Electric Power Systems Research 145 (2017) 166–174

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Fuzzy Optimization for the Operation of Electric Vehicle Parking Lots

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ARTICLE INFO

Article history:
Received 11 August 2016
Received in revised form 5 November 2016
Accepted 4 January 2017
Available online 11 January 2017

Keywords:
Electric vehicles
Parking lot
Fuzzy optimization
EV mobility uncertainty

ABSTRACT

Integrating electric vehicles (EVs) into the smart grid has become a topic of great interest lately due to the potential benefits it provides. Since EVs are expected to be parking most of the time, it is expected that EVs will play a role in competitive business environments like parking lots (PLs). However, the parking lot operator (PLO) is exposed to many uncertainties, including those associated with the electric energy market and EV mobility. This paper proposes a fuzzy optimization model that aims at maximizing the PLO's profit while satisfying EV owners' charging requirements. It is assumed that the PLO bids EV charging schedules in the day-ahead market of energy. The PLO can, then, balance any deviation from its day-ahead schedule in the real-time market. The uncertainties of the profits due to market price fluctuations are taken into consideration. Also, the uncertainties associated with the EV mobility, such as the EV type mix using the parking lot (PL), their initial and final states of charge, and their departure time, are also considered. In addition, the effect of the charging efficiency is investigated. The simulation results show that the proposed fuzzy optimization algorithm leads to higher realized profits than those of the deterministic benchmark algorithm. Also, the results show that the proposed algorithm is robust and offers high profitability even with high levels of uncertainty.

1. Introduction

The number of electric vehicles (EVs) to be integrated into the power grid is expected to increase in the coming few years [1]. EVs have many positive benefits. They can help in carbon emission reduction [2], petroleum independence, and the integration of renewable energy resources [3]. However, the anticipation of a large penetration of EVs brings up many technical challenges that need to be addressed. As EVs need more frequent charging than gasoline-powered vehicles due to the limited capacity of their batteries, the associated transportation infrastructure must provide more electric charging stations along the main road networks and at other diverse points [4]. Moreover, drivers need to have their EVs charged within a certain time frame, e.g. before they depart from their offices, their homes, and the like. Hence, charging stations should have the ability to schedule multiple requests having different time constraints, charging rates, and power consumption dynamics [4,5]. As a result, problems related to the process of charging a random number of EV batteries with random energy demands need to be addressed.

Potential benefits of EV scheduling to different stakeholders using data collected from over 2000 non-residential electric vehicle supply equipment (EVSEs) were investigated in Ref. [6]. It was shown that up to 24.8% decrease in the aggregate monthly bill was possible, and the aggregated peak load was reduced with median peak shed values around 30–42% for each month. The effect of multiple EV charging on the distribution transformer was addressed in Ref. [7]. It was suggested that the off peak tariff would have an effect over the EV owners, and the loss of life of the transformer would only be affected after a specified amount of vehicles penetration which is relatively high. EV charge control schemes for controlling frequency and voltage and deferring investment were considered in Refs. [8–11].

Different algorithms for reducing peak power demand while satisfying the different constraints specified in each charging request were investigated in Refs. [4,12]. However, the uncertainty of the EV mobility was not considered. A bi-layer optimization of EV scheduling to improve the grid operation and to accommodate renewable energy was proposed in Refs. [13,14]. However, EVs' driving characteristics were not considered.

Uncertainties associated with EV mobility were considered in Refs. [15–17]. In Ref. [15], an algorithm was presented to manage a large number of plug-in hybrid EVs (PHEVs) charging at municipal parking in an optimal way. The algorithm attempts to maximize the average state of charge (SOC) at the next time step

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http://dx.doi.org/10.1016/j.epsr.2017.01.008
0378-7796/

Nomenclature

IN	Income of the parking lot
C	Cost of the energy bought by parking lot
PT	Expected profits of the parking lot obtained from the optimization
β	Price of energy charged by the parking lot to the customer
ρ	Forecasted day-ahead energy price (¢/kW h).
AV	EV availability (1 for available, 0 for unavailable)
st	Starting time for EV charging
dt	EV Departure time
Δt	Duration of time interval
NEV	Total number of EV charging stations at the parking lot
PC	Parking lot capacity due to transformer rating (kW)
POP	Preferred operating point, i.e. scheduled charging rate
$SOCI$	Initial state of charge
$SOCF$	Required final state of charge
MC	Maximum battery capacity
MR	Maximum charging rate of the EV
EVP	Estimated percentage of EVs remaining after unexpected departure
A_Dep	Accumulated probability of the unexpected departure
λ	Fuzzy objective
μ_x	Membership function
$\tilde{PT}$	Fuzzy set of the profit
$\overline{PT}$	Upper bound of the profit
$\overline{MR}$	Upper bound of the charging rate inequality
$\overline{MC}$	Upper bound of the battery capacity inequality
$\overline{SD}$	Upper bound of the final state of charge inequality
pt	Fuzzy variable associated with the profit inequality
mr	Fuzzy variable associated with the charging rate inequality
mc	Fuzzy variable associated with the battery capacity inequality
sd	Fuzzy variable associated with the final state of charge inequality
K_{PT}	Percentage of uncertainty in the profit
K_{MR}	Percentage of uncertainty in the maximum charging rate
K_{MC}	Percentage of uncertainty between the initial and the battery capacity
K_{SD}	Percentage of uncertainty between the initial and the required final state of charge
i	Index for numbering the EVs
t	Time index
EV	Electric vehicle
PL	Parking lot
PLO	Parking lot operator

