds a network from scratch, so it can be used to model the initial network. The brownfield model type expands the initial network to accommodate additional network users. The brownfield model can be used to make sensitivity analysis.

The RNM is structured into four different layers, which include several abstraction levels: (i) logical, (ii) topological, (iii) electrical, and (iv) quality of supply. The logical layer comprises the basic network structure, defined as graphs composed of nodes and branches. The topological layer includes information about the geospatial coordinates of each network element. On the other hand, the electrical layer adds the electrical attributes related to the grid. Loads, DG, transformers, cables and overhead lines are all defined in this layer. Finally, the quality of supply layer provides the information about system reliability.

The most critical information required by the greenfield RNM is the location and amount of contracted demand, including high, medium and low voltage (HV/MV/LV) consumers and the location and installed capacity of DG. Furthermore, the location and installed capacity of transmission substations, acting as supply points, are also part of the input data. The brownfield RNM requires data corresponding to the existing network facilities, such as capacity and location of HV/MV substations and MV/LV transformers. It also includes the layout, impedance and capacity of the HV, MV and LV electrical lines and protection devices. Regarding the planning scenario, the new network users also have to be characterized.

The RNM uses a detailed library for standard network facilities for all voltage levels and for each item of equipment: cables, overhead lines, distribution transformers, substation components and protection devices. They are characterized with technical data and with investment costs. These equipments are used by the model to design the reference network from scratch and/or to reinforce the existing network.

B. Model Adaptation

The planning algorithms in previous versions of the models worked assuming a peak instant. Therefore, all the variables in the algorithms were complex numbers. The power of consumers was estimated in a so-called peak hour using simultaneity factors, as explained in (Mateo et al., 2011). This simplification is adequate for standard load scenarios. However, in this paper the impact of different EV charging strategies on network reinforcements are compared. For this purpose it is necessary to analyze not only a peak instant but hourly profiles. Thus, the variables of the algorithms must be vectors of complex numbers.

The planning algorithms compare different network solutions using a branch-exchange technique. Each network topology is a candidate. For each candidate the power flow is typically evaluated, requiring satisfying voltage and thermal limits for every electrical line or transformer. In order to apply the planning algorithms to hourly profiles it is necessary to calculate one power flow and to check electrical and thermal restrictions for each hour.

To sum up, two main model adaptations are made: to increase variables' dimension and to update the restrictions of the planning algorithms. Next, a brief explanation of both adaptations is given.

Related to variables' dimension, an implementation of the envelope/letter paradigm has been made, as explained in (Coplien, 1991), see Fig. 1. Any variable of the algorithms has a value of type CValue. This base class can behave as a complex array (CArray) or as a complex number (CComplex), depending on the context; thanks to an internal pointer to itself. It is very similar to a smart data type. Operations of CArray, CComplex, and between CArray and CComplex have been defined. In this way, most of algorithms do not depend on the type of their variables. They are programmed as if they used CValue. For example, the power flow algorithm can run with hourly profiles or with peak values.

From the planning algorithms point of view three restrictions are added. Once all the power flows are run, equations (1), (2) and (3) describe the evaluation of the voltage and thermal limits, using the maximum or the minimum of these magnitudes.

$$U_{min} \leq Min\left(U_{i,h}\right) \tag{1}$$

$$Max\left(U_{i,h}\right) \leq U_{max} \tag{2}$$

$$Max\left(S_{j,h}\right) \leq S_{max\,j} \tag{3}$$

Where Umin and Umax are the minimum and maximum allowed voltages, Smaxj is the maximum power flow at electrical line or transformer j, Ui,h is the voltage at a node i at hour h, Sj,h is the power flow at electrical line or transformer j and at hour h.

C. Methodology

The methodology used to assess the impact of electric vehicles is summarized in Fig. 2. First, the networks have to be modeled. The main information that is taken into account to build this initial network is the following:

- Every consumer location and contracted power.

- Transmission, HV/MV and MV/LV substations locations.
- Standardized equipment library: electrical lines, substations, etc.
- A set of general technical and economic parameters.

These data are used to build the model of the initial network for each distribution area, using a greenfield RNM. As described in the following section, five distribution areas are analyzed, from rural to urban networks.

The following step is to select the set of scenarios to be analyzed, including sensitivities to several parameters. The definition of scenarios is given in section III, comprising several PEV penetration levels, PEV charging point location, and charging strategies. For each selected scenario the electric vehicles penetration is estimated, setting the number of electric vehicles, the location of every single electric vehicle and their 24-hour charging profiles.

The initial networks are then expanded for each sensitivity scenario to accommodate the new PEV charging points, using the brownfield RNM. The expanded network is planned taken into account network power flows, and voltage and current constraints. The RNM plans new transformers and feeders to accommodate the additional demand in the distribution grid. Finally, network and transformer substation costs are assessed using the standardized equipment library. Costs are broken down into three levels: low voltage feeders, MV/LV transformer substations, and medium voltage feeders. The impact is assessed by analyzing the expansion network costs for each scenario.

For example, Fig. 3 shows a zoom-in of the distribution network in one of the areas analyzed, where LV feeders are in thin black lines, MV/LV transformers are represented by green circles, MV feeders are in thick red lines. Consumers with and without PEVs are represented by yellow and white squares, respectively.

