PLANNING OF FAST CHARGING STATION PLACEMENT

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ABSTRACT

The concept of electrical-mobility is becoming even more attracting worldwide and Fast Charging Stations (FCSs) will start appearing in the near future directly connected to MV networks. Consequently, a correct expansion plan of the electric distribution system cannot pass over the knowledge or the prediction of the consumption of this new load. In the paper, daily demand profiles of the FCS, modelled by the authors in a previous work, are used in a new planning tool to find the optimal allocation of public fast charging stations in a given network structure. The tool applies an evolutionary Multi-Objective philosophy, based on the Non-dominated Sorting Genetic Algorithm-II, in order to minimize the negative effects of concentrated and intense absorptions of power in the FCSs across the distribution network without penalizing their diffusion in the urban texture.

INTRODUCTION

The global warming problematic and the increasing trend and high volatility of the fossil fuels prices are leading policy makers to ensure an increase in the renewable sources exploitation and to promote, simultaneously, the conventional vehicles replacement by Electric Vehicles (EVs). However, while their integration in moderate quantities does not provoke any considerable troubles, their broad adoption would most likely create some drawbacks in grids' operation and management, like congestions, low/high voltage issues and load imbalances between phases, [1]. These problems may become a reality in the next decades since, according to the International Energy Agency projections, the sales of passenger light-duty EV will boost from 2020 on and might reach more than 100 million of EVs sold per year worldwide by 2050.
From the grid point of view, key questions are when and where drivers will recharge their vehicles. The primary source of charging will rely on normal charging boxes, located at home or in the parking at work and operated manually by the driver or, preferably, remotely managed by a suitable control system. In both cases, 3 kW AC slow chargers will be spread in the LV system (home chargers) or concentrated in some parking lots and connected to the LV or MV networks. Alternatively, fast charge will occur when previous charging options are not available or when, in the middle of a trip, the battery approaches minimum SoC (State of Charge). Fast charging refers to DC charging poles with nominal power equal to or higher than 50 kW. Consequently, a Fast Charging Station (FCS) will be characterized by high momentary peak power absorptions (multiple poles charging simultaneously) and they must be connected to MV networks.
For those reasons, new tools are needed to assess the EV impact on the electric distribution network and to correctly plan the expansion of the power system. On this topic is mainly focussed the research project partially described in this paper. The first step of this activity has been a careful definition of a daily profile of the power absorbed by a FCS, in order to achieve a good knowledge of the behaviour of this new kind of load avoiding cost-ineffective network investments and/or power quality deterioration. In [2] the authors presented a Monte Carlo simulation methodology able to consider several aspects that may influence the request of fast charge. At the end of this stochastic process, a daily load profile is obtained described by an expected power absorption and a relative standard deviation for each interval. This representation is fundamental for the planning process of the future Smart Distribution Systems that requires probabilistic models for a better representation of the uncertainties in the planning data, and the introduction of the risk concept in the selection of planning solutions [3].
In the paper, this representation is used by a new planning tool for the optimal allocation of FCSs in a given network structure. The tool applies an evolutionary Multi-Objective (MO) philosophy based on the Non-dominated Sorting Genetic Algorithm-II (NSGA-II), in order to minimize the negative effects of concentrated and intense absorptions of power in the FCSs across the distribution network without penalizing their diffusion in the urban texture. In order to improve the results of the allocation, the optimization procedure is also able to use the main attributes of the traffic streams (e.g. patterns, density, and velocity) in different sectors of the examined territory to choose the most fitting FCS's consumption profile.
Ultimately, the proposed tool will have not only the power to optimize fast charging station locations with respect to different mobility and regulatory scenarios but also to identify the critical limits of EV penetration in a given MV system.