taking into consideration uncertainties of the initial SOC, the arrival time and the time for completing the morning commute. Input data were derived from normal distribution curves based on transportation statistical data. However, in order to make real-time decisions based on Ref. [15], a large amount of raw data needs to be processed, which increases computation burden. Multi-stage stochastic model of EVs aggregators was considered in Ref. [16] to participate in day-ahead and intraday electricity markets. The authors addressed the performance of the EVs aggregator in the presence of the demand response exchange. Because stochastic programming involves generating a scenario tree, the computational cost becomes excessively high as the number of uncertain parameters increase. Minimizing the overall load variance in the grid taking into consideration the stochastic nature of the EV availability was considered in Ref. [17]. However, the uncertainties of the initial and required final state of charge were not considered.

In Ref. [18], a hierarchical optimal algorithm was proposed to schedule the charging of EVs to maximize the revenue of the charging service provider while satisfying customer charge demands and transformer capacity constraints. It was assumed that the arrival and departure times and the initial SOC of each EV are all stochastic but with known probability distributions. However, the presented algorithm is quite complicated and the computational burden increases exponentially with the length of the operation horizon and the number of EVs connected to the charging system.

The algorithms presented in Refs. [15–18] concern a utility or an aggregator that serves a large number of EVs. In these cases, the EV characteristics and EV mobility characteristics can be predicted with reasonable accuracy due to the law of large numbers. In contrast, a parking lot operator (PLO) serves a small subset of EVs, which makes their characteristics and EV mobility data much harder to predict. This makes the optimization of EV charging for a PLO a particularly interesting problem. However, few research works have addressed this problem. An algorithm for real-time energy management of a grid-connected PHEVs charging parking lot (PL) was considered in Ref. [19]. It was developed based on statistical and forecasting models to reduce the overall daily cost of PHEVs charging and mitigate the impact of the charging park on the main grid. However, the algorithm does not employ any optimization model to solve the problem.

A centralized EV charge scheduling system for PLs of a city using a realistic vehicular mobility/parking pattern focusing on individual parking lots was presented in Ref. [20]. The approach utilized both day-ahead and real-time scheduling components to maximize the total PL revenues and the total number of EVs fulfilling their requirement. The system starts charging from the time slot in which the buying price is the cheapest irrespective of the EV time availability, which is risky and sub-optimal. In Ref. [21], a stochastic model was developed to generate scenarios indicating the behavior of EVs. For simplicity, it was assumed that only one type of charging stations is available in the system, hence the maximum charging rate is unified. In addition, the EV specifications were assumed to be the same for the whole fleet, which is unrealistic. Furthermore, the uncertainty of the initial SOC was not taken into account.

This work is motivated by the need to address the optimization of EV charge scheduling for a PLO considering EV mobility and market uncertainties while maintaining the problem size tractable. A novel linear fuzzy optimization approach is proposed for this purpose. Fuzzy optimization was successfully implemented to various power system problems [22–26] as it can incorporate the uncertainties while maintaining the problem tractable [27]. To the best of the authors' knowledge, fuzzy optimization has never been used for dealing with the uncertainties associated with EV mobility.

The aim of the formulated optimization problem is to maximize the profits of the PLO while satisfying the EV owners' requirements. Unlike most of the fuzzy applications reported in the literature [23,24,26], the proposed fuzzy optimization approach is based on fuzzifying (i.e. defining a membership function for each of) the problem uncertain constraints rather than the problem uncertain parameters. This simplifies the optimization problem and reduces substantially its complexity. Specifically, the uncertainties associated with the market prices, initial SOCs, maximum battery capacities of the incoming EVs, and final SOCs required by the EV owners at departure are modeled using the proposed linear fuzzy optimization. In addition, unexpected departure times for some EVs is considered. Two case studies are considered. In one case, the PLO applies a fixed charging tariff to all EVs. In the other case, the PLO applies a multi-tier charging tariff structure to give the EV owner the choice of charging faster but at a higher price.

The specific contributions of this paper to the state of the art in EV charging for a PLO are:

1. Fuzzy optimization is implemented for the first time for optimizing the operation of an EV parking lot.
2. The uncertainties of EV characteristics, EV mobility data, and market aspects are addressed concurrently.
3. All the previous applications of fuzzy optimization to power system problems associate a membership function to each fuzzy parameter [23,24,26]. The approach presented in this work is based on associating a membership function to each fuzzy constraint.

2. Scheduling of EV Charging for a Parking Lot – Benchmark Deterministic Optimization Approach

In this work, the case for an EV parking lot is considered. The parking lot operator (PLO) purchases the energy needed to charge the EVs from the day-ahead energy market. Therefore, it is required to send hourly day-ahead bids. Since the PLO is considered as a price taker, the bids will be defined solely by the kW quantities it would like to purchase from this energy market. The PLO will then sell this energy to the EVs in real time (RT) at a pre-defined energy tariff. If the energy needed in RT deviates from that purchased from the day-ahead market, the PLO has to pay for balancing services. A unidirectional power flow to the EVs is assumed.

