EFFICIENT INTEGRATION OF ELECTRIC VEHICLES THROUGH OPTIMAL COORDINATED CHARGING AND REACTIVE POWER SUPPORT

Damir JAKUS
University of Split – FESB- Croatia
damir.jakus@fesb.hr

Josip VASILJ
University of Split – FESB- Croatia
jvasilj@fesb.hr

Boško POLJAK
University of Split – FESB- Croatia
bosko.poljak.00@fesb.hr

Danijel JOLEVSKI
University of Split – FESB- Croatia
danijel.jolevski@fesb.hr

ABSTRACT

This paper presents a central control algorithm for EV optimal charging management with EV reactive power support. Based on the distribution network technical properties and limitations, as well as EV charging requirements defined by end consumers, the proposed algorithm defines the optimal EV charging strategy with reactive power support to avoid distribution network overloading as well as large voltage drops. The central control coordinates the operation of EVs while considering EV energy requirements and planned departure time. In case of possible grid overloads or large voltage deviations, the DSO sends signals to EV charging stations to reduce active power charging and to support grid voltage through reactive power support. The proposed control algorithm is cast as a linear optimization problem and demonstrated on a modified IEEE 33-bus network. The case study shows the benefits of including EV reactive power support to reduce EV energy curtailment due to distribution network capacity limitations or large voltage deviations in specific operating conditions.

INTRODUCTION

Globally, the number of EVs is on the rise and according to the International Energy Agency (IEA), the global stock of EVs reached 16.2 million in 2021, and is projected to reach between 50 million and 85 million by 2025, depending on the level of policy support. By 2030, the IEA projects that the global stock of EVs could reach between 200 and 270 million [1]. At the end of 2021, the number of electric vehicles (EVs) in the European Union (EU) is estimated to be around 5.5 million. This represents a significant increase from previous years, driven by increased consumer awareness, government incentives, and improvements in battery technology. The EU has set a goal to have at least 30 million zero-emission vehicles on the road by 2030, in order to reduce greenhouse gas emissions and improve air quality. These trends and projections be affected by factors such as economic conditions, technological advancements, and policy changes . However, considering the current trends and goals for reducing carbon emissions, it is likely that the number of electric vehicles will continue to grow in the coming years.

The main challenge for distribution network operators in the near future is related to the integration of electric vehicles in distribution grids. Depending on the charger rated power, each EV can consume active power equal to a whole household load or several times more if equipped with a high-capacity fast charger. This additional consumer load could potentially lead to network operational problems due to larger voltage drops and grid congestions in peak hours accompanied by high EV charging patterns. One way to address these issues it to invest more capital in grid reinforcement and extension which will allow the integration of EVs into the system. Additional investments will undoubtedly be necessary when certain threshold levels are reached, but in the starting phase of EV integration, they can potentially be avoided or significantly reduced if smart coordinated charging of EVs is deployed.

In addition to EV smart charging which is primarily focused on controlling active power consumed by EVs, utilization of EVs for reactive power support could additionally increase network EV hosting capacity. Authors in [2] propose a robust multi-objective methodology for determining the optimal day-ahead EV charging schedule while complying with unbalanced distribution grid constraints. Using the branch flow model-based relaxed optimal power flow authors in [3] formulate a robust coordinated optimization problem as a mixed integer second-order cone (SOC) programming problem for controlling active and reactive power. Authors in [4] develop hierarchical coordination frameworks for optimal active/reactive power management of number of spatially distributed EVs while accounting for distribution grid level constraints and EVs charging costs. Optimised bidirectional Vehicle-to-Grid (V2G) operation, for a fleet of Electric Vehicles (EVs) connected to a distributed power system is presented in [5]. For improving the efficiency of optimization process, an advanced genetic algorithm associated with elite preservation policy is proposed in [6]. Control architecture for an on-board EV charger which can support grid through active and reactive power control is presented in [7]. Authors in [8] propose a two-stage optimization approach with active and reactive power control to coordinate electric vehicles with both grid-to-vehicle and vehicle-to-grid capabilities to satisfy both grid requirements and electric vehicle prosumer requirements.

