Energy Management Strategy based Charging Coordination for Electric Vehicle Integrated Distribution Grid

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*Abstract*— This paper presents smart charging coordination of EVs in an LV distribution network using an energy management strategy while considering the price sensitivity of drivers. According to the electric vehicle's state of charge (SoC) level, three priority groups are specified: *high-priority*, *low-priority,* and *normal-priority*. Different charging time slots are offered to drivers at different prices, referred to as red, blue, and green time zones. The process begins with a power flow program that is executed at each step, and the EV can be placed permanently on a charging node once all constraints have been checked. An objective function is defined for this problem that minimizes production costs by considering constraints on bus voltages and maximum allowed power consumption. The simulations' results prove the proposed algorithm's validity for shifting loads while meeting all the constraints of the network and EVs.

Keywords—Electric vehicle, smart grid, energy management, driver behavior, demand response

# Introduction

The increase in greenhouse gas emissions, widespread climate change, and the shortage of fossil fuels have prompted the development of alternative fuel vehicles [1]; With the continued growth of EVs, their importance as flexible loads has grown dramatically. However, the uncontrolled charging of these vehicles can cause serious grid problems such as a peak in demand, a decrease in transformer life expectancy, efficiency degradation, voltage instability, and, as a result, an increase in EV charging costs for EV owners. Therefore, EV charging coordination has become an essential requirement for the electrification of transportation systems. Although the electrification of the transportation systems has many advantages, on the other hand, it can be considered challenging and may set up threats to the power grid in terms of increasing demand if not appropriately managed [2]–[4]. Therefore, it is necessary to design charging scheduling for EVs to manage the increasing demand so that power systems do not encounter mentioned problems.

In electrical networks, EVs are regarded as flexible loads. As a result, they can be controlled in terms of charge/discharge at different time intervals, avoiding peaks in the load profile [5]. At an individual EV level, EV owners are offered bids to participate in the distribution system operation actively. However, at the node level, an EV aggregator optimally allocates available charging power to meet EV charging requirements and cost benefits. A distribution system operator integrates an electricity price market clearing mechanism at the distribution network level with the optimal power flow technique to ensure distribution network reliability [6].

One method used for EV charging coordination is an energy management strategy to perform load shifting. This method requires computational complexity and considers different EV parameters to prioritize their charging schedules; therefore, some researchers have proposed different energy management strategies to achieve this requirement. A decentralized algorithm using the flexibility of EV loads to fill the valleys in electric load profiles was proposed in [7] to schedule EV charging optimally. In another study, a decentralized control method for scheduling EV charging loads is proposed to fill the overnight load valley while meeting customers' charging requirements, which was implemented by calculating a probability transition matrix as the control signal to guide EV charging processes based on submitted EV charging schedules at the aggregator side [8].

The study in [9] presented a distributed EV coordination management that took advantage of both the flexibility of EV demand and the vehicle-to-grid EV capability. To coordinate EV charging, a technique for valley-filling strategy was presented in [10]. The capacity margin index was established and used to identify the target time slots for EV charging on which the power grid has plentiful surplus power, and the charging priority index was defined and used to determine the charging priority of EVs on each time slot in this scheme. In another study, the proposed method prioritizes the charging schedule based on peak time slots and market prices [11]. While in our research, we present an energy management algorithm that performs the load shifting of EVs, which considers the price sensitivity of drivers upon the mentioned parameters to optimize the charging coordination of EVs. The rest of the paper is as follows:

In section 2, the energy management strategy formulation is proposed by developing the problem consisting of the constraints of the network and EVs and also the parameters related to drivers. In section 3 the simulation results are presented, and in section 4, conclusions are made considering the effectiveness of the proposed method.

# energy management strategy formulation

This paper presents an energy management strategy as a charging coordination program in various EV penetration levels. Four scenarios are considered as 0%, 16%, 32%, and 47% penetration levels of EVs in the distribution network. The solution proposed in this paper considers constraints related to the network and EVs simultaneously. On the other hand, the price sensitivity of drivers during the charging prioritization process is taken into account to determine the time of charge based on the drivers' preferences.