DEFINITION OF FCS LOAD PROFILES

In every power system planning study it is essential the characterization of all customers in terms of electric power consumed or generated. For new loads, like the

FCS, where historical statistics are not available, this could become a critical issue because an incorrect representation can easily take to underestimate or overestimate their impact on network planning and operation. As briefly described in the previous section, in [2] the authors presented a Monte Carlo simulation methodology able to consider several aspects that may influence the request of fast charge for EVs: the driven distance of each journey, the speed and the gas consumption (that depend on the driving style), the departure time, the initial SoC (taking account also of the existence of home charging facilities), the SoC threshold that induces the driver to recharge its EV, the possible occurrence of a queue in the FCS during peak recharging hours, and some others. At the end of this stochastic process, the methodology gives a daily demand profile with an expected demand value and a standard deviation for each interval (Fig. 1).

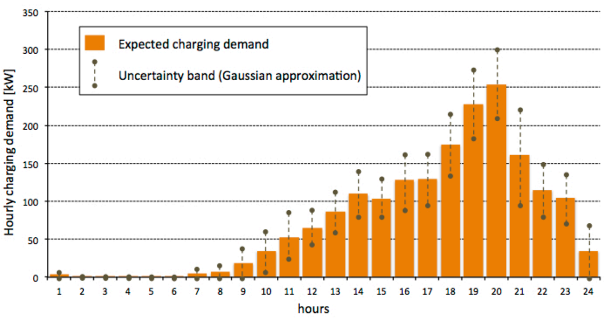

Fig. 1 - Example of the daily power demand profile of a FCS calculated in a region with a traffic stream of 20000 EVs (80% of commuters and 20% of non regular drivers), an average daily covered distance of 100 km and 100% of domestic slow charging availability (hypothesis: charging pole always available – no waiting time).

If no limit is given on the number of FCSs, the methodology assesses the daily demand profile associated with the total energy request for fast charging. Then, this profile is scaled to the single FCS assuming that the overall consumption is equally distributed among the charging infrastructures (the EVs are uniformly spread in the area). By so doing, the methodology estimates the minimum number of FCSs that avoids the occurrence of vehicles' queues for recharging (no waiting time). On the other hand, if a fix number of FCSs is imposed lower of the previous ideal number, the maximum values of the demand in each hour of the load profile is bounded to the maximum power available, and some saturation effects start to appear delaying the time of recharge for some EVs. In these cases, the average duration of the fast recharge increases due to the time spent on the queue, and an average waiting time can be estimated for the specific FCS configuration.

OPTIMAL ALLOCATION OF FCS WITH NSGA-II

A software tool for the optimal allocation of distributed resources, developed by the authors in the past years [4], has been adapted to the optimal allocation of FCSs.

The optimization algorithm is based on a MO technique named NSGA-II. Its peculiar aspect is the classification procedure of the individuals of a generic population (fitness function), based on the concept of Pareto dominance. If the coordinates of a vector $x \in \Re^n$ measure negative attributes, x Pareto dominates a vector $y \in \Re^n$, indicated as $x \prec y$, when $x_i \leq y_i$ for all coordinates i, with strict inequality for at least one coordinate. If an alternative x is not Pareto dominated in a given set of alternatives, it is Pareto optimal. By referring to the topic of the paper, an alternative is a particular allocation of FCSs, whereas the coordinates are the value of the OFs assessed for this FCSs' placement. Thus, the Pareto optimal set (front) of individuals is constituted by those solutions that cannot be improved in any OF without deteriorating some of the other OFs considered. The NSGA-II algorithm sorts a population into different non-dominated levels or fronts (the non-domination rank). Initially, it finds the Pareto optimal set of the current population; then, it excludes temporarily these solutions and searches again the Pareto optimal set among the remaining individuals of the population. This process is repeated until all fronts are identified and associated to all individuals. In order to allot a unique fitness value to each solution, a second attribute is calculated that orders the individuals in each front on the basis of their density along the front (crowding distance).

The typical genetic operators of Selection, Crossover, and Mutation are applied to an initial parent population in order to form a new offspring population. Then, the solutions of the two sets are compared in order to form the new population of parents. This evolution process is repeated for a prefixed number of generations or until no significant improvements have been found in the optimal Pareto set.