This paper describes a method for the efficient integration of electric vehicles through optimal charging and reactive power support. The proposed approach considers distribution network operational constraints such as voltage limits and network components' power rating and on the other hand EV users' requirements such as arrival time, departure time, energy demand, battery capacity, and charging power limits,…. The optimization of EV battery charging and reactive power support is coordinated centrally for EV parking lots which are located across the distribution network (Figure 1.).

MATHEMATICAL FORMULATION

The proposed mathematical model is cast as a linear programming model which is achieved through the linearization of power flow constraints. The objective function (1) is focused on the minimization of EV supply costs as well as costs associated with energy not delivered to EV users due to distribution network constraints:

$$\min \sum_{\substack{i\in EV \\ t\in T}} \left(c_t \cdot P_{i,t}^{EV\_ch} \cdot \Delta t + c_t^v \cdot E_{i,t}^{EV\_violation} \right) \tag{1}$$

Where c_t – energy price, $P_{i,t}^{EV\_ch}$ – EV charging at time t, c_t^v – EV energy requirement violation penalty $P_{i,t}^{EV\_violation}$ - EV energy requirement violation at time t
Linearization of power flow constraints is obtained by expressing bus voltages $V_{i,t}$ in the following form:

$$V_{i,t} = 1 + \triangle V_{i,t} \tag{2}$$
$$\theta_{ij,t} = \theta_{i,t} - \theta_{j,t} \tag{3}$$

where: $\triangle V_{i,t}$ - voltage magnitude deviation of bus *i* at time *t*, voltage phase angle of bus *i* at time *t*, **T** - set of time instances, $\boldsymbol{N}$ - set of network buses, $\boldsymbol{EV}$ - set of EV charging stations

By substituting (2)-(3) in full nonlinear power flow equations and neglecting higher-order terms we get a linearized power flow model expressed as follows:

$$P_{ij,t} = P_{ji,t} \approx (\triangle V_{i,t} - \triangle V_{j,t}) g_{ij} - b_{ij}\theta_{ij,t} \tag{4}$$
$$Q_{ij,t} \approx -(1 + 2\triangle V_{i,t}) b_{ij0} - (\triangle V_{i,t} - \triangle V_{j,t}) b_{ij} - g_{ij}\theta_{ij,t} \tag{5}$$
$$Q_{ji,t} \approx -(1 + 2\triangle V_{j,t}) b_{ij0} + (\triangle V_{i,t} - \triangle V_{j,t}) b_{ij} + g_{ij}\theta_{ij,t} \quad \forall (i,j) \in PL, t \in T \tag{6}$$

where: $P_{ij,t}|Q_{ij,t}$ - active/reactive power flow of line connecting buses *i* and *j* at a time(scenario) *t*, g_{ij} - conductance of line *ij*, b_{ij} - susceptance of line *ij*, b_{ij0} - shunt admittance of line *ij*, $\boldsymbol{PL}$ set of power lines.
Constraints (7) - (10) enforce the active and reactive power balance at each bus:

$$-P_{i,t}^{EV\_ch} - P_{i,t}^{L} = \sum_{j\in B} P_{ij,t} \quad \forall i \in N, t \in T \tag{7}$$
$$-Q_{i,t}^{EV} - Q_{i,t}^{L} = \sum_{j\in N} Q_{ij,t} \quad \forall i \in N, t \in T \tag{8}$$
$$-P_{i,t}^{EV\_ch} - P_{i,t}^{L} + P_{i,t}^{SP} = \sum_{j\in B} P_{ij,t} \quad \forall i \in N^{SP}, t \in T \tag{9}$$
$$-Q_{i,t}^{EV} - Q_{i,t}^{L} + Q_{i,t}^{SP} = \sum_{j\in N} Q_{ij,t} \quad \forall i \in N^{SP}, t \in T \tag{10}$$

Where $P_{i,t}^{L}/Q_{i,t}^{L}$ – active/reactive power consumption at bus *i* at time *t*, $P_{i,t}^{SP}/Q_{i,t}^{SP}$ –- active/reactive power at distribution network main supply point *i* at time t.
In the proposed model, it is assumed that EV charging stations contribute to voltage regulation through reactive power control which is limited to the power factor range cosφ ϵ[0.95-1] cap./ind.:

$$Q_{i,t}^{EV\_max} = \tan\left(\cos^{-1}\varphi_i^{EV}\right) P_{i,t}^{EV\_ch} \quad \forall EV, t \in T \tag{11}$$
$$-QP_{i,t}^{EV\_max} \le Q_{i,t}^{EV} \le QP_{i,t}^{EV\_max} \quad \forall EV, t \in T \tag{12}$$

