



Online optimal variable charge-rate coordination of plug-in electric vehicles to maximize customer satisfaction and improve grid performance



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ABSTRACT

Participation of plug-in electric vehicles (PEVs) is expected to grow in emerging smart grids. A strategy to overcome potential grid overloading caused by large penetrations of PEVs is to optimize their battery charge-rates to fully explore grid capacity and maximize the customer satisfaction for all PEV owners. This paper proposes an online dynamically optimized algorithm for optimal variable charge-rate scheduling of PEVs based on coordinated aggregated particle swarm optimization (CAPSO). The online algorithm is updated at regular intervals of $\Delta t = 5$ min to maximize the customers' satisfactions for all PEV owners based on their requested plug-out times, requested battery state of charges (SOC_{Req}) and willingness to pay the higher charging energy prices. The algorithm also ensures that the distribution transformer is not overloaded while grid losses and node voltage deviations are minimized. Simulation results for uncoordinated PEV charging as well as CAPSO with fixed charge-rate coordination (FCC) and variable charge-rate coordination (VCC) strategies are compared for a 449-node network with different levels of PEV penetrations. The key contributions are optimal VCC of PEVs considering battery modeling, chargers' efficiencies and customer satisfaction based on requested plug-out times, driving pattern, desired final SOC and their interest to pay for energy at a higher rate.

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1. Introduction

High-tech developments in the automotive technology, growing environmental concerns in oil prices have triggered the advent of plug in electrical vehicles (PEVs). However, large fleets of PEV charging will require additional electric power demand that may lead to undesirable peaks in power consumption, transformer overloading, and interruptions. A potential solution is using online and/or offline PEV charging coordination strategies [1–4]. Ref. [3] proposes real-time PEV coordinated charging in residential distribution systems to reduce costs of power generation and losses. Ref. [4] presents real-time PEV charging/discharging coordination without considering customer preferences and variable charge-rates.

Ref. [5] proposes an online auction protocol such that vehicle owners use agents to bid for the charging opportunities. However, all PEVs have the same fixed charge-rate which is not usually the

case in practical applications as vehicles have different battery and charger types, and ratings. Ref. [6] presents online coordination of PEV charging and discharging in a small geographic area based on the unrealistic assumption that no PEVs will arrive when a charging schedule is made. Ref. [7] analyzes the performance of optimal PEV charging coordination including customer satisfaction without considering variable charge-rates. Refs. [8,9] focus on maximizing aggregator revenue without carefully addressing customers' preferences and may not necessarily lead to maximum benefit for customers. Alonso et al. [10] designed the PEV scheduling to fill the valleys of the residential load profile during periods of lower load demands to avoid vehicle charging during peak load hours using a genetic algorithm. In addition, Nguyen and Le [11] presented an optimization problem that aims to minimize the total cost of energy of each PEV user. This work considers time-varying electricity prices and performs daily scheduling. Also, a real-time scheduling method of PEV charging loads is proposed in Ref. [12] to increase voltage security margin in a low-voltage distribution system. A strategy is proposed in Ref. [13] to mitigate the adverse impacts that uncontrolled charging of the PEVs impose on the host power system. However, Refs. [10–13] do not include variable charging rates and ignore battery and charger efficiencies. Ref.

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Nomenclature

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i, j	Counters
m	Node number
n	Total number of nodes

Parameters

α_D, α_{V1} and α_{V2}	Coefficients used to adjust the slopes of the penalty functions
$Bid(\Delta t_k, i)$	The price that the i th PEV owner is willing to pay at current time slot (\$/kWh)
$Bid_{Max}(\Delta t_k)$	Maximum offered bid by all existing PEVs at current time slot (\$/kWh)
C	Ratio of charging or discharging current in A to the capacity of battery in Ah
CR_i^{max}	Maximum charging rate for the i th PEV (A)
$D_{max}(\Delta t_k)$	Maximum demand level that would normally occur without any PEVs during a day where selected to be 0.84 MW corresponding to the maximum load for the selected DLC (MW)
I_i^{Rated}	Rated charger current for the i th PEV (A)
k_1, k_2, k_3	Coefficients used to adjust the objective function based on the priority
L_j	Trip path for j th PEV (km)
L_i^{max}	Rated length path that each type of PEVs can trip (km)
$N_{PEV}(\Delta t_k)$	Number of available PEVs for current time slot
$\eta_{ch}(CR_i^{best}(\Delta t_k))$	Charger efficiency for the i th PEV at the best charge-rate (%)
Q_i	Rated battery ampere hour for the i th PEV (Ah)
R_i	Battery equivalent internal resistance for the i th node (ohm)
$R_{m,m+1}$	Resistance of the line segment between nodes m and $m+1$ (ohm)
$SOC_{initial}(i)$	State of charge of the i th PEV at plug-in time (%)
$SOC_{Req}(i)$	Requested SOC of the i th PEV (%)
$T_{Req}(i)$	Plug-out time of the i th PEV (h)
$V_{oc,i}$	Open circuit voltage for i th node (V)
V_{min} and V_{max}	Lower and upper node voltage limits (per unit; p.u.)
$Y_{m,m+1}$	Admittance of the line segment between nodes m and $m+1$ (ohm)