## Network constraints

For the network, two main constraints are considered: maximum demand as the upper bound for the summation of the total load power (power consumption) and minimum and maximum values for the bus voltage.

The amount of power demand is a practical constraint in solving the energy optimization problem so that there is maximum power for each power system. The total power demand at any given time must be less than or equal to this maximum power. This constraint is expressed in the following inequality:

(1)

where, ∆t is the time interval within 24 hours, *k* is the node number, and *P* is the active power consumption. *D* is the maximum allowed demand for the grid.

Another primary network constraint is the distribution network voltage, for which the upper and lower limits of ±10% ( and ) are usually taken into account. So that in a total of 24 hours, these limits must be observed. This constraint is defined as follows:

(2)

where, *k* and *n* are the node number and the total number of nodes, respectively.

## Objective function

The objective function of the EV charging coordination problem is based on the minimization of the total cost of purchasing or generating the energy for charging EVs as follows:

(3)

where, is the cost of total generation and is the cost per MWh of generation based on the charging time zone.

## Charging priority

In this study, three different charging priority categories are defined as follows to facilitate the charging process and take into account driver satisfaction:

* *high-priority*
* *low-priority*
* *normal-priority*

For EVs with an SoC level lower than 30%, charging priority is labeled as *high-priority*, EVs with an SoC in the range of 30% and 50% are placed in *low-priority* and EVs with an SoC greater than 50% are labeled as *normal-priority*. At any given time, the EVs are classified into the three categories mentioned above based on the SoC level; then, according to the priority group, the energy management strategy is implemented.

## Charging Time Zone

The developed energy management strategy allows EV owners to select one of the following three charging time zones based on their price sensitivity:

**Red charging zone** (high tariff for 18:00h- 22:00h)- coincides with most of the on-peak period and is designated for high-priority EV owners willing to pay higher tariff rates in order to charge their vehicles as soon as possible.

**Blue charging zone** (medium tariff for 22:00h- 01:00h)- is intended for low-priority consumers that prefer to charge their vehicles at partially off-peak periods and pay lower tariff rates.

**Green charging zone** (low tariff for 01:00h- 08:00h)- is the period that most EV charging will probably take place due to the cheapest tariff rates as most low-priority consumers will require their vehicles fully charged for the following day.

According to these zones, cost coefficients are defined as , and . In this paper, the price of electricity is considered 0.1 €/kW, which corresponds to the price of electricity in Hungary. This value is considered the coefficient for the blue zone, and ±5% values are calculated for and as 0.105 € per kWh and 0.095 € per kWh, respectively.

## Energy management strategy

An energy management strategy has been presented in this paper to coordinate multiple EV charging activities while considering network constraints. According to Fig. 1, which shows the proposed strategy, the deployed price-sensitivities-based strategy assigns EVs to charge as soon as possible based on cost minimization. The proposed strategy optimizes voltage profile while considering EV owners defined charging time zone priority and their price sensitivity. Based on the presented algorithm, all the required data, including daily load, price coefficients, time interval, EV information such as SoC, charging power, charging time, price sensitivity, etc., are imported at the first step.

The main program loop moves from EV groups with *high-priority* to those with *low-priority*. Individual EVs are temporarily activated within the designated priority group to determine system performance at all potential EV nodes and priority charging time zone. Price sensitivity is taken into account, and those EVs whose owners are prepared to pay a high tariff will be connected to the network. This strategy selects the EV and charging start time that results in the lowest system cost (3) over the T span, taking into account the charging duration and current distribution network demand level. If a constraint violation is detected at any node (1)-(2), the smart charging strategy will try the next possible charging start time to meet the constraints.

As a result, it is likely that not all EV owners will be able to charge in their preferred locations. The selected EV is connected to the network and the system load curve is changed once it has been identified which EV node in that priority group can begin charging and at what time resulting in minimum system cost (over the period T). Before moving on to the next priority charging zone, this process is repeated for all nodes in that priority group.