D. Electric Vehicle Parameters

Four sizes of PEVs are taken into account in the analysis, as characterized in (Hasset and Bower, 2011, Ball et al., 2010): (i) L7e quatricycle, (ii) M1 passenger vehicle, (iii) N1 goods-carrying vehicles with a maximum laden mass of 3500kg, and (iv) N2 goods-carrying vehicles with a maximum laden mass 12000 kg.

Each PEV is also characterized by its technology: (i) plug-in battery electric vehicles (PBEV) with no other source than the battery; (ii) plug-in hybrid electric vehicles (PHEV) which use a combustion engine after batteries are depleted; and (iii) plug-in extended-range electric vehicles (PEREV), which use the combustion engine to overcome range limitations. They are all plug-in electric vehicles, which have to be supplied by the electrical distribution grid.

The main parameters that are used to model each electric vehicle are the charging rate and the number of hours required to charge the battery, as shown in Table I. The number of hours required to charge the battery is based on the energy consumption of each electric vehicle and on the distance travelled (Ball et al., 2010). The battery size is a cap for this value.

3. Scenario Description

Several scenarios are studied in order to analyze the impact of PEV charging on distribution network costs. In summary, these scenarios include five distribution networks, three PEV penetration levels for two long term scenarios (years 2025 and 2035), three PEV charging strategies, and two PEV location distributions.

A. PEV Penetration

Three PEV penetration scenarios are taken into account for each year according to (Hasset and Bower, 2011). These scenarios are characterized for different European countries considering the national policies for PEV development and other social and economic considerations. The expected number of PEV for the three scenarios in Spain is shown in Fig. 4: Scenario 1 (Sc1) is a sensible estimate of the PEV uptake that is the most likely to occur in reality; scenario 2 (Sc2) is a more aggressive scenario, which is recommended to use as it may provide better information of the effects for mass integration of PEVs on the grid; finally, scenario 3 (Sc3) is a very aggressive PEV uptake scenario, which is unlikely to be exceeded.

The expected number of PEVs in each scenario is scaled to each distribution area, assuming that the number of PEVs is proportional to the number of consumers in the area. In practice, less PEVs are expected in rural areas than in urban areas. However this is not considered in order to allow comparing the results for the same PEV penetration levels.

B. Distribution areas

A set of representative distribution networks is selected and analyzed. The study cases selected are large-scale real distribution networks, whose topologies are intended to be representative of some typical European distribution networks. The distribution areas comprise: 3 urban areas of different characteristics and sizes (urban-A, urban-B and urban-C), a semi-urban area, and a rural area.

The distribution areas cover large zones. Their main parameters are shown in Tables II and III. The semi-urban area is the largest in terms of consumers, networks lengths, and MV/LV transformers, with about 170,000 consumers and 1GW of installed power. Both the semi-urban and the rural areas have a significant contracted power of medium voltage consumers. All the other areas represent cities, and they predominantly supply low voltage domestic consumers. The urban-A area is the largest urban area, while the urban-C area is the smallest one. Urban-A area includes not only the city itself, but also its surroundings.

The distribution networks are modeled using the greenfield RNM, taking into account the actual location of the consumers, and the HV/MV and MV/LV substations.

C. Charging strategies

Three PEV charging strategies are compared as shown in Fig. 5. The figure only shows the system demand curve, but this curve is the result of a specific charging profile for each single electric vehicle. Extreme scenarios are selected, to allow making a quantitative comparison of the different regulatory policies.

- *Peak charging*. Under this strategy all PEVs are simultaneously charging at the peak hours, from 6 PM until midnight. This scenario represents the consumer’s behavior of plugging-in the PEV when they arrive home. It represents the worst situation when there are no regulatory signals and the customers have no incentive to charge at valley hours.
- *Valley charging*. Under this strategy all PEVs are simultaneously charging during the valley hours, from midnight to 7 AM. In this case the charging of the PEV is such that the PEVs are available in the morning, however, the starting hour is delayed.
- *Smart charging*. In this case the PEVs would charge during the valley hours with a local coordinated control. This control would aim to “fill the valley”, hence guarantee a constant load profile during the valley hours at a system level, to reduce reinforcements as much as possible.

The PEV charging strategies and the consumer profiles are shown at a system level in Fig. 5. Two consumer profiles are modeled: one profile for domestic low voltage (LV) consumers, and another profile for industrial medium voltage (MV) consumers. These daily profiles are based on empirical data publicly available from the Spanish National Energy Commission (Directorate General for Energy Policy and Mines, 2009). Only one single profile is modeled for all consumers of the same voltage level due to the lack of data concerning individual consumers.

D. Electric vehicle location distribution

The PEVs are located on existing network consumers' connections, with two different approaches: random consumer and random bus location. The distribution of PEVs and consumer loads are shown in Fig. 6 and Fig. 7, where the network bus location is on the X axis (ordered by consumer contracted power), and the installed power of consumers and PEVs at each network location is on the Y axis. In Fig. 6 PEVs are located taken into account the number of domestic and industrial consumers in each network bus location; then, more PEVs are placed in network locations with higher demand. In Fig. 7 the PEVs are located randomly in every network bus location.