The PL is assumed to be located in a city center, which is expected to be very busy during day hours and much less active at night. Since the EVs are available for charging only opportunistically, the PLO has to deal with several uncertainties during energy scheduling. These include the EV availability times, their battery capacities, maximum charging rates, and initial and final SOCs. These uncertainties stem from the fact that the PLO does not know a priori the type of EVs joining in the day-ahead (*MC* and *MR*), the initial battery status (*SOCI*), and the EV owner preferences (*SOCF*, *st*, *dt*, and β). These uncertainties will be incorporated in Section 3. For the deterministic approach (used as a benchmark) presented in this section, though, forecasted values of these parameters are used as inputs for the optimization of day-ahead energy schedules.

As a market participant, the PLO seeks to maximize its expected profits, defined by income and costs, while satisfying operational and physical constraints. For a PLO, the expected daily income is the revenues obtained from selling energy to the EV owners. This can be expressed as:

$$IN = \sum_i \sum_t \beta_i \cdot AV_{it} \cdot POP_{it} \cdot EVP_t \tag{1}$$

β_i is a pre-determined charging tariff that is set by the PLO depending on the charging speed requested by the EV owner. Basically, relation (1) states that the PLO income from the i-th EV at time t is equal to the charging tariff (β_i) multiplied by the charging schedule (POP_{it}) as long as the EV is available (AV_{it}), i.e. plugged in. EVP_t is a parameter used to account for the possibility of unexpected departure of EVs. This can be estimated by considering the percentage of the remaining EVs to be charged. The calculation of EVP_t for a certain hour t is a function of the accumulated probability of the unexpected departure of all EVs at that hour, A_Dep_{it}, which is a function of the time of scheduled trips for each EV during the day. This can be expressed as follows:

$$EVP_t = 1 - \frac{1}{NEV} \sum_{i=1}^{NEV} A\_Dep_{it} \quad \forall t \tag{2}$$

$$A\_Dep_{it} = \sum_{h=1}^{t} A\_Dep_i(h), \quad \forall i, st \le t \le dt \tag{3}$$

The PL expected cost comes from buying the energy that is needed to charge the EV fleet from the day-ahead energy market. The daily expected cost of the PL is:

$$C = \sum_i \sum_t AV_{it} \cdot POP_{it} \cdot \rho_t \cdot EVP_t \tag{4}$$

The optimization problem can be formulated as:

$$\underset{POP_{it}}{\text{maximize}} \quad PT = IN - C \tag{5}$$

subject to:

$$AV_{it} \cdot POP_{it} \ge 0 \quad \forall i, t \tag{6}$$

$$AV_{it} \cdot POP_{it} \le MR_i \quad \forall i, t \tag{7}$$

$$\sum_t (AV_{it} \cdot POP_{it}) \Delta t + SOCI_i = \min(SOCF_i, MC_i) \quad \forall i \tag{8}$$

$$\sum_i AV_{it} \cdot POP_{it} \le PC \quad \forall t \tag{9}$$

Constraints (6) and (7) are given to ensure positive charging rates to EVs (i.e, unidirectional power flows) and to limit the scheduled charging amount by the maximum charging rate of the EV. Relation (8) is an equality constraint that is included to ensure that the battery will charge to the level required by the EV owner. If $SOCF_i$ is not set by the user, the default value of MC_i will be enforced at the end of the charging period. Relation (9) is included to limit the total charging amount of all EVs at any hour by the maximum capacity of the transformer feeding the parking lot.

3. Scheduling of EV Charging for a Parking Lot—Proposed Fuzzy Optimization Algorithm

As mentioned above, the optimization of PLO schedules involves a number of uncertain parameters (e.g. ρ, *SOCI*, *SOCF*, *MC*, and *MR*). In the deterministic approach, forecasted values of these parameters are used. In this section, the proposed fuzzy optimization will be presented as an approach for incorporating the uncertainties associated with these parameters in order to enhance the optimization outcomes.

Fuzzy set theory was first introduced in the 1960's by Zadeh in his famous publication 'Fuzzy Sets'[27]. Fuzzy set theory is a mathematical tool that facilitates the modeling of imprecise or conflicting decisions. The significance of this concept comes from the fact that the conventional logic where everything is bivalent (true/false, 0/1) is not suitable enough to solve real life problems, especially in engineering where the possibilities are multivalued. Fuzzy set theory can be used in optimization to model the uncertainties associated with some parameters in the objective function and constraints. This can be done by transforming the uncertain objectives and constraints into satisfaction functions of fuzzy sets, noting that some constraints can remain crisp. If this is applied to a linear program, using linear satisfaction functions maintains the problem linear. Optimality is achieved by maximizing the intersection of the satisfaction functions of the problem of interest [26,28]. Mathematically, fuzzy optimization can be stated as:

$$\text{maximize} \quad \lambda \tag{10}$$

where

$$\lambda = \min\left\{\mu_{Z1}, \mu_{Z2}, \ldots, \mu_{Zn}, \mu_{C1}, \mu_{C2}, \ldots, \mu_{Cm}\right\} \tag{11}$$

μ_{Zi} is a membership function which shows the satisfaction level of the degree of closeness of the i^{th} objective to the optimal solution. The uncertainty of each objective is taken into account by defining a minimum limit with a membership function of zero (which means that no solution below this limit is accepted), defining a maximum limit with a membership function of one (which means that any solution above this limit is accepted), and assigning satisfaction levels between 0 and 1 for any other values of the objective. Similarly, the constraint μ_{Cj} is the membership function that defines the satisfaction level of the degree of closeness of the j^{th} constraint to the optimal solution. The *min* function determines the minimum of the satisfaction levels. The membership functions are all defined in the range of [0,1]. During the optimization, λ will take the least value of all satisfaction levels. As λ is maximized, individual fuzzy satisfaction levels related to objectives and constraints are consequently optimized.

