SOFTWARE FOR THE OPTIMAL ALLOCATION OF EV CHARGERS INTO THE POWER DISTRIBUTION GRID

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ABSTRACT

Smart Grids development is strongly positioned as a way to achieve the global objectives of increasing efficiency of the power grids and improving the integration of distributed energy resources into the grid. One of the branches of development into Smart Grids is based on the energy storage; its purpose is to contribute to the energy balance making possible a simpler control tool. On this sense fully electric vehicles (FEV) are strongly positioned as the solution for energy storage in power distribution grid. That is why automobile industry, electric system operators and governments are striving to develop competitive infrastructure for fully electric vehicles integration.

This paper presents a tool developed for the optimal allocation of different types of charging stations (CSs) into a real medium voltage (MV) power grid from Slovenia. This tool includes a study of the impact of this optimal solution on the grid not only under an electrical point of view but also taking into consideration geographical and demographic parameters. In particular, this paper presents the specifications of the algorithm included in this tool and shows results and conclusions concerning to the MOBINCITY project.

INTRODUCTION

The fast development of the global society is producing a faster growth of the global energy demand due to the fact that developed countries have greater energy consumption per capita than less-developed countries (Figure 1). This fact produces a disturbing environmental problem together with the increase of the difficulty of controlling the energy balance between generation and demand. If we add to this situation the integration of Distributed Energy Resources (DER) and Fully Electric Vehicles (FEV) in the network, it seems obvious that a change on the current power grids evolving in Smart Grids is necessary [1].

Summarizing, the main challenges that Smart Grids will face are the increasing presence of DER (mainly renewable energy sources), the integration of a large number of FEV in the network and the need of improving security on energy supply and reducing dependence on non-renewable energy sources [2].

Smart Grids development is strongly positioned as a way to achieve the global objectives of increasing efficiency of the power grids and improving the integration of DER in the grid. Unlike conventional grids, Smart Grids are based on a two-way flow of information. This bidirectional flow allows not only that generation resources respond to consumer's requirements (as it occurs on a conventional grid) but also that consumer's loads adapt their power requirements to the needs of the grid along the time. This fact makes Smart Grids more efficient and reliable than conventional grids.

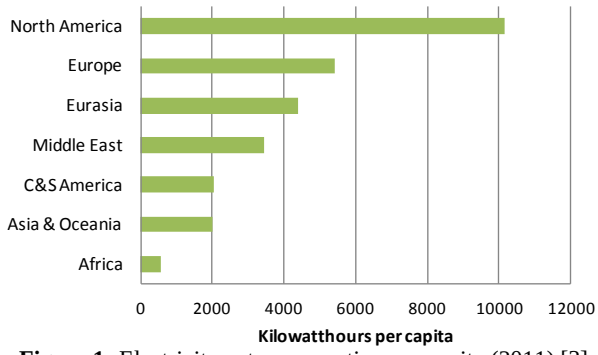

Figure 1: Electricity net consumption per capita (2011) [3]

Aiming to contribute to the development of Smart Grids finding solutions to these challenges, the project called MOBINCITY takes place. Thus, one of the specific objectives established within this project is to define efficient and optimum charging strategies adapted to user and FEV needs and grid conditions.

The information described in this paper is focused on the optimization software whose purpose is to identify the optimum allocation of a defined number of FEV charging stations (CSs) in a distribution grid and, from this solution, analyze the impact of FEV fleet into the stability of the power grid and how DER contribute to improve FEV integration.

The analysis results of this paper correspond to the real MV power grid of Ljubljana (Slovenia), composed by 1828 nodes (Figure 2). These results will be taken into account during the development of advanced control methodologies and strategies for the management and control of clusters of FEV charging points in the Slovenian electric car deployment.

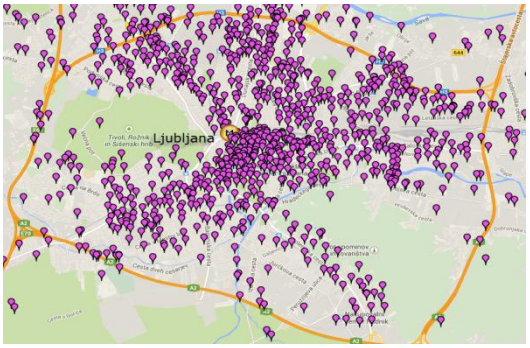

Figure 2: Map of Ljubljana (Slovenia)

OPTIMIZATION SOFTWARE

In this section the developed optimization algorithm and the designed scenarios will be presented. As a part of the optimization algorithm, constraints and requirements to be met and the optimization methodology used for achieving the optimal solution of the CSs allocation will be described next.