The first approach is more realistic, as more PEVs are expected in buildings with a higher number of households. However, this approach does not adequately consider local constraints, which may be quite relevant in distribution networks. As the same load profile is used for modeling all low voltage consumers, if the PEVs are also placed proportionally to the consumer demand, then the demand curves of most network buses will resemble the load curve at the system level.

The second approach (shown in Fig. 7) is less realistic, however it captures local constraints. In this case, PEV charging load is higher than consumer load in many network bus locations, and negligible in other locations.

4. RESULTS

In this section, the results of the complete PEV integration in distribution networks are presented. First the influence of the PEV penetration is analyzed. Afterwards, the impact in different distribution areas is assessed. Finally, the influence of the three charging strategies on the system costs is compared.

A. PEV Penetration

The required network reinforcement costs for several PEV penetration levels are presented in Fig. 8. The case study comprises a semi-urban area, with a peak charging strategy and different PEV penetration scenarios, as defined in section III. Incremental reinforcements are presented as a percentage over the total cost of the reference distribution network, in order to facilitate the extrapolation and comparison to other distribution areas.

As expected, the results show that the higher the number of PEVs (Sc3 in year 2035 compared to Sc1 in year 2025) the higher the reinforcements required, both in LV & MV feeders and MV/LV transformer substations. More reinforcements are expected in MV/LV transformer substations, as the capacity of the transformers is a major constraint. The reinforcements needs in the low and medium voltage network range between less than 1% up to 13% for the scenario with the highest penetration (Sc3 in year 2035). Conversely, the need for installing additional transformation capacity varies between less than 1% up to 30% for Sc3 in 2035. These results indicate that PEVs can be easily integrated into the distribution network with very low reinforcement costs for the low penetration scenario (Sc1 in year 2025). An increase in the transformation capacity is needed for higher penetration levels in the semi-urban area analyzed.

The incremental cost in MV/LV transformers for a new PEV connection is presented in Fig. 9. The unit cost for the low penetration scenario (Sc1 in year 2025) is 50 €/PEV connection, while in high PEV penetration (year 2035) there is a cap value of 380 €/PEV. For low PEV penetration levels, the network has some spare capacity and is able to integrate a certain level of PEVs without requiring significant reinforcements. However, as the PEV penetration increases, more reinforcements are required. When the spare capacity is exhausted, the reinforcements required per PEV connection reaches a cap constant value, which is associated with the incremental capacity required. Hence, total reinforcement costs are proportional to the number of PEVs for high penetration scenarios.

The total reinforcement costs according to Fig. 8 would be quite high in the worst scenario, as the percent values are referred to the cost of the distribution networks. However, the charging infrastructure

(PEV connector and connection cable) is in the range of 200 € to 1700 € (Gómez et al., 2011). Therefore, the estimated distribution network costs (in the peak charging scenario) would be similar to the costs of the charging infrastructure.

B. Distribution area influence

In this section we analyze the implications of the network characteristics on the PEV network impact. Five distribution areas are modeled. The distribution network incremental costs are presented in Fig. 10, for the peak charging scenario, and the highest PEV penetration level (Sc3 in year 2035). Network costs include the reinforcements required in LV feeders, MV/LV transformer substations, and MV feeders. The incremental costs are computed over the cost of each network equipment.

The three urban areas show a similar tendency. However, urban-C area is quite small and its medium voltage network is not heavily loaded. Therefore, it can withstand high PEV penetration without requiring MV feeder reinforcements. It is observed that in urban areas LV feeders require more reinforcements than MV feeders. The semi-urban area shows intermediate results between the urban and rural areas, being closer to the tendency of the urban areas.

From the results, it is observed that the rural area would require the higher reinforcement costs, compared with other areas for the same penetration levels. Notwithstanding, this is not expected to be an issue in the short term, as less PEV penetration is expected in rural areas (Hassett and Bower, 2011). In the other analyzed distribution areas, the major constraint for PEV penetration and peak charging is the capacity of the MV/LV transformer. In percentage, the over costs are twice or three times higher than the costs for feeder upgrading. Reinforcements are quite high, in the order of 30%, because year 2035, Sc3, and peak charging were assumed in this analysis.

C. Charging Strategy and electric vehicle location distribution

In this section, the impact of PEV integration on network costs due to different charging strategies and PEV location is studied. The analysis takes into account the highest PEV penetration scenario, corresponding to Sc3 in 2035. Results are summarized in Fig. 11 and Fig. 12, for different distribution areas, PEV charging strategies and PEV locations (as defined in Fig. 6 and Fig. 7, respectively). One can see in both figures that the reinforcement costs for charging at peak hours are quite high, while for smart charging they drop close to zero.

When PEVs are located randomly to consumers (Fig. 11), there are almost no local issues. Smart charging is the optimal option with no reinforcements required, except for the rural distribution area, where some transformation capacity is still required. Shifting the charging to valley hours results in similar very low network costs for all distribution areas. Finally, as indicated in the previous sections charging at peak hours requires the highest investments, which can reach up to 35% of network costs for rural and semi-urban networks.