Coding of a solution

In the optimal allocation proposed, the network topology is assumed fixed, all the branches are known, and the evaluation of the objective functions depends only on size, expected daily demand profile and location of FCSs. For those reasons, each solution has been coded by using a vector, whose size is equal to the number of MV/LV nodes, in which each element contains the information on the presence of a FCS unit.

Daily demand profile for each FCS

The aforementioned methodology for the definition of the daily fast recharge profile assumes the same shape for all the charging stations in a generic region. However, thinking to the traditional petrol stations in a typical city, this is not true, and the exploitation of the filling infrastructures depends on the traffic streams. Therefore, in order to make the allocation results more linked to a specific territory, a rough representation of the EV's traffic flows has been used: the MV substations of the electric distribution network have been classified into three sub-areas characterised by different EV numbers (high, medium and low density). Then, given a genetic individual (FCS configuration), it is known the ratio between the numbers of EVs and fast charging stations in each sub-area, allowing the algorithm to assign a specific daily profile to all the FCSs in the corresponding sub-area.

Objective Functions

The MO optimization has been conducted by representing the goals of three different stakeholders: the Distribution Network Operator (DNO), the FCS owner and the EV drivers.

The DNO's perspective

The appearance of FCSs on the MV distribution networks is seen by the DNO as a sudden increment of the total load to supply. Thus, the preference of the DNO is that the FCSs are few and favourably placed so as to minimize their impact on the network costs (both CAPEX and OPEX). The Net Present Value (NPV) of the network investment, C_U, is calculated with (1):

$$C_U = \sum_{j=1}^{N_{branches}} C_{0j} = \sum_{j=1}^{N_{branches}} \left(B_{0j} + M_{0j} - R_{0j} \right) \tag{1}$$

where $N_{branches}$ is the number of network branches, C_{0j} is the net present cost of the j^{th} branch, and B_{0j}, M_{0j}, and R_{0j} are respectively its building and management costs and its residual value transferred to the cash value at the beginning of the planning period by using economical expressions based on the inflation and the interest rates. The NPV of the cost related to the total energy losses in the whole planning period, C_L. is determined with (2):

$$C_L = \sum_{h=1}^{N} \alpha^h \cdot c_{L\_kWh} \cdot E_{L,h} \tag{2}$$

where c_{L_kWh} is the unitary cost of the energy losses, $E_{L,h}$ is the total energy loss in the h^{th} year of the planning period of N years, and α is the actualization rate. In order to simplify the calculation, only the natural growth of the existing traditional load has been considered, whereas the number of EVs (and consequently the shape of the daily charging curve) has been assumed invariant in each year.

The FCS owner's perspective

Clearly, the objective of an investor on FCS is its earning maximization. Hence, he presses to build the charging infrastructures where the traffic streams are more intense (typically, in the main gates of the city). In order to give this goal the canonical form of a function to minimize, this second Objective Function (OF) has been expressed as the difference between the FCS building cost, C_{FCS}, and the revenue from the charging service, R_{FCS}. The first term is evaluated in (3):

$$C_{FCS} = \sum_{s=1}^{N_{FCS}} c_{FCS\_kW} \cdot P_{FCS,s} \tag{3}$$

where N_{FCS} is the number of FCS connected, $P_{FCS,s}$ is the nominal power of each FCS, and c_{FCS_kW} is the unitary building cost per kW of the FCS. As assumption, all the charging infrastructures are built at the beginning of the planning period. The revenue gained by the charging service is evaluated in (4):

$$R_{FCS} = \alpha \cdot \frac{1-\alpha^N}{1-\alpha} \cdot \left(\sum_{s=1}^{N_{FCS}} r_{FCS\_kWh} \cdot E_{FCS,s} \right) \tag{4}$$

where $E_{FCS,s}$ is the annual energy sold for recharging (FCS consumption) that depends on the FCS daily load profile, and r_{FCS_kWh} is the unitary revenue per kWh.