While there are many categories for fuzzy mathematical programming, the problem under study belongs to the category which was initially developed by Bellman and Zadeh [29]. This formulation treats decision making problems under fuzzy goals and constraints. The fuzzy goals and constraints represent the flexibility of the target values of objective functions and the elasticity of constraints. From this point of view, this type of fuzzy mathematical programming is called flexible programming. The method that is adopted here to solve the PL scheduling problem follows the one explained in Ref. [28].

3.1. Objective Function Fuzzification

The profit is a function of uncertain parameters, namely, *ρ*, *SOCI, SOCF, MC, MR*, and *dt*. Since the main goal is to maximize the expected profits, it is essential to determine the profits' fuzzy set. For the daily profits, *PT*, given in (5), a fuzzy set $\tilde{PT}$ is defined as:

$$\tilde{PT} = \left\{ \left[pt, \mu_{pt}\right], \quad \overline{PT} - K_{PT} \le \text{pt} \le \overline{PT} \right\} \tag{12}$$

where μ_{pt} is the membership function of the profit.

It is logical to assume that the PLO will not participate if the expected daily profit is lower than a certain value $\overline{PT} - K_{PT}$, where K_{PT} is a parameter that needs to be set by the decision maker (the PLO in this case). On the other hand, the PLO will always participate if the expected daily profits are greater than or equal to a certain value $\overline{PT}$.

The satisfaction, or membership, function μ_{pt} can be expressed as:

$$\mu_{pt} = \begin{cases} 0 & \text{pt} \le \overline{PT} - K_{PT} \\ \dfrac{pt - \left(\overline{PT} - K_{PT}\right)}{K_{PT}} & \overline{PT} - K_{PT} \le \text{pt} \le \overline{PT} \\ 1 & \text{pt} > \overline{PT} \end{cases} \tag{13}$$

Relation (13) is illustrated graphically in Fig. 1. The setting of the parameters $\overline{PT}$ and K_{PT} will be discussed in Section 5. *pt* is a decision variable associated with μ_{pt}. Now, the membership function

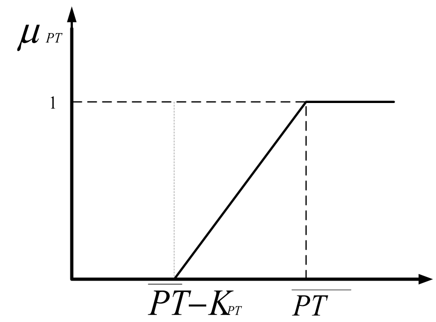

Fig. 1. Fuzzy model of the expected profits.

of the objective uncertainty is translated into a fuzzy constraint as follows:

$$\lambda \le \mu_{pt} = \frac{pt - \left(\overline{PT} - K_{PT}\right)}{K_{PT}} \tag{14}$$

Therefore the objective function turns into a constraint in the following form:

$$\lambda \cdot K_{PT} + \left(\overline{PT} - K_{PT}\right) \le pt \tag{15}$$

Unlike Refs. [23,24,26] where a membership function was defined for each uncertain parameter in the constraints, the approach followed in this work defines a membership function for each constraint that has one or more uncertain parameters. Note that each membership function defined involves the inclusion of a new decision variable. Since this optimization involves four uncertain parameters that appear in only two Constraints, i.e. (7) and (8), using the latter, constraint fuzzification approach, is preferred as it reduces substantially the problem complexity.

3.2. Constraints Fuzzification

Constraint (6) forces the charging rate to be positive since a unidirectional power flow is assumed. Therefore, it will be considered here as a crisp constraint. Constraint (7) limits the charging rate to be less than the maximum charging rate of the battery, *MR*. However, the maximum charging rate is uncertain since it depends on the type of EV that uses the PL. Therefore, constraint (7) will be fuzzified by defining a membership function associated with it. This membership function will be expressed as:

$$\mu_{mr} = \begin{cases} 1 & \text{mr} \le \overline{MR} - K_{MR} \\ \dfrac{\overline{MR} - mr}{K_{MR}} & \overline{MR} - K_{MR} \le mr \le \overline{MR} \\ 0 & \text{mr} \ge \overline{MR} \end{cases} \tag{16}$$

Constraint (7) will be satisfied if the scheduled charging power is less than an upper bound $\overline{MR} - K_{MR}$. However, this bound is uncertain. Therefore, the scheduled charging power can be allowed to go beyond it by a small amount, K_{MR}. The graphical explanation of Eq. (16) is shown in Fig. 2. It is worth mentioning that the optimizer will try to push the scheduled charging power toward $\overline{MR}$ to charge as much as possible in order to increase the profits. The membership function of this uncertain constraint will be translated into a fuzzy constraint as follows:

$$\lambda \cdot K_{MR} + mr \le \overline{MR} \tag{17}$$

Note that λ and *mr* are auxiliary decision variables. $\overline{MR}$ and K_{MR} are parameters to be set by the PLO based on the expected charg-

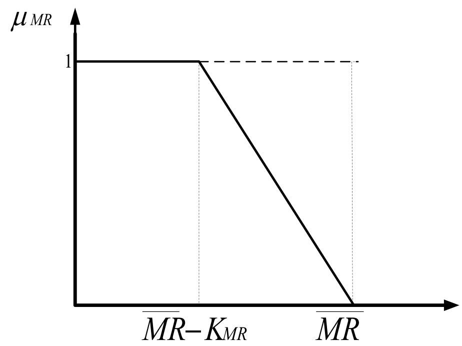

Fig. 2. Fuzzy model of the maximum charging rate.

ing rate of the EVs and the range of variation from the expected charging rate.