The optimal EV charging at a particular charging station is determined based on EV arrival time, energy requirements, departure time as well as battery and charger parameters. Based on this data, it is possible to define the requirements at the charging station level in terms of the cumulative energy demand at certain specific points in time (announced EV departure times). The proposed method finds an optimal way of satisfying these energy requirements while accounting for distribution network constraints. In case when EV energy requirements can't be fulfilled due to network constraints, the algorithm determines minimal energy requirement violation which is necessary to assure normal network operating conditions (voltage conditions, element loading,…).

$$\sum_{t'=0}^{t} P_{i,t}^{EV_{ch}} \cdot \Delta t = E_{i,t}^{EV_{req}} - E_{i,t}^{EV_{violation}} \quad \forall \text{EV}, t \in T \tag{13}$$
$$P_{i,t}^{EV\_ch} \le P_{i,t}^{EV\_max} \quad \forall \text{EV}, t \in T \tag{14}$$

Where $E_{i,t}^{EV\_req}$ – EV cumulative energy requirement at charging station EV at time t, $P_{i,t}^{EV\_max}$ – maximum charging power at charging station EV at time t.

In addition to previous constraints, additional expressions are introduced in the optimization model to avoid voltage problems and network congestion.
For the test case model, the paper will demonstrate the benefits of including EV reactive power support in addition to EV smart charging in extending grid possibilities to supply EV charging and reducing EV energy requirement violations due to network constraints.

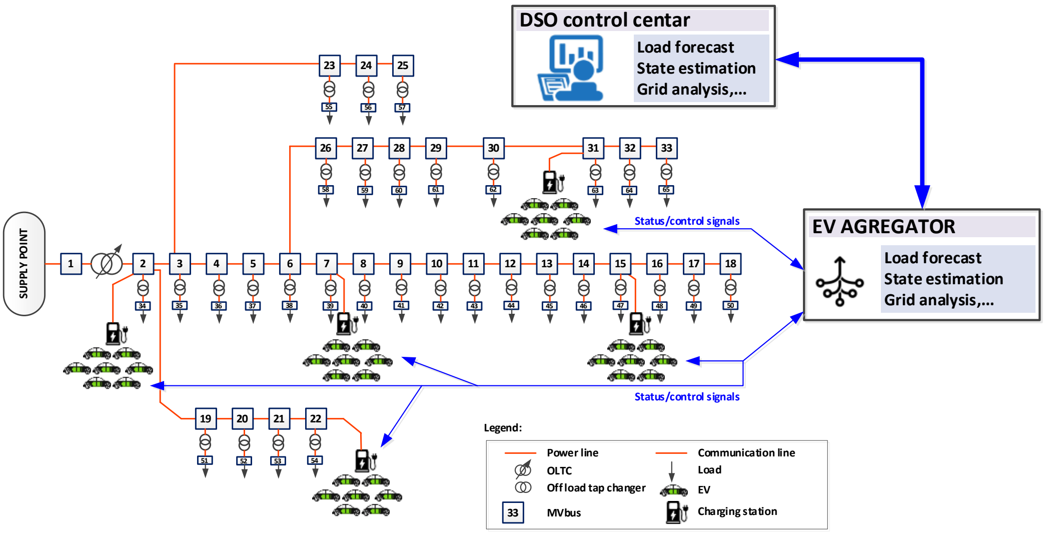

Figure 1 Test case – modified IEEE 33-bus network with EV charging stations

CASE STUDY

The mathematical model described in the previous section was implemented in Python and solved using the Gurobi solver. The model was tested on a modified IEEE 33-bus network which was modified by connecting EV charging stations to busses 2, 7, 15, 22 and 31 (Figure 1.). The network has a radial structure with 32 branches. In the analysis, we assume that the main feeder stretching between the main supply station and bus 18 has a rated capacity equal to 10MVA while all other sub-feeder branches have a rated capacity equal to 5MVA. Also, the upper bus voltage limit is set to 1.1p.u. while the lower limit is set to 0.9p.u.

