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Real-time charging coordination of plug-in electric vehicles based on hybrid fuzzy discrete particle swarm optimization

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A B S T R A C T

The main impact of uncoordinated plug-in electric vehicle (PEV) charging is adding new time-variant loads that can increase the strains on the generation units, transmission and distribution systems that may result in unacceptable voltage drops and poor power quality. This paper proposes two dynamic online approaches for coordination of PEV charging based on fuzzy genetic algorithm (FGA) and fuzzy discrete particle swarm optimization (FDPSO). The algorithms will minimize the costs associated with energy generation and grid losses while also maximizing the delivered power to PEVs considering distribution transformer loading, voltage regulation limits, initial and final battery state of charges (SOCs) based on consumers' preferences. The second algorithm relies on the quality and speed of DPSO solution for more accurate and faster online coordination of PEVs while also exploiting fuzzy reasoning for shifting charging demands to off-peak hours for a further reduction in overall cost and transformer loading. Simulation results for uncoordinated, DPSO, FGA and FDPSO coordinated charging are presented and compared for a 449-node network populated with PEVs. Results are also compared with the previously published PEV coordinated charging based on maximum sensitivity selections (MSS). Main contributions are formulating the PEVs charging coordination problem and applying different optimization methods including online FGA and FDPSO considering different driving patterns, battery sizes and charging rates, as well as initial SOCs and requested final SOCs.

1. Introduction

Recent developments in smart grid (SG) technology along with the growing concerns about the environment have increased the interests of public and electric utilities in PEVs. These vehicles can be beneficial and cost effective to both the consumers and electric utilities if their charging activities are properly coordinated [1]. However, recent studies show that uncoordinated PEV charging can increase the stress on power system, cause voltage drops and rebound peaks [6,31–34]. In general, PEV charging can be performed using centralized [2,3,7–12] and/or decentralized coordination approaches [4,5,13–15].

There are various decentralized methods for PEV charging based on electricity auction [4,13], dual tariffs for PEV owners in several utility service regions [14], and energy cost sharing model [21]. The aim is without relying on a central control unit, each PEV owner be motivated to autonomously adjust its own charging power in response to a communal virtual price signal and its own preferences. However, the outcome of a decentralized approach may or may not be optimal, depending on the information and methods used to determine local charging patterns [22,30]. For instance, dual tariffs are only suitable for the scenario when the market share of PEVs is low [14]. In addition, in decentralized strategies, the network operator uses price incentives to motivate shifting of charging tasks to valleys of the load profile while each PEV owner is responsible for its own charging pattern.

There are also several studies on centralized PEV coordination with various objectives such as valley filling [7], PEV coordination with CHP (combined heat and power) [8] and minimizing distribution feeder losses [3] as well as minimizing the costs associated with energy generation and grid losses [11]. In a centralized PEV coordination strategies, the utility is responsible to coordinate vehicle charging by directly considering grid performance improvements (grid losses and node voltage profiles) while also indirectly looking after PEV owners' benefits by postponing vehicle charging to off-peak hours with inexpensive electricity prices. An aggregator usually makes decisions about the time and rate of all PEV charging in order to achieve near optimal solutions [16]. In addition, the aggregator acts as an interface between customers (PEVs) and the

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grid operator and provides charging services considering benefits of both sides [17–20]. In [10,23], PEVs are assumed to have the same battery sizes and chargers while [10] only considers a static charging scenario. In [11] optimal PEV charging is performed using a maximum sensitivity selections (MSS) based algorithm considering the same battery size, charge rates and SOCs for all PEVs. The 34-node small smart grid test system used in [3] for charging of PEVs in a static state.

Although the above-mentioned studies have examined various aspects of the PEV charging coordination, it is imperative to propose an online centralized and comprehensive algorithm that is applicable to power market with time-varying market energy prices (MEP) considering the charging demand based on customers' behavior for each PEV with different battery sizes and charger types. Furthermore, for online applications, the speed and computing time of the coordination algorithm plays a vital role, as the aggregator will execute it at each timeslot with updated load profiles in order to obtain a new charging schedule.

In this paper two dynamic heuristic based approaches based on hybrid (FGA) and hybrid (FDPSO) optimization are proposed for online charging of PEV batteries in SG. The algorithms minimize the cost associated with energy generation and grid losses while also maximizing the delivered power to PEVs, regulating node voltages and reducing distribution transformer loading. Simulations results for a 449-node SG network are presented and compared with online coordinated PEV charging using MSS [11], GA, DPSO, FGA and FDPSO approaches.