Constraint (8) ensures that the battery will charge to the level required by the EV owner or to the maximum battery capacity, whichever is lower. This constraint is, first, relaxed as follows:

$$\sum_t (AV_{it} \cdot POP_{it})\,\Delta t + SOCI_i \le SOCF_i \quad \forall i \tag{18}$$

$$\sum_t (AV_{it} \cdot POP_{it})\,\Delta t + SOCI_i \le MC_i \quad \forall i \tag{19}$$

Note that although these are formulated as inequality constraints, the optimizer will tend to drive the EVs toward the required targeted SOC, i.e. min(*SOCF*, *MC*). This is because the more the charging of the EVs is, the more the PLO revenues are. Constraint (18) limits the charging of the battery to *SOCF* required at departure. It contains two uncertain parameters *SOCI* and *SOCF*. The PLO is not interested in estimating *SOCI* and *SOCF* individually. Rather, an estimate of the difference between the two quantities is much more important. This difference represents the amount of the energy to be charged to each EV. Therefore, constraint (18) can be expressed in the following form:

$$\sum_t (AV_{it} \cdot POP_{it})\,\Delta t \le SOCF_i - SOCI_i = SD_i \quad \forall i \tag{20}$$

Since this amount is uncertain, it will have a membership function as follows:

$$\mu_{sd} = \begin{cases} 1 & \text{sd} \le \overline{SD} - K_{SD} \\ \dfrac{\overline{SD} - sd}{K_{SD}} & \overline{SD} - K_{SD} \le \text{sd} \le \overline{SD} \\ 0 & \text{sd} > \overline{SD} \end{cases} \tag{21}$$

Inequality (18) will be satisfied if it is less than an upper bound $\overline{SD} - K_{SD}$. However, going beyond this bound by a small value K_{SD} could be acceptable. The graphical explanation of (21) is similar to that in Fig. 2. Therefore, the membership function of the uncertainty will be translated into a fuzzy constraint as follows:

$$\lambda \cdot K_{SD} + sd \le \overline{SD} \tag{22}$$

In a similar manner, the constraint in (19) will be a fuzzy constraint as follows:

$$\lambda \cdot K_{MC} + mc \le \overline{MC} \tag{23}$$

with its membership function:

$$\mu_{mc} = \begin{cases} 1 & \text{mc} \le \overline{MC} - K_{MC} \\ \dfrac{\overline{MC} - mc}{K_{MC}} & \overline{MC} - K_{MC} \le mc \le \overline{MC} \\ 0 & \text{mc} > \overline{MC} \end{cases} \tag{24}$$

Finally, constraint (9) will be set as a crisp constraint to limit the total charging amount of all EVs at any hour by the maximum capacity of the transformer feeding the parking lot.

In the new fuzzified formulation of the optimization problem, the objective is to maximize the minimum satisfaction level of all membership functions. The complete fuzzy model becomes:

$$\text{maximize} \quad \lambda \tag{25}$$

Subject to: Constraints (6), (9), (15), (17), (22), (23).

The decision variables of the fuzzy model are POP_{it}, *pt*, *mc*, *mr*, and *sd*.

There are two scenarios to be considered. The first one is with no priority given to any of the EVs. In this case, one charging tariff will apply to all EVs. The second scenario will have several charging tariffs based on how fast EV owner would like to finish charging.

4. Realization of profits in real time

The optimization problem is solved a day ahead to decide on the hourly bids that the PLO will make to buy the necessary amounts of energy for the next day. Also, the hourly charging schedules, *POP*, for each expected EV are obtained. However, the amount of energy needed by the EVs in real time might deviate from that scheduled in the day-ahead. In this case, the PLO will deal with the balancing market, or spot market, to buy the deficit energy or sell the surplus energy. In this work, it is assumed that if the PLO has surplus energy in real time, it can sell that energy to the spot market at a price that is less than the day-ahead market price. Conversely, if there is a deficit, the PLO can buy additional energy from the spot market, but at a price that is higher than the day-ahead market price. This rule is implemented to encourage market participants to submit accurate energy bids in the day-ahead market.

Due to the lack of sufficient historical data for EVs in parking lots (e.g. *SOCI*, *SOCF*, *MC*, *MR*, and *AV*), Monte Carlo simulation (MCS) is used to quantify the realized PLO profits using the schedules obtained from each of the two optimization approaches. In MCS, a large number of scenarios is generated for different EV profiles. Then, for each scenario, the realized profits are calculated based on the optimal schedules obtained from the previous day and the realized needs of the EVs in real time. The average realized profits over a large number of scenarios are obtained and compared for both the deterministic case and the fuzzy case. Clearly, the realized profits reflect better the quality of performance of each of the optimization approaches than the expected profits obtained from the optimization stage.

5. Case study

The optimizations and MCS are performed for a parking lot with 100 charging stations in the lot and 800 kW maximum power capacity. For day-ahead scheduling, price forecasting is done using the ARIMA method. For real-time realization, historical market prices obtained from ERCOT market [30] are used. It is assumed that the EV fleet consists of three types of EVs, Nissan Leaf, Mitsubishi i-MiEV, and Tesla Model S. The technical specifications of these three kinds of EVs can be found in Refs. [31–33].