EV drivers' perspective

From the point of view of EV drivers, the charging stations should be easy to reach and with a charging pole always available in order to recharge their battery immediately. Thus, their wish is to have as many FCSs as possible uniformly spread on the territory. This goal has been formalized with the minimization of the time needed to recharge. Excluding the technical time for recharging the battery (that depends on the fast charging power and the SoC of the battery), this OF is composed of two terms: the waiting time at the FCS due to the presence of other EVs, and the time necessary to reach the FCS. Consequently, the EV drivers' perspective has been expressed by (5):

$$OF_{EV} = \frac{\sum_{a=1}^{N_a} T_{wait,a} \cdot N_{FCS,a}}{\sum_{a=1}^{N_a} N_{FCS,a}} + T_{FCS\_arrive} \tag{5}$$

where N_a is the number of sub-areas of vehicles' density into which the territory (e.g. the city) has been divided, $T_{wait,a}$ is the average time that EV drivers have to wait before charging, estimated by the Monte Carlo methodology previously described on the basis of the density of EVs and the number of FCSs ($N_{FCS,a}$)in the a^{th} sub-area, and T_{FCS_arrive} is the average time needed to reach the FCS and to start the charging operation. If in the a^{th} sub-area no FCSs are present, this time has been assumed very large.

CASE STUDY

The network considered for the study is the representative urban network for the Italian MV distribution system, developed in the ATLANTIDE project [5]. A primary substation, with a 40 MVA transformer, feeds 96 MV nodes grouped into eleven feeders (Fig. 2). A mix of residential, commercial, offices, and small industrial customers absorbs 18 MVA at the peak of the starting year, with a constant power demand growth rate of 2% per year in the whole planning period of 10 years.

Considering that domestic slow charge will be the

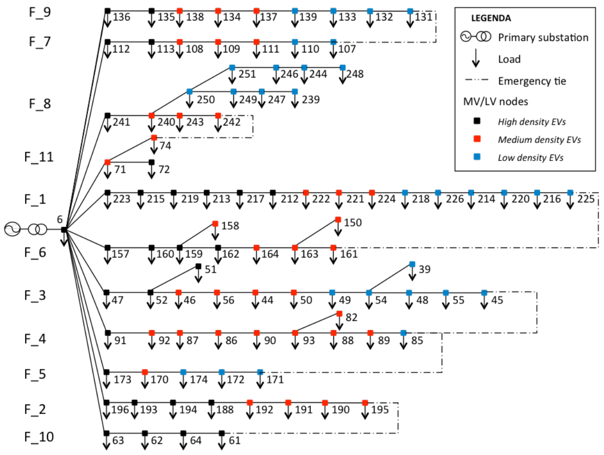

Fig. 2 - Urban representative distribution network.

preferred charging option, the drivers that prevalently use the FCS will be commuters. The extension of the region, which commuters come from, allows identifying an average covered distance and its variability, which strongly influence the shape of the FCS load profile. In the simulations, 5000 EVs pass daily through the area covered by the distribution network, most of them being commuters (80%) with an average covered distance of 30 km. The network nodes have been classified in terms of EVs density in three sub-areas: 5000, 3000 and 1000 EVs respectively for the high, medium and low density sub-areas. In order to simplify the analysis, every FCS has 6 charging poles of 50 kW for a total nominal power of 300 kW. The life cycle of the charging facility has been assumed equal to the planning period. The unitary building cost of the FCS has been assumed 400 €/kW, whereas the unitary revenue of the recharging is 0.1 €/kWh. The set of different daily demand profiles, parameterized in terms of EVs per FCS, are depicted in Fig. 3. All the cases not included in this set have been obtained scaling the nearest charging profile.

