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Dynamic resource allocation for parking lot electric vehicle recharging using heuristic fuzzy particle swarm optimization algorithm

Hao Wu[a,*], Grantham Kwok-Hung Pang[a], King Lun Choy[b], Hoi Yan Lam[b]

[a] Department of Electrical and Electronic Engineering, The University of Hong Kong, Pokfulam Road, Hong Kong
[b] Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong

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ABSTRACT

A parking lot (PL) dynamic resource allocation system for recharging electric vehicles (EVs) is introduced in this paper. For scheduling purposes, a day is divided into sequential timeslots. At the beginning of each timeslot, the dynamic system can determine an optimal charging schedule for that timeslot, as well as plan for subsequent timeslots. An EV may arrive at a PL with or without an appointment. Considering the variation in electricity prices during the day, the objective is to minimize the cost of electricity used to charge EVs by scheduling optimal electric quantities at the parking timeslots of each EV. The optimal solution satisfies the EV's charging rate limit and the PL's transformer limit. Based on particle swarm optimization (PSO), fuzzy systems and heuristics, this paper describes a heuristic fuzzy particle swarm optimization (PHFPSO) algorithm to solve the optimization problem. From the case studies, the results show the proposed dynamic resource allocation system has a significant improvement in satisfying charging requests and in reducing the electricity cost of the PL when compared with other scheduling mechanisms.

1. Introduction

Electric vehicles (EVs) typically charge at public parking lots (PLs) equipped with power outlets, which would take hours to fully recharge the battery. With the rapid growth of EV populations [1], it is essential to employ a resource allocation system to schedule the limited public PLs and satisfy the electric requirements for power infrastructures. The main limitations of EV PL systems include long charging times, uncertain parking periods, varied charging demands and transformer limits. Currently, most of the PLs manage the EV charging requests on a first-in-first-serve (FIFS) strategy.

The motivation for proposing a dynamic PL resource allocation system is given as follows. First, in some big cities where people mostly live in apartments and work in the urban areas, only a small proportion of EV owners can afford to install a private charging pile to recharge their EVs. Many other EV owners drive to some super-charging stations to recharge their vehicles while they run a few errands, typically within an hour. An alternative would be for EV owners to recharge their vehicles during parking in a public PL with specialized EV charging facilities. In this case, the vehicles are parked for a longer duration, from two or more hours. EV recharging can also take place in an office building PL while their owners go to work during daytime. Hence, it is essential for a PL to have a resource allocation system to manage the EV charging during parking.

Secondly, the PL should have a transformer limit due to the power grid and safety precautions. In this case, the PL should balance the allocated electric quantities in each timeslot to satisfy the transformer limit. Each timeslot is typically set as 30 min in this study. Also, considering the charging specifications, the allocated electric quantities cannot exceed the maximum charging rate of each EV. Hence, the PL should determine an optimal charging schedule that satisfies both the transformer limit and the charging rate limit.

Thirdly, most current commercial PLs use the FIFS scheduling mechanism to deal with the parking and charging requests from EVs. Due to the transformer limit, a PL with a FIFS mechanism cannot optimize the distribution of the charging resources to the vehicles, and some of the late arrival requests cannot be fulfilled. Hence, the PL should use some optimization schedule to take care of the charging requests.

* Corresponding author at: RM511, Chow Yei Ching Building, Department of Electrical and Electronic Engineering, The University of Hong Kong, Pokfulam Road, Hong Kong.

E-mail addresses: haowu@eee.hku.hk (H. Wu), gpang@eee.hku.hk (G.K.-H. Pang), kl.choy@polyu.edu.hk (K.L. Choy), cathy.lam@connect.polyu.hk (H.Y. Lam).

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Lastly, the PL providing a service to recharge the EVs has to buy a large amount of electricity from the power company. Knowing that many power companies provide a time-of-use price that varies at different times, the PL would aim to lower the cost by purchasing in a low-price period. Supposed the electricity is sold to the EV owners at a fixed price rate, the PL can make more revenue by determining an optimized strategy to allocate more electric supply during the low price period, and less amounts when the price is high.

The main contributions of this study are as follows. Firstly, a viable PL operation system is designed to manage the charging requests for vehicles that arrive with or without appointments. The dynamic system determines a charging schedule for the immediate timeslot. Secondly, the aim of the optimization model is defined to best satisfy the EV charging requests and minimizes the PL's electricity cost concurrently. Thirdly, a resource allocation model based on the proportion-based assignment method is proposed to improve the efficiency in generating the initial solutions for optimization. Lastly, a PHFPSO algorithm is proposed to solve the optimization problem with the use of the PSO algorithm, fuzzy systems and heuristics, and the results show that the PHFPSO can determine an optimized solution and outperform other algorithms.

The related work is described in Section 2. Section 3 introduces the operation model. The problem formulation is given in Section 4. In Section 5, the methodology for solving the optimization problem is presented. The simulation case studies are given in Section 6, and conclusions and future work complete this paper in Section 7.