# Simulation

The proposed energy management strategy is simulated with a detailed system topology consisting of a high-voltage (HV) feeder and low-voltage (LV) home network integrated with EVs. The selected system is a modification of the IEEE 31 bus 23 kV distribution system combined with several residential LV 415 V networks that are shown in Fig. 2 [12]. Each LV feeder consists of 19 nodes named *a* to *s* representing customer households and also additional loads as EVs. Moreover, the line parameters of the low-voltage residential system are presented in TABLE I.

## Load profiles

Modeling the residential load changes (without EV power demand) over a 24-hour period is carried out using a typical residential load curve based on actual recordings from a distribution transformer. The load data used in this study includes 48 samples for every 24 hours that are sampled every half hour. The average daily residential load profile for all 19 nodes on one node over 24 hours of a weekday is shown in Fig. 3. The peak power consumption of a house is assumed to be, on average, 2 kW with a power factor of 0.9.

## Definition of EV's Features

In order to implement the proposed energy management strategy for EV charging coordination, a set of EV features is defined. In the first step, 50 EVs with different characteristics are specified. These features consist of the following:

* State of charge (SoC): it can be considered a random integer value between 10 and 100 and expressed as a percentage. Due to the random nature of the parameter, the priority groups are different for each round of the program; therefore, it is a dynamic technique in terms of determining which EVs need to be charged at any given time.
* Charging power (P): as the charging is considered a home-charging scenario, three different values are determined for the required charging power as 7 kW, 4 kW, and 2.4 kW
* Charging time: this parameter is specified based on the defined charging power; thus, 8h, 10h, and 12h are considered for EVs with 7 kW, 4 kW, and 2.4 kW, respectively.
* Price sensitivity: this parameter is characterized as a binary value (0 or 1). If it is 1 for an EV owner, the driver is sensitive to the price and prefers to charge his/her EV in blue and green zones; thus, he/she would not pay a high tariff to charge immediately.

In the next step, considering SoC level and charging time, a new parameter is defined as *real charging time,* which calculates the required charging time for each EV as follows:

(4)

This value is rounded to an integer to be precise in considering the queue's waiting time.

Then, based on the SoC level, charging priority is determined as

* *High-priority for*
* *Low-priority for*
* *Normal-priority for*

Therefore, one more parameter is added to the EVs characteristics as *emergency charging*. The result for a set of EVs is shown in TABLE II:

Then, EVs are clustered into three categories based on their *emergency* *charging* status. In each category, EVs are sorted based on their SoC values so that EVs with lower SoC levels can be placed for charge earlier. Considering the sensitivity of EV owners to the price, at this stage, drivers who are not sensitive to the price and can pay high tariffs are selected to charge their EVs during the peak hour because the charging process based on the home charging scenario starts at 18:00:00 which is categorized as the red charging zone. EVs in the *low-priority* group are in second place, and based on the penetration level of EVs, if all the EVs in the *high-priority* group are connected to the network and we need to charge more EVs, after sorting this group based on SoC level, they will be charged in order. Then there is the *normal-priority* group, which has SoC higher than 50% and is not placed in charging priority.

Four different scenarios are designated to be performed in simulations, including the scenario without EV penetration, 16% penetration level (with nodes *o*, *b* and *q*), 32% penetration level (with nodes *o*, *b*, *k*, *f*, *h*, *q* randomly designated with red, blue and green priorities, respectively) and 46% penetration level (with nodes *o*, *b*, *j*, *k*, *f*, *g*, *h*, *m*, *q*). The energy management strategy for smart EV charging coordination with a time step is implemented, then all the obtained results are presented and discussed in the following sections.

## without EVs penetration

In this case, it's assumed that no EV is charged through the network and only normal loads, say residential loads, consume energy. The voltage magnitude results of 19 nodes at a specific time (14:00) are shown in Fig. 4. As expected, the highest voltage drop appears in nodes *k*, *m*, *j,* and *l*, which are located at the endpoints of the network, and in order to charge EVs, these points should be considered. It is expected that the constraints for all the nodes are met while implementing smart charging coordination.

As seen in Fig. 5, the voltage magnitude for the first node connected to the medium voltage system is constant and equal to 1 p.u. For the other nodes, voltage drops during the 24 hours. The lowest voltage magnitude occurs in node *j* at 22:00; this time, the voltage magnitude is close to 0.92 p.u, which is acceptable.