In the analysis shown in Fig. 12 local issues are also considered, by simulating PEVs in consumers with low demand. In this case, peak charging and smart charging costs increase, but they are still maxima and minima as in the previous analysis. However, valley charging reinforcements are quite different. In this case, valley charging would reduce network costs compared to peak charging, but a smart charging strategy could reduce network costs even further.

For any of the previous scenarios, if PEVs are charged during peak hours, network reinforcements are generally required, as there is a direct increase in the peak load of installations. However with valley PEV charging, reinforcements are only required when the demand at previously valley hours surpass the demand at previous peak hours. In the system demand curves (Fig. 5) the demand at valley hours is lower than the demand at peak hours, even when vehicles are charged at valley hours. Therefore, valley charging only requires significant reinforcements when there are local issues, such as high PEV demand in network bus locations with little customer demand (Fig. 7).

Finally, if the system demand curve needs to be replicated locally, reinforcements are expected to be rather low if PEV charging is at valley hours. In this case, a multi-tariff scheme for PEV charging would be a fair alternative, as the smart charging strategies have similar benefits but may require higher investments in communications. However, if PEVs are charged at consumers' houses, which currently have low demand, costs may increase significantly, even in valley charging scenarios. In this case, this would bring out the necessity of smart charging in order to reduce distribution network investment costs.

5. CONCLUSIONS

This paper contributes with the adaptation of RNMs to analyze planning horizons taking into account 24 hour profiles. Two main adaptations are made. One related to variables' dimension and another related to restrictions of the planning algorithms. Besides, the models are applied in a wide set of large-scale real distribution networks, integrating also the predicted plug-in electric vehicles (PEV) penetration scenarios and PEV technical data from the European MERGE project.

The impact assessment shows that the plug-in electric vehicle (PEV) charging strategy is a critical issue to be considered for the massive integration scenarios. If no incentive actions are taken, consumers would usually charge the PEV when they go back home. In this case, the reinforcements required to accommodate high penetrations of PEVs would be quite high, up to 30% in year 2035 for the higher penetration levels.

Concerning valley charging an interesting result is obtained. If PEVs are placed in network locations with many consumers, charging at valley hours is enough to almost eliminate the need of reinforcements. However, if the system demand curve is not replicated locally (i.e. several PEVs are placed in network locations with little consumer demand), then smart charging is required to sufficiently minimize network reinforcements.

The comparison of the distribution areas also shows that rural areas cannot accommodate high PEV penetration levels, although this is not expected to happen in the short term. By contrast, in urban areas the capacity of the medium to low voltage transformer substations turns out to be the major constraint, followed by low voltage feeders.

The analysis of the penetration levels shows that the total reinforcements would be quite dependant on the final number of PEVs. When the spare capacity of the networks is exhausted, total reinforcements would be roughly proportional to the number of PEVs.

Finally, results show that PEV charging tariffs should encourage charging at valley hours as opposed to charging at peak hours. However, a simple dual-tariff (peak and valley periods) has the drawback that many consumers may connect at the beginning of the valley period, which could result in a demand even higher than the previously peak hour. Therefore, making use of the smart-meters' capability, a new multi-tariff scheme would be required so that consumption is spread all along the valley. From the point of view of technology, PEVs should be equipped with a simple timer to allow customers to select the starting or finishing charging hour.

Moreover, in some scenarios smart charging could reduce network costs even further, with a local control aiming to fill the load during the valley hours. Under this strategy a detailed cost-benefit analysis may be required to evaluate if the network savings compensate the communication and smart control infrastructure.

6. LIST OF SYMBOLS

Sj,h	Power flow at electrical line or transformer j and at hour h.
Smaxj	Maximum power flow at electrical line or transformer j
Ui,h	Voltage at a node i at hour h
Umin	Minimum allowed voltages

Umax Maximum allowed voltages

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I. BIOGRAPHIES

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TABLE I. TECHNICAL CHARACTERISTICS OF THE ELECTRIC VEHICLES ANALYZED.

Vehicle	Mean Battery Capacity [kWh]	Energy consumption [Wh/km]	Distance travelled [km/day]	Standard Charging Rate [kW]	Number of Charging Hours per Day
L7e – PBEV	8.7	112.2	27.4	3	1
M1 – PBEV	29.0	160.8	38.3	3	2
M1 – PHEV	8.2	156	38.3	3	2
M1 – PEREV	17.0	253	38.3	3	3
N1 – PBEV	23.0	160	56.0	3	3
N1 – PHEV	8.2	160	56.0	3	3
N1 – PEREV	17.0	160	56.0	3	3
N2 - PBEV	85.0	590	136.0	10	8

TABLE II. NUMBER AND POWER OF CONSUMERS IN EACH DISTRIBUTION AREA.

	Number of Consumers		Installed power of consumers (kW)	
	LV	MV	LV	MV
Urban-A	106,978	197	564,913	3,133
Urban-B	34,567	355	227,004	4,958
Urban-C	8,173	212	53,785	1,638
Semi-urban	154,984	15,171	816,663	204,538
Rural	25,637	921	120,987	41,293

TABLE III. MV&LV FEEDERS AND SUBSTATIONS

	LV Feeders	MV Feeders	MV/LV Transformer Substations	HV/MV Substations
	km	km	Number	Number
Urban-A	678	780	838	13
Urban-B	313	285	412	2
Urban-C	31	60	93	3
Semi-urban	1,058	600	1,089	7
Rural	378	567	267	3

Fig. 1. Classes for storing several types of values.