The integration of EVs increases the distribution network load as well as voltage drops across the network. EV charging station energy requirement is modeled based on EV statistics which include information on arrival time, departure time, energy requirement, EV/charger maximum charging power. Based on this simulation, EV energy requirements are aggregated on the charging station level and used in further calculations. The DSO needs to fulfill energy requirements at the moment of each EV departure, so cumulative energy requirement curves can be specified at the level of each charging station with the requirement specified at the time of each EV departure. Using this approach, the proposed algorithm needs to fulfill the cumulative energy requirement at the time of each EV departure while in the time between departures, it can flexibly charge EV while accounting for network constraints.

Two control strategies were considered for the analyzed test case:

- **CASE 1: Smart charging** – in this case charging process is managed and optimized by a central control system in a way that only controls active power consumption. The central control system monitors the power grid and adjusts the charging rate of the EV based on the network conditions and EV user requirements (energy requirement, estimated departure time,…). The main objective of this approach is to fulfill EV user energy requirements at the time of announced departure. Even with the objective defined in such a way, there is still a possibility that EV energy requirements will not be fulfilled to the full extent in certain conditions given that DSO can not maintain normal grid conditions through flexible active power charging.
- **CASE 2: Smart charging + EV reactive power support** – in this case DSO in addition to smart charging uses EV reactive power support to manage network conditions. This test case assumes that EVs are equipped with devices that allow them to provide reactive power to the grid when needed. In the analysis, we assume that the EVs can operate with a power factor between 0.95cap-0.95ind.

Figure 2. shows the network load for the representative day as well as cumulative energy demand both for network load and EVs.

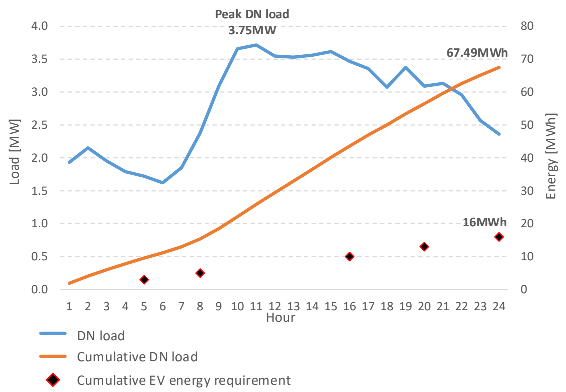

Figure 2 Distribution network load and cumulative EV energy requirements for the representative day

Total daily network consumption not including EV consumption equals to 67.49MWh with a peak load equal to 3.75MW. On top of this, the EV energy requirement for a representative day is equal to 16MWh (~23% of the "regular" network load). This additional energy consumption due to EV charging increases network peak load, and the proposed method needs to optimize EV charging profiles to avoid grid problems while meeting EV user energy needs.

CASE 1: Smart charging

The method described in section 2 can easily be transformed into smart EV active power charging by limiting EV operation to a unity power factor ($\boldsymbol{\varphi_i^{EV}} = 0$). This modification implements the assumptions of Case 1 smart charging control strategy.

By looking at Figure 2 we can expect potential grid problems (overloads, large voltage drops) to appear if they even happen, in the period of day between 10h-20h when the regular distribution load is high. If the EV energy requirement is also high in this period, we can expect potential charging curtailments to appear.

The proposed algorithm optimizes charging profiles for each EV charging station to minimize charging curtailment and fulfill EV energy requirements. Figure 3 shows optimal charging profiles for Case 1.