2. Problem formulation

Online coordination of PEV charging is a dynamic and real time optimization problem that requires formulation of a comprehensive objective function and a high-speed optimization method to capture near-optimal solutions. In this paper, the optimization variable is the charging status of PEVs, where charging rate is variable for different PEV types. However, during the charging progress it is considered that charging rate is constant. The nonlinear objective function of Eq. (1) is defined for the PEV coordination problem to maximize the delivered charging power ($F_{DCP}(t)$) to PEVs at each timeslot (Δt = 5 min), while the costs associated with energy generation ($F_{cost\text{-}gen}(t)$), and grid losses ($F_{cost\text{-}loss}(t)$) are also minimized:

$$Max \quad F(t) = \frac{F_{DCP}(t)}{F_{\cos t-loss}(t) + F_{\cos t-gen}(t)} = \frac{\sum_{i=1}^{N_{PEV}} (\text{Delivered charging power}(i,t))}{\sum_t \mathrm{K_E} P_{loss}(t) + \sum_t \mathrm{K_{t,G}} D_{total}(t)} \quad \text{for} \ t = \Delta t, 2\Delta t, \ldots, 24\,\text{h} \tag{1}$$

where $P_{loss}(t) = \sum_{k=0}^{n-1} R_{k,k+1}(|V_{k+1}(t) - V_k(t)||y_{k,k+1}|)^2$, K_E and $K_{t,G}$ are the costs per MWh of losses [11,12] and generation (Fig. 3(b)), respectively; Δt = 5 min is the timeslot; k and n are the node number and total number of nodes; $R_{k,k+1}$ and $y_{k,k+1}$ are the resistance and reactance of the line segment between nodes k and $k+1$, respectively.

Eq. (1) is subject to the following voltage (Eq. (2)), demand for each timeslot (Eq. (3)), and SOC constraints (Eq. (4)) to preserve power quality and supplying the base and PEV loads.

$$V_{\min} \le V_k(t) \le V_{\max}, \quad \text{for} \quad k = 1, \ldots, n \tag{2}$$

$$D_{total}(t) = \sum_{k=1}^{n} P_k(t) = \sum_{k=1}^{n} (P_{Load_K}(t) + P_{PEV_K} \le D_{\max}(t)) \quad t = \Delta t, 2\Delta t, \ldots. \tag{3}$$

where $D_{\max}(t) = Max\,\{DL(\Delta t), DL(2\Delta t), ..., DL(m\Delta t)\}$, m = 1, ..., 288

$$SOC(i,t) \le SOC_{Req}(i) \le SOC_{\max}, \; i = 1, \ldots, N_{PEV} \tag{4}$$

where V_{min} and V_{max} are the lower and upper voltage limits, respectively; $D_{max}(t)$ is the maximum demand level that would normally occur without any PEVs during a day. In this paper, $D_{max}(t)$ is selected to be 0.84 MW corresponding to the maximum load for the selected DLC. $SOC(i,t)$ is the SOC for the ith PEV at t, $SOC_{Req}(i)$ is the requested SOC for the ith PEV, $SOC_{\max}$ is the state of charge of each battery when the battery is fully charged, P_{Loadk} is the base-load power, DL is the daily load at mth timeslot, and P_{PEVk} is the consumed power for the PEV at node k.

In this paper, $SOC_{initial}$ at plug-in time is driven from driving pattern for each PEV [29]:

$$F(t) = \begin{cases} \alpha_i - (\alpha_i - \beta_i) \times \dfrac{L_j}{L_i^{\max}} & L_j \le L_i^{\max} \\ \beta_i & \text{otherwise} \end{cases} \quad \text{for} \quad i = 1, 2, 3, \quad j = 1, \ldots\ldots, N_{PEV} \tag{5}$$

where i indicates the type of PEVs, j is number of PEVs, L_j is the trip path for jth PEV, and $L_i^{\max}$ is the rated length path that each type of PEVs can trip [29]. In this paper, the selected values for parameters α_1, α_2 and α_3 are 0.85, 0.8, and 0.75, β_1, β_2 and β_3 are 0.15, 0.2 and 0.25; and L_1, L_2 and L_3 are 40, 50, 60 miles, respectively. In addition, three types of PEVs including e-Golf (Type 1), Honda Fit (Type 2), Ford C-Max (Type 3) with chargers' rates of 7.2, 6.6, 3.3 kW and corresponding battery sizes of 24, 20, 7.6 kWh (with 88% efficiency) are considered [28].

It is also assumed that aggregator has access to PEV information using smart metering technology to monitor their locations, charger types, battery sizes, initial and requested SOCs ($SOC_{initial}$ and SOC_{Req}). The scheduling horizon starts at 16:00 h for 24-h, and is divided into 288 timeslots of Δt = 5 min. As a result, after plugging a new PEV at Δt, the grid loads will be updated and the proposed coordination algorithm will be executed to obtain a new optimal charging schedule. In addition, in this paper no constraint is assumed for the charging time and vehicles might be plugged-in at any time during the 24-h time horizon. However, if vehicles are plugged-out before the designated departure time (next day at 6am) then they may not be fully charged.

In this paper, the backward-forward sweep method is used to calculate load flows and bus voltages [3], and it is considered that the generation capacity is large enough to supply both base and charging load in all timeslots. It should be noted that if a PEV owner prefer to charge without being schedulable, the PEV will be part of the base load. As the optimization is real-time, changing the base load does not affect on the optimization results.

3. Proposed online heuristic based coordination algorithms for PEV charging

Many practical problems including optimal PEV coordination have discrete nature; therefore, two PEV charging approaches incorporating fuzzy reasoning based on DPSO [25] and binary genetic algorithm are developed to solve Eqs. (1)–(4).

3.1. DPSO formulation

The discrete version of PSO is very similar to the original continuous algorithm except for the state equations listed below (Eqs. (6)–(8)). In DPSO formulation, the position and velocity of each particle are vectors in the d-dimensional binary solution space $x_i \in \{0 \quad 1\}^d$ and the continuous space, respectively. The