For MCS, a pool of 100,000 EVs is generated with different arrival and departure times, battery capacities, maximum charg-

Table 1
Values of different fuzzy percentages for different cases.

	Percentages for basic case (%)	Percentages for sensitivity analysis (%)
K_{PT}	10% of $\overline{PT}$	10–40
K_{MR}	20% of $\overline{MR}$	10–40
K_{SD}	20% of $\overline{SD}$	10–40
K_{MC}	20% of $\overline{MC}$	10–40

ing rates, and initial and final state of charges. The probabilistic models given in Ref. [15] are used to model the uncertainties in EV arrival times, expected departure times, and initial SOCs. A truncated normal distribution is used to represent the EV arrival and departure times where $X \approx N\left(\mu, \sigma^2\right)$ is assumed to be a normal distribution with the mean (μ) and the variance σ^2. The parking time and the expected arrival time lie within an interval (a,b). To validate the probabilistic modeling, the authors in Ref. [15] generated the random input under a truncated normal distribution and then compare the simulation result with the historical data of an office parking deck in a city in Canada, during weekdays. For the most part, the simulated number of EVs connected to the grid at any given time matches the actual data quite well. The initial SOC is modeled as a random variable under log-normal distribution.

For the three types of the EVs, it is assumed that the EV pool consists of Nissan Leaf, Mitsubishi i-MiEV, and Tesla Model S with percentages of 50%, 20% and 30%, respectively. Consequently, the battery capacities and maximum charging rates are assumed to follow the same proportions. The final state of charge is assumed to be a random variable varying within 80-100% of the maximum battery capacity.

To run the optimization, 100 EVs are randomly selected from the pool generated above and used as input data for both the deterministic and fuzzy optimizations.

Each constraint in (5)-(9), for the deterministic optimization, that is a function of one or more uncertain parameter is associated with its corresponding fuzzified Constraint in Eqs. (15), (17), (22), (23). For the profit fuzzy constraint (15), the bound $\overline{PT}$ is assumed to be equal to the average daily expected profit that is obtained from the deterministic case and K_{PT} is assumed to be 10% of that value. This allows the expected profit to be less than the one obtained from the deterministic case by 10% in order to handle the risks due to the uncertainties. If the profit is higher than$\overline{PT}$, it is always accepted and, hence, the corresponding membership value is 1. For constraint (17), $\overline{MR}$ is equal to MR_i in the deterministic case. The same applies to constraints (22) and (23), where $\overline{SD}$ is equal to ($SOCF$-$SOCI$), $\overline{MC}$ is equal to (MC-$SOCI$). The values for K_{MR}, K_{SD}, and K_{MC} are given in Table 1. The same percentage of 20% is assumed for the three parameters above for simplicity. Later, the sensitivity of the solution to these assumed percentages will be investigated for the ranges given in Table 1.

Two cases are investigated for the charging tariff β. A case where β is a fixed tariff that applies to all EVs. In this case, the charging tariff is 10 cents/kWh, which reflects the national average cost for electricity in the U.S. for the past three years [34]. In the second case, a multi-tier charging tariff is used. That is, the EV owner can choose from among several charging speeds, each of which has a different tariff.

The optimization problems are solved using the MATLAB-based CVX toolbox.

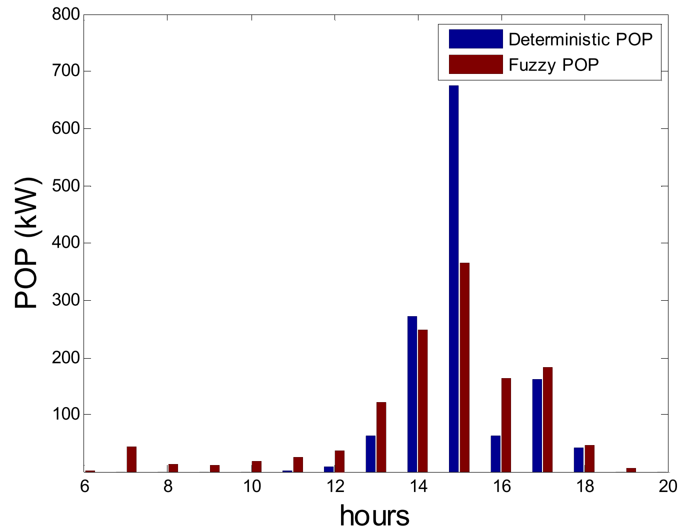

Fig. 3. Charging schedules of the deterministic and fuzzy formulations.

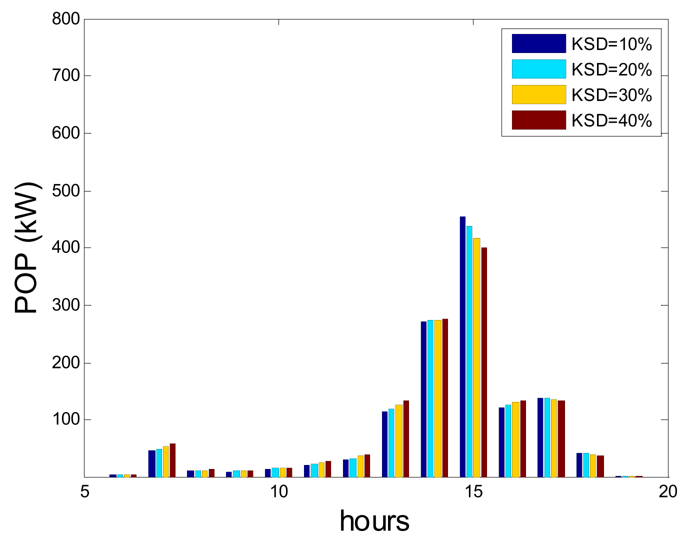

Fig. 4. Sensitivity of the fuzzy solution with respect to K_{MR}, K_{SD}, K_{MC}.