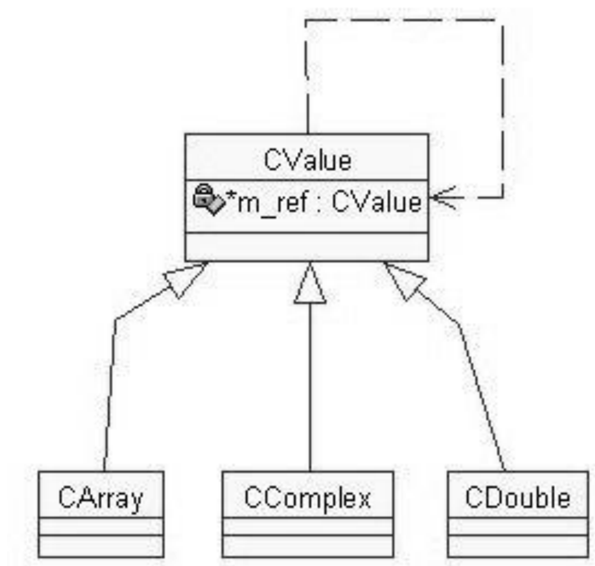

Fig. 2. Methodology.

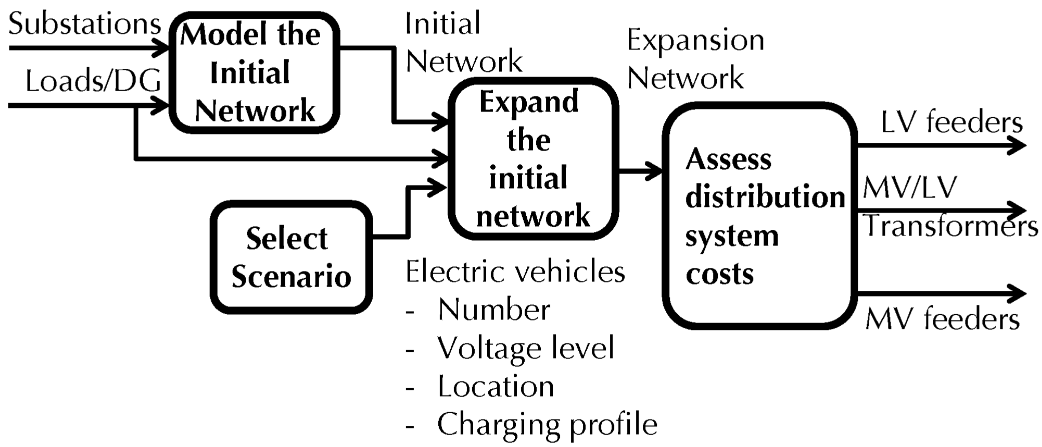

Fig. 3. Zoom-in of the Urban-A Area.

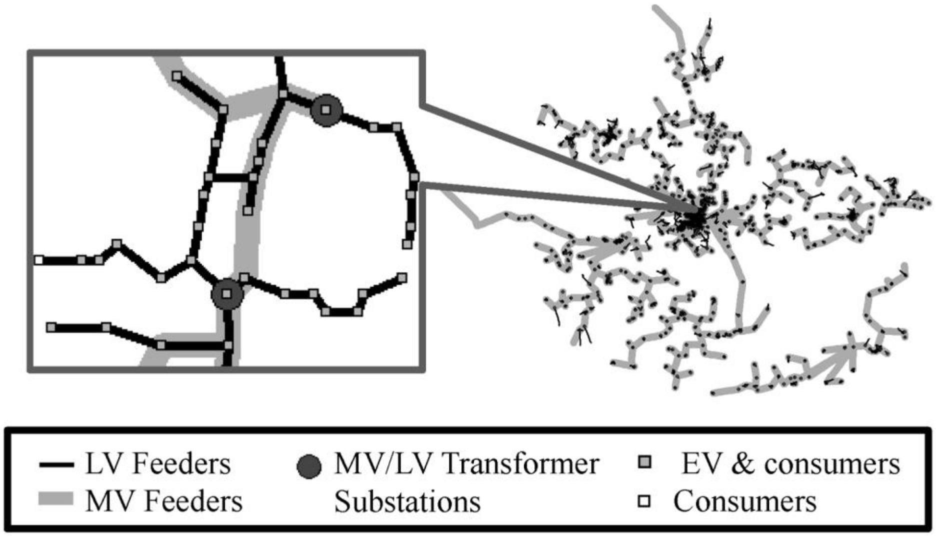

Fig. 4. Electric vehicle scenarios in Spain.