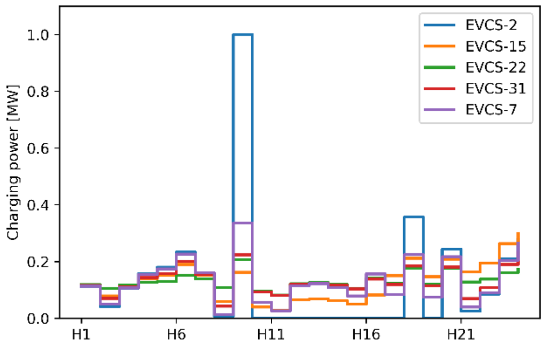

Figure 3 Optimal charging profiles for Case 1(Smart charging)

From figure 3 we can see a large spike off the charging profile around 9 AM which is especially indicative at EV charging stations connected to buses 2 and 7. This happens because the proposed algorithm tries to fulfill EV energy requirements in the next time interval to the maximum extent possible before there is a significant rise in standard network load (network peak load occurs around 11 AM). This then allows to slightly reduce EV charging in the next time steps due to grid constraints while meeting EV energy requirement needs almost to the amount specified by the users. Although this approach uses smart charging control, in this test case such a control strategy is not sufficient to avoid grid problems so charging curtailment is necessary to avoid grid problems.

Figure 4 shows the network voltage profile range while figure 5 shows the distribution network loading range for this EV charging strategy. From the figures 4 and 5 we can see that the main reason for EV charging curtailment is a large voltage drop with bus voltages reaching lower bounds set to 0.9p.u. On the other hand, network capacity is sufficient to integrate this level of EVs given that distribution feeders are loaded significantly below their rated capacity.

From figure 8 we can see that EV energy requirement targets for hours 16h (target missed by ~0.45MWh) and 20h (target missed by ~0.35MWh) are not met.

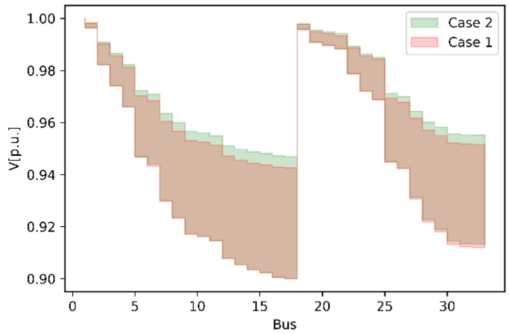

Figure 4 Voltage profile for different charging control strategies

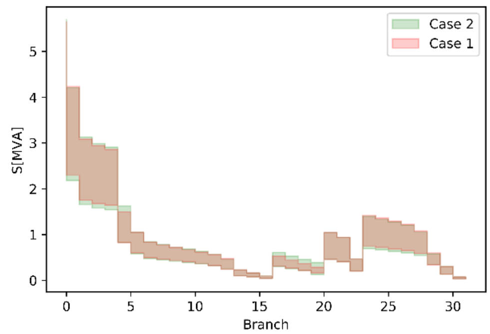

Figure 5 Line loading range for different charging control strategies

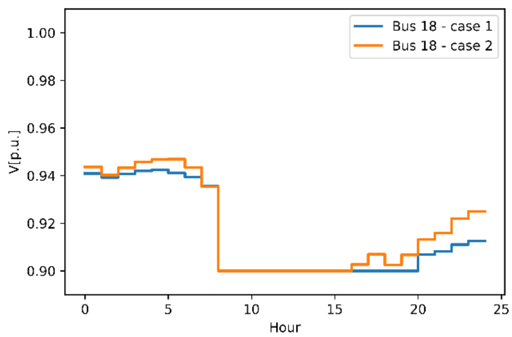

Figure 6 Voltage change on bus 18 for different charging control strategies

CASE 2: Smart charging + EV reactive power support

By applying the algorithm described in section 2, we can achieve better grid conditions and reduce EV energy requirement mismatch in critical periods when even the network base load is also high. Figure 7 shows optimal charging profiles obtained for Case 2. We can see higher charging rates between periods 12-17h due to EV reactive power support. EV reactive power support helps to reduce energy requirement mismatch (target at 16h missed by ~0.09MWh).