6. Results

6.1. Simulation with Fixed Charging Tariff-Optimization Results

For these tests, β is assumed to be fixed at 10 cents/kW h. The scheduled *POP* of the deterministic case and the proposed fuzzy case are shown in Fig. 3. The expected profits from these schedules in the day-ahead market are \$78.1 for the deterministic case and \$72.0 for the fuzzy case. Note that the expected profits in both approaches are the evaluation of the objective functions during the optimization stage (day-ahead). These profits are not necessarily realized. If the forecasts were all exact, the expected profits and realized profits would be identical. In reality, forecasts are rarely exact. Hence, the realized profits usually deviate from the expected ones. In order to compare how well each approach would do in reality, the average realized profits using MCS will be evaluated later.

The sensitivity of the fuzzy solution to the percentages of uncertainties in charging rate,K_{MR}, difference between initial and required final state of charge, K_{SD} and difference between initial state of charge and battery capacity,K_{MC}, is investigated. Fig. 4 shows the results when these percentages are simultaneously set at

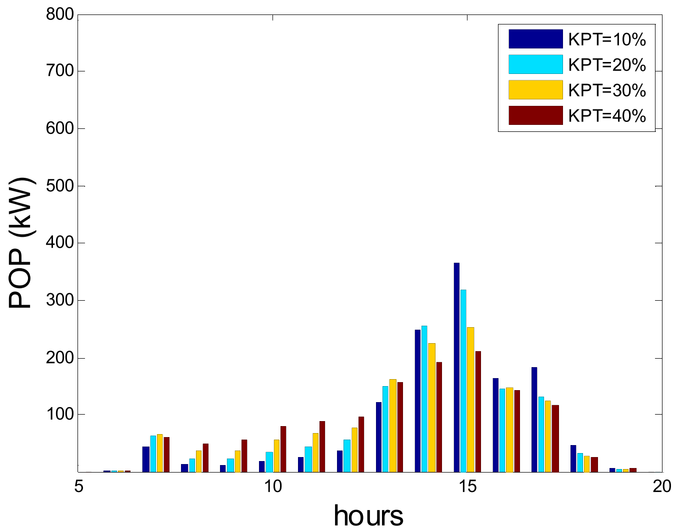

Fig. 5. Sensitivity of the fuzzy solution with respect to $K_{PT.}$

Table 2
Expected profits by varying $\boldsymbol{K_{PT}}$..

K_{PT}	Profit ($)
10%	72.0
20%	66.0
30%	59.9
40%	53.5

10, 20, 30, and 40%. It can be seen that the scheduled *POPs* are almost the same and the corresponding expected profits for each case in the day-ahead market is about $72 for all cases. This confirms the robustness of the proposed fuzzy approach since the optimal solution is not very sensitive to the values selected by the PLO.

The sensitivity of the fuzzy solution with respect to the value of $K_{PT,}$ which represents the uncertainty in profits, is also performed, and the corresponding results are shown in Fig. 5. In this case, K_{MR}, K_{SD}, and K_{MC} are kept constant at 20% while K_{PT} is varied from 10 to 40%. The corresponding expected profits are given in Table 2. It can be seen that by increasing K_{PT}, the expected profits in the day-ahead market decrease. This is also obvious from Fig. 5 where increasing K_{PT} leads to more uniform schedules over time and less profits. This is due to abandoning the opportunity of bidding higher charging schedules in low-price periods of the energy market. It is worth mentioning that for all the cases mentioned above, optimization results show that all EVs are expected to be charged to the desired final SOC.

6.2. Simulation with Fixed Charging Tariff-MCS Results

To estimate the realized profits in real time, 10,000 Monte Carlo simulations are carried out. In each simulation, 100 EVs with different profiles are randomly selected from the EV pool described in Section 5. For all simulations, the average profit is calculated for both the deterministic and fuzzy schedules using the same selected 100 EVs for fair comparison. As mentioned in Section 4, the spot market is included in the realization to be used for balancing. The realized profits obtained from using the optimal schedules of the deterministic and fuzzy cases, given in Fig. 3, is shown in Table 3. It can be noted that the proposed fuzzy approach results in about 16% increase of realized profit than the deterministic approach. This proves that the proposed fuzzy approach treats the uncertainties involved in this problem in an efficient and effective manner. For both the deterministic and fuzzy cases, all EVs in all Monte Carlo simulations have been charged to the desired final state of charge.

Table 3
Realized profits in real time.

Schedule Used	Profit ($)
Deterministic	77.3
Fuzzy	89.7

Table 4
Realized profits by varying $\boldsymbol{K_{PT}}$.

K_{PT}	Profits ($)
10%	89.7
20%	86.3
30%	85.1
40%	81.8

Table 5
Charging tariff based on desired departure time.