2. Literature review

Some approaches have been proposed in the literature to solve the EV charging problem for power grid and PLs, which include power grid coordination, charging station recommendation, PL planning, EV charging pricing, and charging schedule decision model.

In order to manage the potential high peak demand of EV charging at residential distribution areas, some demand response (DR) systems were studied in Refs. [2–7] for a smart grid. A hierarchical coordinated charging framework and a vehicle-to-grid (V2G) scenario were proposed in Refs. [8,9] to solve the optimization operation problem in a distribution system operator (DSO). Considering the benefit of a renewable energy source (RES) but with drawbacks such as the intermittent nature and uncontrollability Refs. [10–13] proposed some optimization methods to manage a multi-energy system at a charging station. Besides that, an energy storage (ES) unit was used to minimize the impact of uncertainty and inaccurate prediction in Refs. [13,14].

Another approach is to determine the capacity and location of PLs in Refs. [15–17]. Starting with some candidate charging stations, Ref. [18] proposed a real-time charging station recommendation system for EV taxis. In Ref. [19], a coordinated bidding of ancillary services for V2G was proposed to maximize profits. Further studies determined the charging price so as to maximize the profit in Refs. [13,20].

A novel strategy allowing vehicle-to-vehicle (V2V) charging was proposed in Ref. [21]. It aimed to minimize the total cost, which included the electricity cost and the damage to the EV batteries due to extra charging cycles. The decision was determined using binary variables denoting the charging and discharging states of each EV. A small number of EVs were used to evaluate the performance, but the computational time was very high. Ref. [22] proposed a real-time charging scheme to coordinate EV charging decisions and to accommodate demand based on the electricity price and the demand curtailment request from the utility company. The objective was to maximize the number of EVs for charging at each scheduling period and to minimize the electricity bill. The schedule used a binary decision approach for determining the on-off strategy of each charging pole.

Differing from the binary decision approach, Ref. [23] proposed a PL management system to determine the optimal charging strategy for the EV charging in day-time. The objective was to minimize the charging cost of the station considering the electricity cost and a penalty cost if EV demand was not satisfied. In Ref. [24], authors also developed an optimal schedule for EV charging using a game-theoretic approach. However, the vehicle profiles they used overlapped for 30 time intervals and the charging demands were very low, so that the candidate solutions were easily found. In Refs. [25,26], some optimization intelligent-based algorithms were proposed for determining the charging schedule, and [27] designed new accelerated particle swarm optimization (APSO) algorithms to solve the same problem. The aim was to maximize the average State-of-Charge for all EVs at the next time step. However, in the optimization model, the decision was only for the EVs being charged in the next time step. Hence, this may not provide an optimized schedule without considering the whole parking period of the EVs.

Separated layers/scenarios/schemes was proposed to handle EVs with and without appointments in Refs. [28–30]. Two scenarios were proposed in Ref. [28] to determine a charging schedule considering the aggregator's revenue and customer demands and cost. The static charging scenario was for the known customers of the aggregator, while the dynamic charging scenario was for those customers who came and left without any advanced notice. The decision was fixed for these EVs in the static schedule. If a new customer comes without advanced notice, the determined schedule cannot be changed, even if a better solution exists. A PL management system for a centralized EVs recharging system was proposed in Ref. [29] for maximizing the PL revenue or maximizing the total number of EVs fulfilling their requirements. They defined a two-layer scheduling model to deal with regular and irregular EVs. They used an optimization algorithm to determine the schedule for the routine layer, and used the first-in-first-serve (FIFS) and earliest-deadline-first (EDF) mechanisms to deal with the irregular EVs. However, their optimization model can only deal with regular EVs but the FIFS and EDF are used to handle the irregular EVs, which may not lead to6 an optimal decision. Ref. [30] proposed a global optimal scheduling scheme and a locally optimal scheduling scheme for EV charging and discharging. The aim was to minimize the total cost of all EVs and the decision involved the charging and discharging power of each EV at each timeslot. A global and local scheduling scheme was defined to deal with the appointed and non-appointed EVs respectively. In their local optimization model, the power load may exceed the transformer limit.

2.1. Decision methods

In the literature, different methods, such as decision strategies/mechanisms, linear programming (LP), mixed-integer linear programming (MILP), dynamic programming (DP), game theory and computational intelligent algorithms, are used to obtain solutions.

In most commercial PLs, some scheduling strategies/ mechanisms are used to manage the charging requests for EVs, such as FIFS and EDF. Accordingly, the FIFS and EDF mechanisms are widely used as the baseline scheduling method such as in Refs. [22,23,28,29]. Some references [6,14,15,21,22,28–30], defined the problem as a linear optimization problem, which can be solved by mathematical methods such as LP and MILP. Refs. [6,28] used CPLEX to solve the LP problem. A dynamic programming method was implemented in Ref. [23] to determine the optimal charging strategy knowing the short-term future and long-term prediction information. In addi-