Variables

$C_S(\Delta t_k, i)$	Customer satisfaction level for current time slot at i th node (%)
$C_S(\Delta t_{k+1}, i)$	Customer satisfaction level for next time slot at i th node (%)
$CR_i^{best}(\Delta t_k)$	Optimized charging rate for the i th PEV at current time slot (A)
$Dt(\Delta t_k)$	Total load at current time slot (MW)
$DL(\Delta t_k)$	Daily load at current time slot (MW)
$FD(\Delta t_k)$	Penalty function for demand (distribution transformer loading) at current time slot
$FV(\Delta t_k)$	Penalty function for node voltage at current time slot
$I(\Delta t_k, i)$	Charging current for the i th PEV at current time slot (A)
$P_{Load}(\Delta t_k)$	Base-load power at current time slot (MW)
$P_{PEV,i}(\Delta t_k)$	Consumed power for the i th PEV (kW)
$SOC(\Delta t_k, i)$	State of charge of the i th PEV at k th time slot (%)
$T_{Remain}(\Delta t_k, i)$	The remaining available time for charging the i th PEV at current time slot (h)
V_i	Terminal voltage for i th node (per unit; p.u.)

[14] assumes that electric vehicles drivers are insensitive to charging costs and discharging benefits. In addition, in Ref. [15], the PEV charging and wind power scheduling were integrated.

In Ref. [26], a cost minimizing strategy benefiting is proposed, but does not consider fairness in charging for all PEVs. A real-time charging coordination of PEVs based on hybrid fuzzy discrete particle swarm optimization (PSO) was presented in Ref. [27]. In addition, in Ref. [28] a multi-agent system that coordinates EV charging in distribution networks has been proposed using a distributed control method. A multi-objective scheduling strategy is formulated to charge a number of PEVs while a fuzzy solution is proposed to achieve the best compromise between the two objective functions in Ref. [29]. Moreover, Ref. [30] used the population-based metaheuristics approach to solve the optimization problems. Another study [31] also shows that optimizing the charging schedule can reduce grid voltage drops and power losses as well as optimizing the load profiles.

In performing PEVs charging coordination considering customer satisfaction, some vehicles can submit requested plug-out times along with the associated requested state of charges (SOC_{Req}). Meeting these requirements is not a big problem when all the vehicles plug-out at their requested departure times. However, when unexpected departures of PEVs occur, the conventional schemes such as those proposed in Refs. [3–6], may not be able to provide acceptable levels of satisfaction fairness among the users. Moreover, some vehicles may not be fully charged at the end of charging horizon. The problem can be resolved by using variable charging rates as a strategy to adapt the power drawn by the charger from the grid to the load, in order to fully exploit grid capability and provide a high degree of user satisfaction.

While the objective functions of Refs. [14,15] are optimization of aggregators' income and the cost of energy without addressing customers' satisfactions. In Ref. [16], the variable-based charging of PEVs is investigated; however, requested plug-out times and customers' preferences are not considered.

The main objective of this paper is to perform optimal PEV charging coordination to maximize all customers' satisfactions without exceeding grid constraints. This is done by (i) allowing customers to specify their own charging demands including requested plug-out times, desired departure SOC and the higher electricity prices they are willing to pay, (ii) developing an optimization problem where the decision variables are the charging rates updated at time slots of $\Delta t = 5$ min, and (iii) solving the problem using coordinated aggregated particle swarm optimization (CAPSO). We rely on the quality and speed of the CAPSO solution for accurate and quick online PEV charging [24,34,35]. Among the artificial intelligent based algorithms, the CAPSO is known to achieve near optimal solutions with better convergence characteristics. Simulation results for uncoordinated PEV charging, as well as CAPSO with fixed charge-rate coordination (FCC) and variable charge-rate coordination (VCC) are compared for a 449-node network. The proposed algorithm takes into consideration random plug-in times, initial SOC, requested plug-out times, requested final SOC and maximum charging rates of PEV batteries.

2. Modeling of battery and charger for PEVs

Coordination of PEVs in smart grid requires accurate modeling of its battery profile and charging characteristics. Many modern battery chargers are capable of achieving high efficiency values; however, their charging efficiencies indicate significant dependency on the charging rate due to the internal battery resistance [19–21]. This is particularly important in calculating the actual stored energies and SOC at different times during the charging period. Fig. 1(a) shows a sample experimental data of the average

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