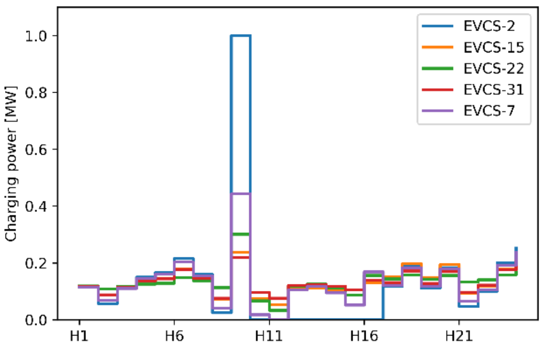

Figure 7 Optimal charging profiles for (Case 2-Smart charging + EV reactive power support)

From figures 4 and 6 we can see that even with EV reactive power support, in this test case example, there is still a problem of large voltage drops in periods with high base load and EV charging requirements. The critical bus with the lowest voltage is bus 18 which is located at the end of the main feeder with voltages reaching lower limits for large periods. By including EV reactive power support we were able to slightly extend network charging capabilities in this critical period without increasing voltage drop. Given that in this test example voltage drops are high even without the EV, the algorithm will force EV chargers most of the time to operate at a power factor 0.95 cap. giving reactive power to the grid to increase voltage conditions.

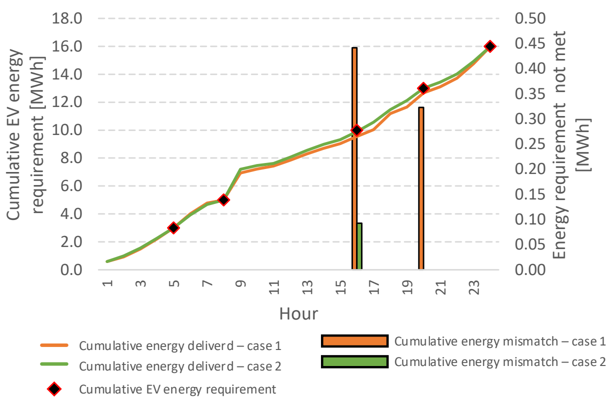

Figure 8 Comparison of EV energy requirement fulfillment/charging curtailment

CONCLUSION

This paper describes a method for efficient integration of electric vehicles through optimal coordinated charging and reactive power support. The proposed mathematical model is cast as linear programming model which is achieved through the linearization of power flow constraints. The proposed control logic can help to improve the distribution network operating conditions, extend EV charging capabilities of the existing grid, and reduce the costs associated with traditional methods of providing reactive power support. Reactive power support from EVs represent still a relatively new field of research and technology, and not all EVs are currently able to provide this kind of support.

Acknowledgments

This work was funded by the European Union through the European Regional Development Fund Operational Programme Competitiveness and Cohesion 2014–2020 of the Republic of Croatia under project KK.01.2.1.02.0228 “Research and development of smart-grid charging station for electric vehicles within the construction of a rotary parking system”.

REFERENCES

[1] IEA – International Energy Agency, “Global EV Outlook 2022”

[2] Knezović, K., Soroudi, A., Keane, A. and Marinelli, M. (2017), Robust multi-objective PQ scheduling for electric vehicles in flexible unbalanced distribution grids. *IET Gener. Transm. Distrib.*, 11: 4031-4040.

[3] H. Gao, J. Liu and L. Wang, 2018, "Robust Coordinated Optimization of Active and Reactive Power in Active Distribution Systems," *IEEE Transactions on Smart Grid*, vol. 9, no. 5, pp. 4436-4447

[4] J. Wang, G. R. Bharati, S. Paudyal, O. Ceylan, B. P. Bhattarai and K. S. Myers, 2019, "Coordinated Electric Vehicle Charging With Reactive Power Support to Distribution Grids," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 1, pp. 54-63

[5] S. -A. Amamra and J. Marco, 2019, "Vehicle-to-Grid Aggregator to Support Power Grid and Reduce Electric Vehicle Charging Cost," *IEEE Access*, vol. 7, pp. 178528-178538

[6] Huang, Z., Fang, B. & Deng, J., 2020, “Multi-objective optimization strategy for distribution network considering V2G-enabled electric vehicles in building integrated energy system”, *Prot Control Mod Power Syst* 5, 7

[7] Aakash Kumar Seth; Mukhtiar Singh, 2021, "Control of On-Board Electric Vehicle Charger", *Artificial Intelligence and Sustainable Computing*, 2021.

[8] Boonseng T, Sangswang A, Naetiladdanon S, Gurung S., 2021, “A New Two-Stage Approach to Coordinate Electrical Vehicles for Satisfaction of Grid and Customer Requirements”, *Applied Sciences*, 11(9), 3904