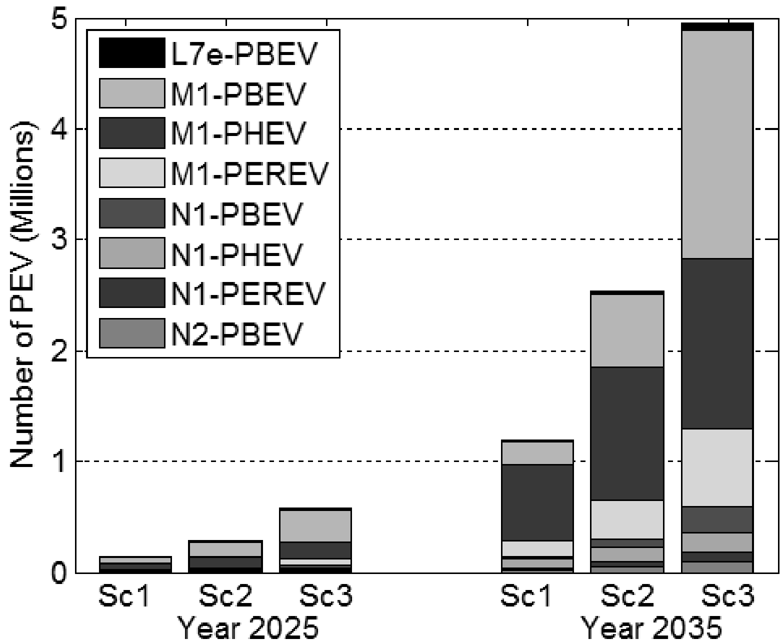

Fig. 5. Electric vehicle charging strategies.

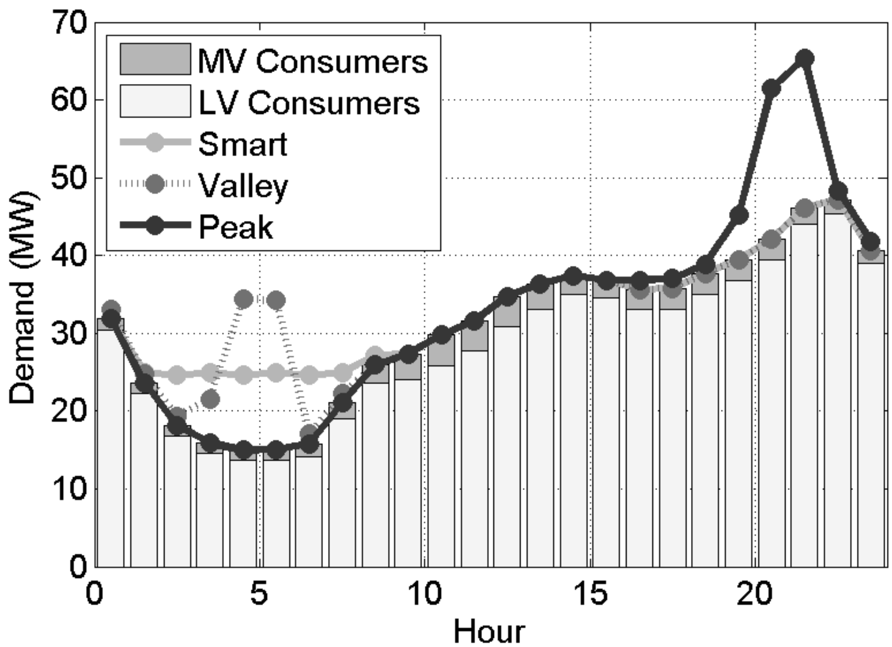

Fig. 6. Electric vehicle located randomly for each consumer.

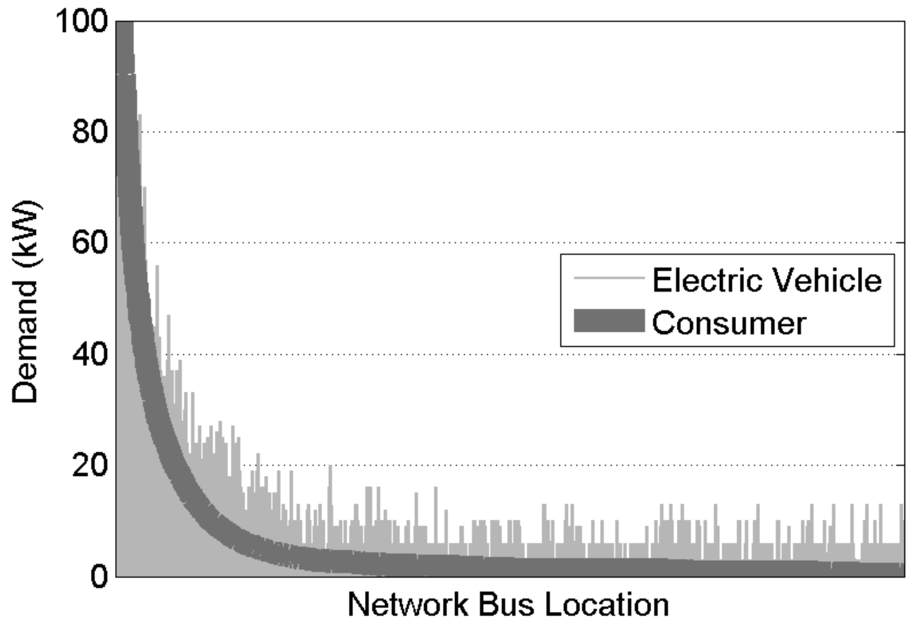

Fig. 7. Electric vehicle located randomly for each network bus location.