RESULTS AND DISCUSSION

The MO optimization has been carried out assuming a population size of 500 individuals and a maximum number of genetic iterations equal to 50. The Pareto optimal set of solutions is illustrated in Fig. 4, Fig. 5 and

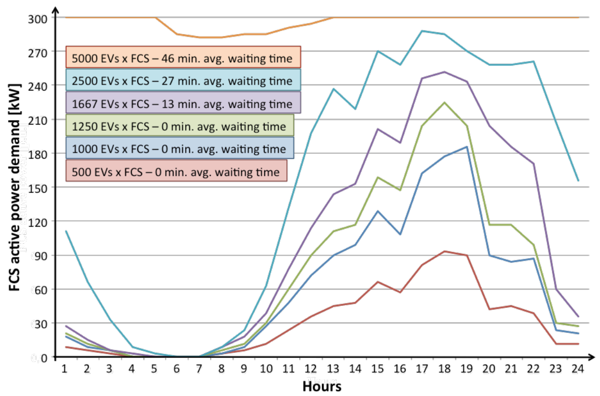

Fig. 3 - Set of daily recharge profile for different EVs' concentrations.

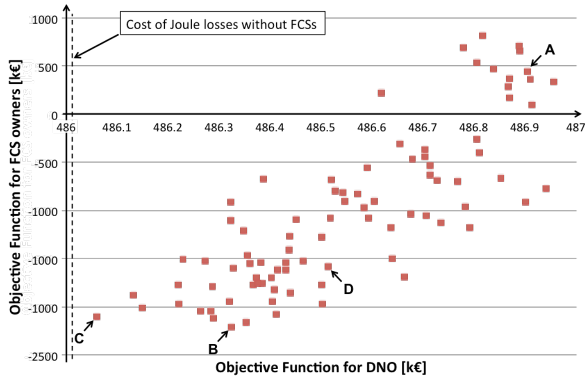

Fig. 4 - Optimal Pareto set: DNO vs. FCS owners.

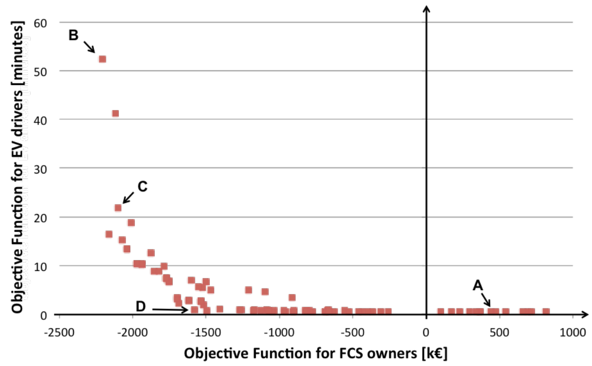

Fig. 5 - Optimal Pareto set: FCS owners vs. EV drivers.

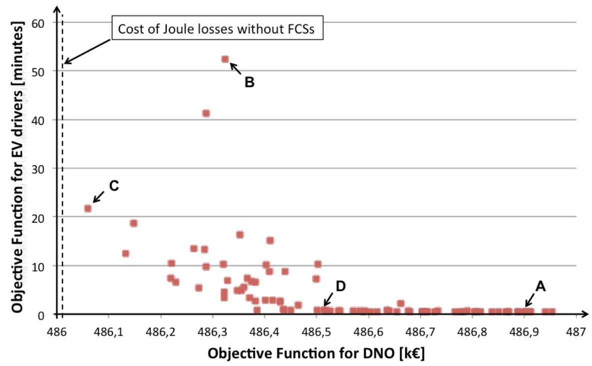

Fig. 6 - Optimal Pareto set: DNO vs. EV drivers.

Fig. 6 for all the three possible pairs of Objective Functions. An in depth analysis of the solutions, often assisted with a Decision Theory tool, allows the planner to select the most adequate according to his goals or the best compromise over the Pareto set.