## 16% penetration level of EVs

In this scenario, 16% of the total number of EVs can be charged on nodes *o*, *b* and *q*. The results are shown in Figs. 6,7,8. As can be seen, all the constraints for the network are met, and as it is expected, the lowest voltage magnitude occurs in nodes *j* and *i* and the lowest value for the voltage magnitude is 0.91 p.u at 22:30. The voltage drops in all nodes occurred after 18:00 as the extra EV loads are added to the network, except for node 1 that is connected to the external grid. In this case, the total cost is 23.04 € for all the EVs that are charged.

As can be seen in Fig. 7, the highest voltage drop occurs in node *r* and in the red charging zone from 18:00 to 22:00. The minimum value for the voltage magnitude is 0.93 p.u which occurs at 19:00.

As illustrated in Fig. 8, the constraint related to the maximum demand is satisfied. This figure shows the summation of the load demand in all nodes in every time step in green, and the maximum demand for the grid is equal to 0.084 MW. The maximum value of P is equal to 0.0621 MW which occurs at 22:30.

## 32% penetration level of EVs

In this scenario, 32% of the total number of EVs can be charged on nodes *o*, *b*, *k*, *f*, *h*, *q*. The results are shown in Figs. 9,10,11. As observed, all the constraints for the network are met and the lowest voltage magnitude occurs in nodes *j* and *i* as they are located at the end of the grid. The lowest value for the voltage magnitude is 0.91 p.u at 21:00. Eexcept for node 1, which is connected to the external grid, the voltage drop rose during the 24 hours span compared to the previous scenario. In this case, the total cost is 51.828 € for the whole EVs that are charged.

As shown in Fig. 10, the highest voltage drop occurs in node *r*. The minimum value for the voltage magnitude is 0.91 p.u which happens at 10:30. Although there are some fluctuations in voltage profile, the constraint for voltage is met and voltage drop is less than 10%, which is acceptable.

According to Fig. 11, the constraint related to the maximum demand is satisfied. This figure shows the summation of the load demand in all nodes in every time step in green while the maximum demand for the grid is equal to 0.084 MW. The maximum value of P is equal to 0.063 MW which occurs at 10:30.

## 46% penetration level of EVs

In this scenario, 46% of the total number of EVs can be charged on nodes *o*, *b*, *j*, *k*, *f*, *g*, *h*, *m*, *q*. The results are shown in Fig. 12. As seen, all the constraints for the network are met, and the lowest voltage magnitude occurs on nodes *j*, *l* and *i* and while lowest value for the voltage magnitude is 0.9 p.u at 00:00. In this case, the total cost is 97.481 € for all charged EVs.

As shown in Fig. 13, the highest voltage drop occurs in node *r* over the whole simulation time as the number of charged EVs increases. The minimum value for the voltage magnitude is 0.913 p.u which happens at 22:30. Although there are some fluctuations in the voltage profile, the constraint for voltage is satisfied, and the voltage drop is less than 10%.

As demonstrated in Fig. 14, the constraint related to the maximum demand is satisfied. This figure shows the summation of the load demand in all nodes in every time step in green, while the maximum demand for the grid is equal to 0.084 MW. The maximum value of P is equal to 0.081 MW which occurs at 01:00.

# Conclusion

This paper presented an energy management algorithm for EV charging coordination considering network and vehicle constraints and drivers' price sensitivity. The simulation was performed in four different cases, showing that power demand significantly increases during peak hours in all cases. This situation worsens when the number of EVs that must be charged gets higher, which can affect the drivers who are more sensitive to price. Therefore, the proposed strategy considers charging priority groups and three charging time zones to optimize the EVs charging procedure. In this method, after scheduling higher priority EVs, there is enough capacity without violating system constraints for other charging priority groups. Compared with the realistic uncoordinated EV charging scenarios, a general improvement in system performance and reduction in operational costs is observed. Furthermore, the voltages at all nodes are regulated within limits, even under large EV penetrations.

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