As mentioned before, the main aim of this algorithm is the optimal CSs allocation in a local area without disturbing the network. For this reason, not only electric criteria are taken into account as a part of the SW but also socioeconomic and mobility criteria are considered:

- **Electric criteria**. The aim of these criteria is to optimize the solution under the point of view of electrical considerations for a medium voltage distribution grid.
- **Socioeconomic criteria**. Geographical and demographic variables, such as distances among CSs or demographic density per CS, are taken into account on these criteria.
- **Mobility criteria**. Behaviour of FEV ownership is taken into account on the scenarios definition.

Optimization Algorithm

To achieve the final solution taking into consideration the described criteria, the optimal allocation algorithm will optimize the results according to the following variables and will validate that the considered constraints are satisfied.

The first electrical variable to analyze is the voltage deviation on grid's nodes (secondary substations) where a CS will be located. The optimization model developed ensures stability by means of guarantying that the value of the voltage for each node, with a CS assigned, is inside the interval defined by the nominal voltage ± 7%. Equation (1) defines the coefficient used in the cost function to satisfy this restriction (F_V). The variable N is the total amount of nodes in the grid where a CS would be placed, V_i is the value of voltage at the node "i" and μ_i is a penalty coefficient whose value is zero if the voltage is outside the allowed range and it is equal to one in the other case.

$$F_V = \frac{\sum_{i=1}^{N}[(1-|1-V_i|)\cdot\mu_i]}{N} \qquad (1)$$

The next electrical variable taken into consideration is the load factor of the transformers located into a node with a CS assigned. In this case, the constraint is to ensure that the result of dividing real power per nominal power is lower than 0.8 (80%) for each node. With the aim of maximize the free capacity of each transformer, it has been defined the F_Q coefficient (2) into the objective function. The variable Q_i refers to the load factor of a transformer located into the node "i" taking into consideration the current power demand and expected FEV charging demand at this node. The variable ε_i is a penalty coefficient whose value is zero if the load factor of the transformer at the node "i" is greater than 0.8 and it is one if it is lower or equal to this threshold.

$$F_Q = \frac{\sum_{i=1}^{N}[Q_1\cdot\varepsilon_i + (1-Q_i)\cdot(1-\varepsilon_i)]}{N} \qquad (2)$$

The last electrical variable taken into consideration refers to the grid losses. By means of the electric current on the distribution grid branches and their resistance, the branch losses are calculated. At the objective function, the F_P coefficient (3) is defined based on this equation and its aim is to minimize losses in the grid. The P_{base} term refers to losses on the distribution grid with no CSs (baseline scenario), the P_{max} value refers to losses on a supposed scenario where every branch of the grid is working under maximum load conditions and, finally, the P_{CS} are losses in the simulation scenario taking into account CSs allocation and FEV charging processes.

$$F_P = 1 - \frac{P_{CS} - P_{base}}{P_{max} - P_{base}} \qquad (3)$$

Referring to geographical criteria, the aim is ensuring that the maximum geographical area is covered by the final allocation of CSs. Thus maximizing the distance between CSs by means of using *euclidean* distances between the geographical coordinates of its nodes "i" and "j" is the main condition to achieve. In addition, minimizing the dispersion of geographical location guarantees that the algorithm does not allocate all CSs in the suburb area. The mixture of these two criteria by means of the F_D coefficient (4) makes possible a balanced final solution under a geographical point of view. Variables in this equation are d_{avg} that corresponds with the average *euclidean* distance, the *dis* variable that refers to the dispersion of the allocation solution and two weight variables ($\omega 1$ and $\omega 2$).

$$F_D = \frac{\omega_1 d_{avg} - (1-\omega_1)\cdot dis}{\omega_1 d_{avg}} \qquad (4)$$

Finally, this algorithm takes into account demographic criteria: demographic density and CSs density. The purpose for the first one is ensuring that the allocation of CSs affect the maximum number FEV ownership. For this, the coefficient F_{DD} (5) is defined into the cost function, as the quotient between the total population of the solution D_{total} and the maximum population possible D_{max} (corresponding with the solution where all the CSs are allocated into the township with the greater population). The total population term D_{total} is the result of summing the population of each township where each CS is located.