Looking at the DNO's point of view, it can be observed that the Italian representative urban network appears electrically strong. Indeed, for any solutions of the Pareto set (but also for the other configurations examined during the MO optimization) no network upgrades are required due to the installation of the FCSs. In other word, the existing conductors and transformers are abundantly oversized to hold the increase of demand related to the EVs' fast charging. This result has a general validity for big cities, where the services' infrastructures are typically designed to meet the natural growth of the demand for several years,

but it could fail in urban contexts with medium or small load density, for which this oversize is lighter. Moreover, it must be observed that the absence of network upgrades is also motivated by the non-coincidence of the peak demand between the FCS and the existing load profiles (the first occurs at 18:00 whereas the latter is shifted towards 21:00). However, a full analysis should consider also the additional demand of the domestic slow charge, disregarded in this paper.
In any case, due to this result, the DNO Objective Function depends only on the cost of the Joule energy losses. Its generalized minimum increment for all the solutions over the existing value (without FCSs) confirms the robustness of the distribution network and the good placements obtained from the optimization. The best configuration (solution C) is identified by a minimum number of FCSs (three, one for each sub-area) connected in the feeders with the lowest energy demand (Fig. 7), conditions that allow minimizing the overall energy losses.
A careful inspection of Fig. 4 shows that the goals of DNO and FCS owners are in good agreement. In fact, also for FCS owners there is convenience to install a low number of charging facilities in order to limit their investments and maximize their incomes. The best configuration (solution B) is characterized by three FCSs connected in the sub-areas with medium or high traffic density (Fig. 7). This behaviour is corroborated by the worsen solutions (those with a positive value of the Objective Function that corresponds to a net economic loss), all marked by a high number of FCSs (always greater than 30). In the development of this research, the goals of these two stakeholders could be more differentiated by modelling those commuters that decide to recharge their EVs outside the urban boundaries each time they encounter a queue to recharge. In this case, the FCS owners will tend to install the minimum number of charging facilities that avoids or limits these events.
Finally, in absolute contrast with the previous stakeholders, the EV drivers aspire to maximize the number of FCSs so as to minimize the charging time. In

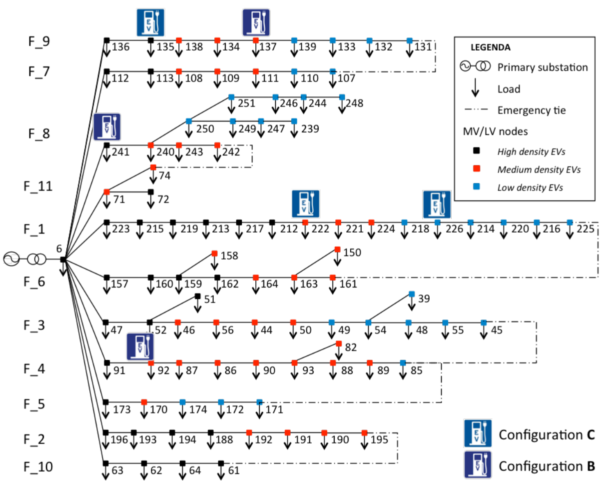

Fig. 7 - Best FCS configurations for DNO and FCS owners.

fact, the best configuration (solution A) exhibits 39 FCSs optimally spread on the network with absence of queues and a reduced average distance to the nearest charging facility.
A good compromise among contrasting goals can be generally found in the knee of the Pareto front. For instance, solution D corresponds to a configuration with 12 FCSs sufficient to minimize the risk of queue occurrence at the charging stations, to produce a good profit to the FCS owners and to keep acceptable the impact of the fast charging facilities on the distribution network.

CONCLUSIONS

The definition of a Fast Charging Station daily load profile has been the first step of a more complex study that aims at identifying the optimal number and position of FCS in given area taking account of the expected consumption for fast recharge. Since the effective FCS power demand is directly influenced by the number of charging facilities available as well as by the traffic conditions, an integrated probabilistic planning algorithm is proposed for the optimal placement of FCSs. The proposed methodology, based on a Multi-Objective approach, allows considering multiple contrasting goals in order to drive the research towards a configuration not only economically and technically convenient but also robust in respect to the selected objectives.

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