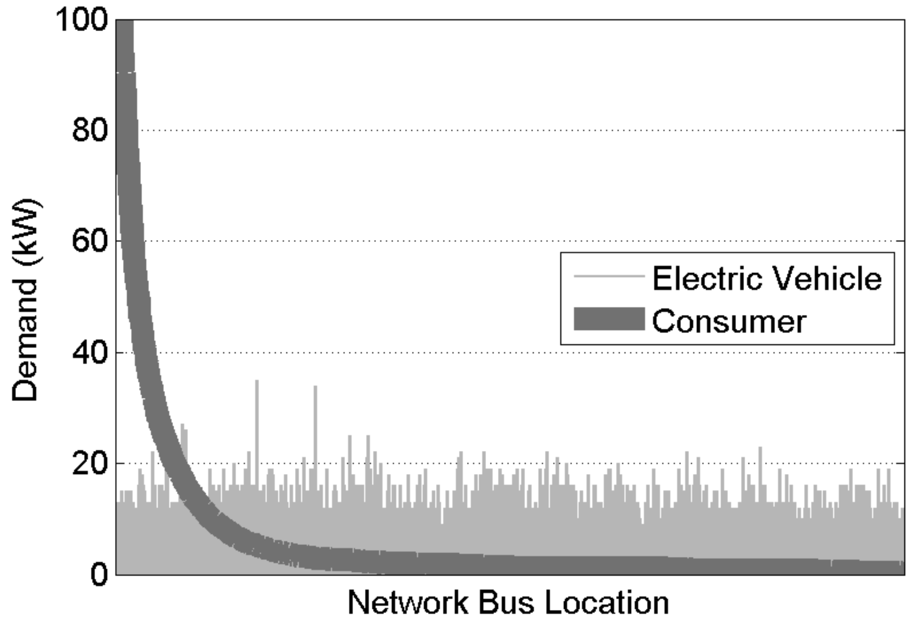

Fig. 8. LV feeder, MV/LV transformer substation and MV feeder reinforcements for each PEV penetration scenario, in the semi-urban area using peak charging.

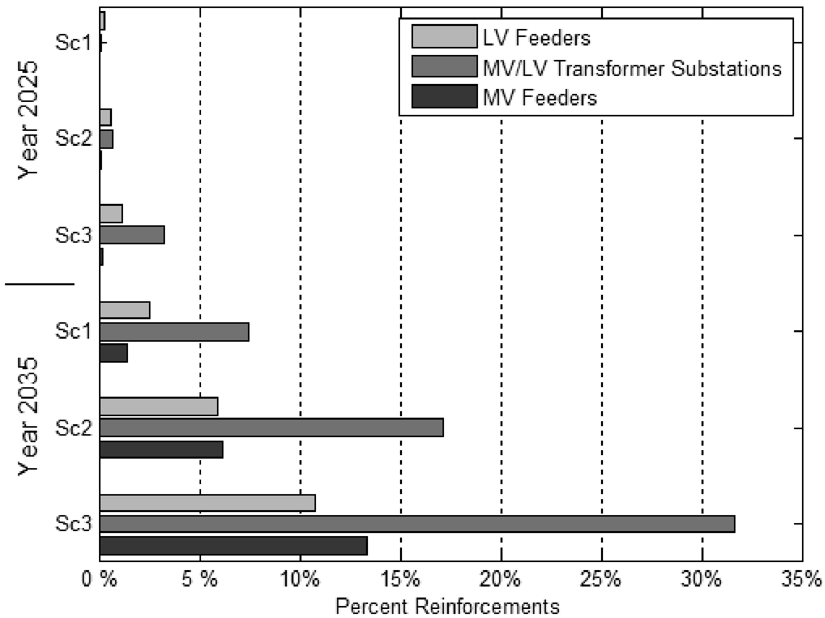

Fig. 9. MV/LV transformer substation reinforcements per electric vehicle in the semi-urban area using peak charging.