$$F_{DD} = \frac{D_{total}}{D_{max}} \qquad (5)$$

The aim of the second criterion is trying to achieve that all townships have at least one CS. Thus, the F_{DC} coefficient (6) is defined as the quotient between the number of townships included into the solution M_{actual}

and the number of townships included into the analysis M_{total}.

$$F_{DC} = \frac{M_{actual}}{M_{total}} \quad (6)$$

In order to evaluate the best solution for optimal allocation of CSs taking into account criteria described before, methodology based on evolutionary algorithms techniques is used. Particularly, the techniques used are the ones based on genetic algorithm theories where a "*population*" composed of m "*individuals*" (possible solutions) is evaluated by means of a cost function that contains the above criteria. For obtaining the final optimization algorithm solution, it is assigned a "*fitness*" value to each "*individual*". The assigned value is based on a previous definition of the importance of each criterion into the final solution. In relation to the calculation of these "*fitness*" values, two different methods have been implemented: the first one based on linear multiobjective optimization methodology and the second one based on Pareto Frontier methodology [4].

Scenario Definition

As described before, mobility criteria related to the behaviour of FEV ownership is taken into account by means of the scenario definition. This information is grouped into two main sections. The first one makes reference to the FEV behaviour and the second one characterizes the CSs and the drivers' preferences.

Concerning with the FEV behaviour, the following variables are selected to characterize the scenarios: the FEV fleet; the typical consumption per FEV (kWh/km); the typical battery capacity (kWh) and the average day trip distance per FEV (km).

For the analysis included into this paper, the value of some of these variables has been fixed. In particular, the typical consumption defined is 0.20kWh/km, the typical battery capacity is 20kWh and the assumed average day trip distance is 38km [5].

Regarding the use of the CSs, this model considers up to three different CS types, taken from European pilot experiences based on international standards [6]: Slow (SC), Fast (FC) and Rapid (RC). The values that characterize the charging process for each CS in the scenario are configurable with the intention of improving functionalities of this SW. The electrical conditions that characterize each model of CS into the present paper are:

- **SC:** 3kW load power; 6h duration.
- **FC:** 7kW load power; 3h duration.
- **RC:** 50kW load power; 0.5h duration.

Finally, to complete the definition of the use of the CSs, it is assumed that the 70% of the FEV charges are made using SC, the 25% using FC and the rest using RC, with daily distribution shown in Table 1.

Table 1: Preferences of use for each CS type

CS Type	Star Time	Finish Time	Certainty (%)
SC	20:00	2:30	70
FC	7:00	18:30	70
RC	5:00	23:30	70

FINAL RESULTS

This section contains final results from the optimal allocation SW for each of the selected scenarios. The output of this SW will be not only the optimum allocation of the CSs but also the analysis about the expected electrical behaviour of the grid, the local renewable energy contribution to FEV charging demand and geographical and demographic ratios.

Table 2: Scenarios defined in the test.

Scenario	FEV fleet	Amount of CSs		
		SC	*FC*	*RC*
S1	500	50	20	5
S2	1,000	50	20	5
S3	10,000	50	20	5
S4	10,000	0	0	1

Table 2 includes the detail for the test scenarios defined. Scenarios S1, S2 and S3 maintain the same amount of CS while the FEV fleet is increased. Scenario S4 maintains the same FEV fleet than S3 but concentrated at only one RC (corresponding with a great power demand concentrated at one node).

Additionally, a photovoltaic (PV) plant connected to the grid is assumed in S1. This renewable energy resource is characterized by the load profile concerning to summer season (Figure 7) and it is connected to a specific grid node.

The current version of the algorithm assumes that the CSs have unlimited capacity meaning that they are able to provide as much energy as the FEV fleet requires to them. Figure 3 includes the FEVs' electric demand concerning for S1 [7].

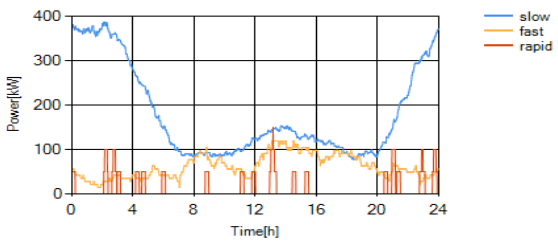

Figure 3: Total FEV charging pattern concerning to S1

Electrical Behaviour

Once the allocation of the CSs in the grid nodes has taken place, the algorithm provides useful information regarding the main grid parameters allowing a simple identification of the most problematic nodes.

Information about the evolution of the voltage value (referenced to the nominal value, p.u.) for each node

along a day (24h) is shown in Figure 4.

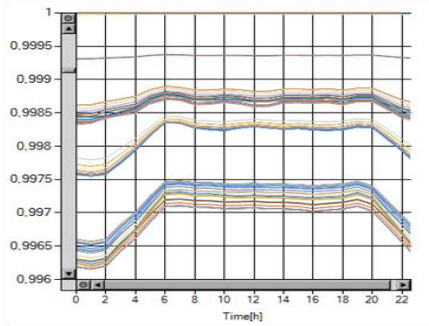

Figure 4: Voltage evolution for each node of the grid (S3).

This graph validates that the final solution ensures the stability of the network by means of maintaining voltage values inside the interval defined by the nominal voltage ± 7%. Thus, it is appreciated that the greater demand energy, the greater voltage deviation is.

Other information included into this tool, for validating voltage stability, is the evolution of the voltage deviation along each branch of the grid (Figure 5). This analysis allows identifying the nodes in a branch with higher voltage deviations and allows checking if stability constraint is maintained too. If the scenario is not stable, this analysis allows identifying the node where voltage stability is broken.

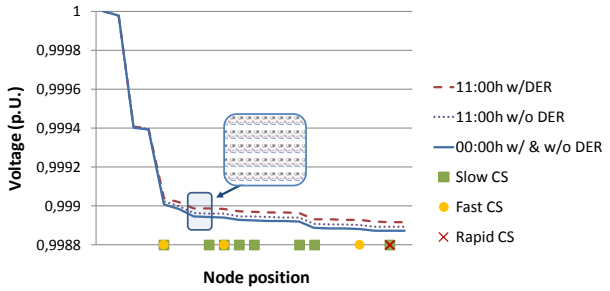

Figure 5: Voltage deviation for a branch of the grid at 0:00 h and 11:00 h with and without DER (S1).

The graph above (Figure 5) shows how voltage deviation at 0:00 h is greater than at 11:00 h (as identified before on Figure 4). Additionally, into this graph it is appreciated the influence of distributed energy resources (DER) on the voltage evolution. First, at 00:00 h there are no differences between both situations because the PV plant is not injecting power to the grid but at 11:00 h the PV plant is injecting to the grid 100 kW approximately. This situation makes that the voltage values of the nodes become closer to the nominal value of the voltage improving the stability of the grid.

Finally, concerning to the load factor evolution on the transformers, through the following graph (Figure 6) it is validated that the final solution from the optimal allocation algorithm satisfies the stability condition that limited this value up to 80%.

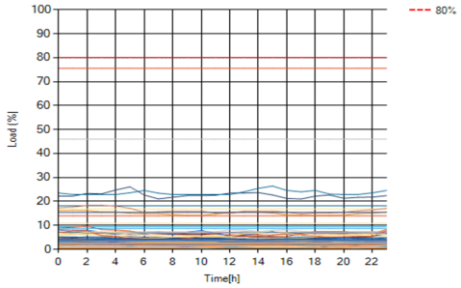

Figure 6: Load factor evolution for each transformer in the grid (S1).

Contribution of DER

The optimization software to allocate CSs along the grid allows analysing the contribution of DER to the FEV load demand. Actually, this SW allows taking into consideration only DERs that are currently allocated into the grid but it is possible to analyse the impact of future DER too.

As represented in Figure 7, the program allows comparing load profiles from DER generation and FEV demand and calculates the percentage of the demand that will be supported by these DER resources.

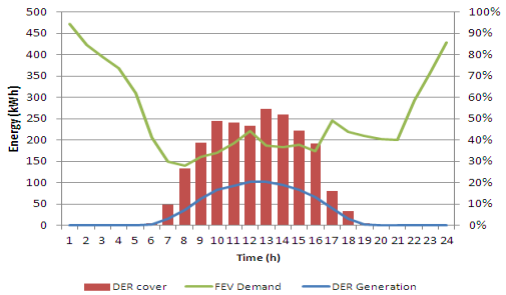

Figure 7: Contribution of DER to FEV load demand (S1).