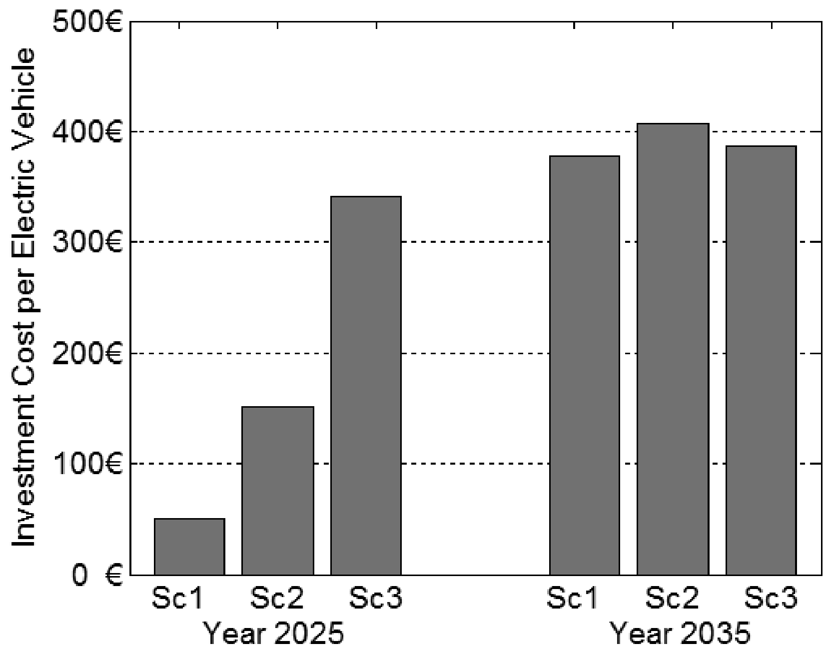

Fig. 10. Investment costs in the distribution areas using peak charging, in scenario Sc3 and year 2035.

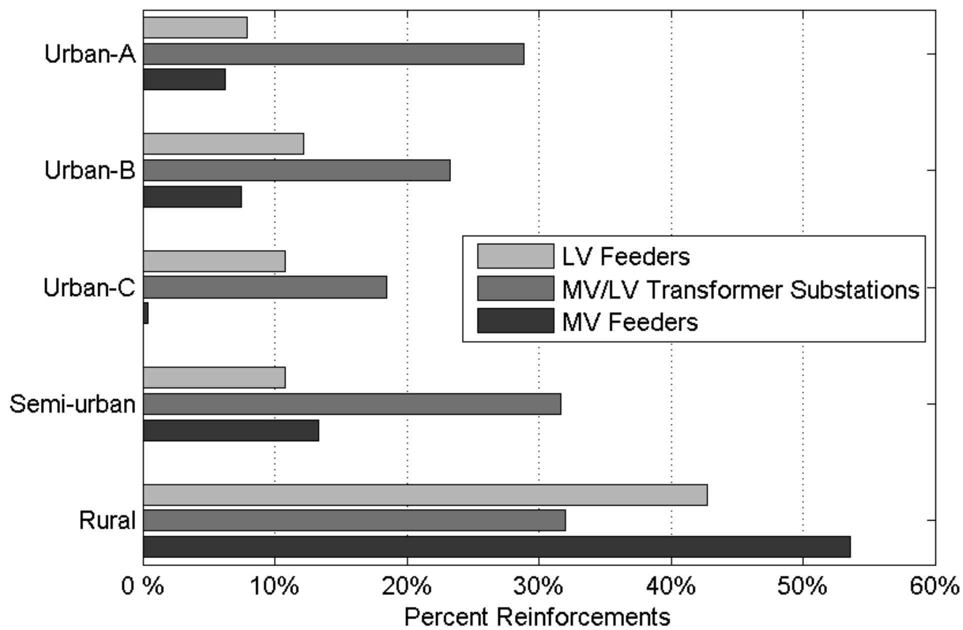

Fig. 11. Investment costs in MV/LV transformer substations in the distribution areas for three charging strategies in scenario Sc3 and year 2035. PEVs located randomly for each consumer.

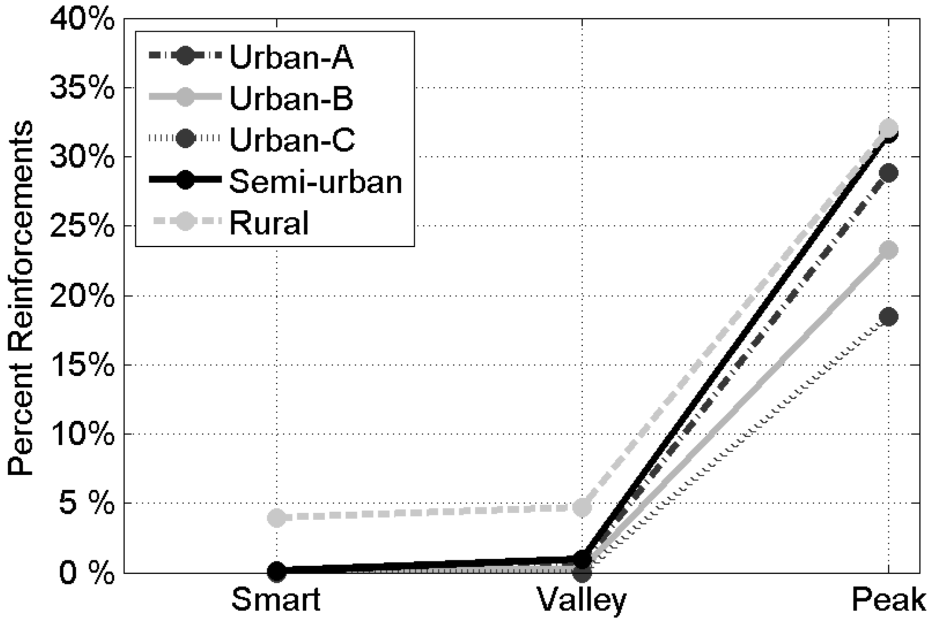

Fig. 12. Investment costs in MV/LV transformer substations in the distribution areas for three charging strategies in scenario Sc3 and year 2035. PEVs located randomly for each network bus location.