CONCLUSIONS

This paper describes the analysis done for testing the impact of a FEV fleet on a real grid by means of a SW developed for achieving the optimal allocation of the CSs into this grid. Conclusions incorporated into this paper are associated with the results of the best possible solution (taking into consideration criteria described above). Table 4 summarizes electrical conclusions about the stability of each tested scenario.

Table 4: Electrical stability's summary

Scenario	Voltage (± 7%)	Capacity (≤ 80%)
S1	✓	✓
S2	✓	✓
S3	✓	×
S4	✓	×

Concerning to electrical criteria, it is observed that the voltage variable is more stable than the load factor parameter. On this respect, Figure 8 represents the impact of a big amount of FEV load demand (greater than 10.7

MW) concentrated in only one node. As appreciated, the greater voltage deviation is lower than the maximum allowed (nominal voltage ± 7%) despite of the huge load demanded by the node of the grid.

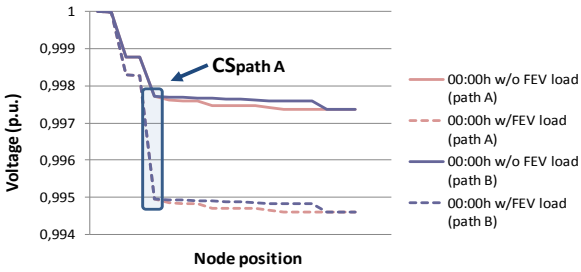

Figure 8: Influence of FEV on the voltage variations into the grid (dotted line corresponds with S4).

Regarding to the impact on the load factor, it is checked that the conditions used for defining S3 produce the instability of the grid (regarding to load factor criteria but not to voltage criteria). This situation does not change despite of selecting the F_Q coefficient as the main criterion to achieve into the cost function. Nonetheless, by means of comparing graphs in Figure 9, it could be asserted that this algorithm improves the load factor electrical criteria when the priority is given to the coefficient F_Q (maximum value from 180% to 105%) despite of it is incapable of achieving the stability threshold (down to 80%). This result will be improved if the number of CSs is increased (increasing the distribution of the load between the nodes).

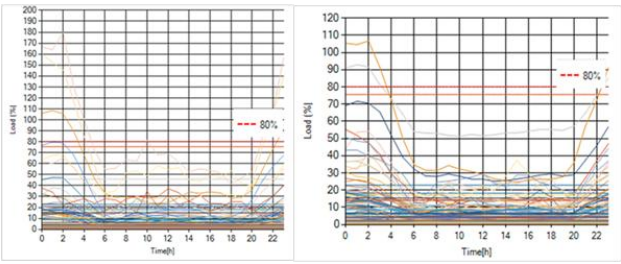

Figure 9: Load factor evolution in S3 (left: taking into account F_V, F_Q and F_P; right: taking into account F_Q).

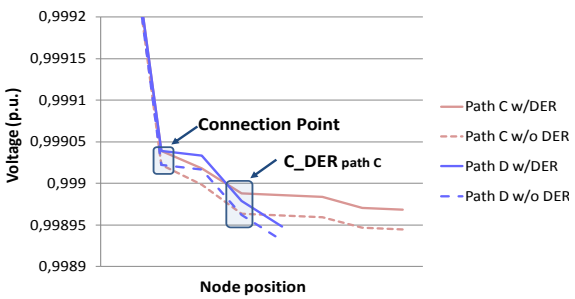

Figure 10: Influence of DER on the Path C where it is placed and on connected paths like the Path D (S1).

In relation to the impact of DER integrated into the grid, the simulation of S1 has demonstrated that DERs contribute improving the stability of the grid where they are located (Figure 10). In addition, it is appreciated that the DER located in a node (C_DER) improves not only the stability of the nodes in its branch (Path C) but also it improves the stability of the nodes in other branches (i.e. Path D) that have at least one common node with the first branch (Path C). According to this, Figure 10 and Figure 8 depict the evidence that branches sharing one or more nodes in the same grid are sensitive to variations on the load value of every of their nodes.

As a conclusion, the algorithm described into this paper for the optimal allocation of CSs into a grid reproduces quite rightly the behaviour of the grid when a distributed load appears. On updated versions of the algorithm, the developments will focus on improving the behaviour of the load factor at the expense of worsening voltage values avoiding the instability of the grid.

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