β (¢/kWh)	Required time to finish charging (hours)
10	$T \geq 8$
15	$4 > T > 8$
20	$T \leq 4$

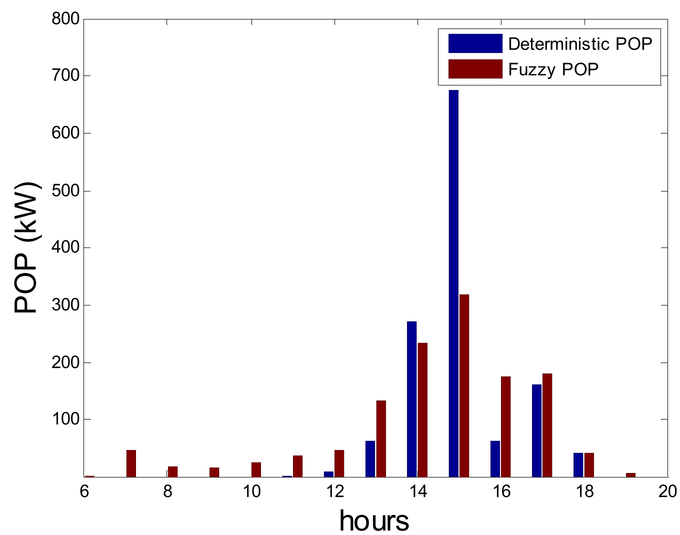

Fig. 6. Charging schedules of the deterministic and fuzzy formulations with multi-tier charging tariff.

Moreover, realizations for the schedules in Fig. 5 obtained by varying K_{PT} are carried out and the results are given in Table 4. It can be shown that by increasing the value of K_{PT} (more uncertainty), the realized profit decreases. However, in all cases, the profit with the proposed fuzzy approach is higher than that of the deterministic case given in Table 3. This shows that the proposed algorithm is robust and it can efficiently handle high levels of uncertainties.

6.3. Simulation with Multi-tier Charging Tariff

For this case, if the EV owner needs to finish earlier, he/she is given a higher priority for charging, provided that he/she will pay a higher tariff. The multi-tier charging tariff structure is given in Table 5. Fig. 6 shows the scheduled *POP* for the deterministic and fuzzy optimal solutions for the multi-tier tariff structure. The corresponding expected profits are $107.1 and $97.7 for the deterministic and fuzzy cases, respectively. In both cases, the expected profit applying a multi-tier tariff is higher than that of a single-tier tariff since some EV owners are willing to pay more to finish charging faster.

Table 6
Realized profits in real time considering multi-tier charging tariff.

Schedule used	Profit ($)
Deterministic	99.3
Fuzzy	110.0

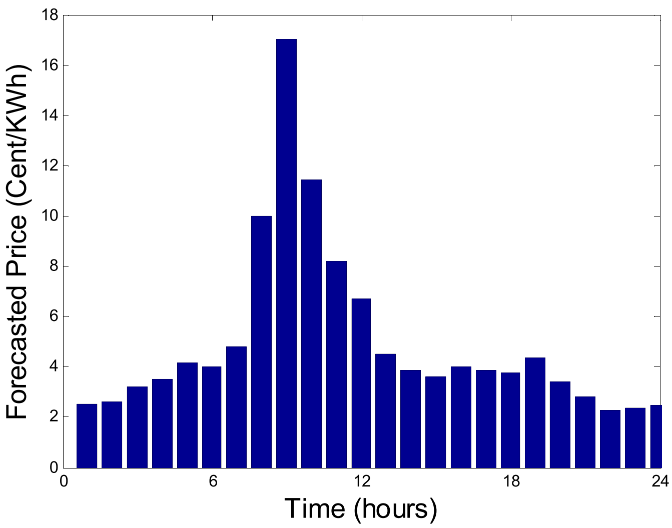

Fig. 7. Forecasted energy prices.

Table 6 shows the realized profits from the deterministic and fuzzy cases when a multi-tier tariff is considered. It can be seen that fuzzy optimization results in a 10.8% increase in realized profits than the deterministic results. It is interesting to note from the schedules shown in the figures that, in general, the fuzzy optimization gives rise to lower peak loading than the deterministic optimization. The peak deterministic loading is 700 kW while the peak fuzzy loading is less than 500 kW. In both cases, the peak loading happens at about 3 p.m. because this is one of the lowest-price periods, as shown in Fig. 7. In the deterministic case, this low price incentivizes the bidding of very high *POP* since forecast uncertainties are neglected. In the fuzzy case, however, though price is forecasted to be low in this period, this forecast is known to be uncertain. This leads the PLO not to rely completely on its price forecast, but rather manage its risk by scheduling *POP* at more moderate levels.

6.4. Effect of Charging Efficiency Consideration

In the previous simulations, the charging efficiency was assumed to be 100%. In this section, the effect of charging efficiency will be investigated by considering 90% charging efficiency. In order to include this factor, the first term on the left hand side of relation (8) is multiplied by the charging efficiency. Moreover, the corresponding fuzzy relations (22) and (23) are modified accordingly. Due to the reduced efficiency, there will be some losses during the charging process. Since the PLO is obligated to charge the EV battery to the final desired state of charge, more power needs to be scheduled to the battery to cover the required energy as well as the losses. This will increase the amount of energy that the PLO will sell to the EV owners as well as the purchased energy from the market. Therefore, the final profits will change.

In this test, the charging tariff β is assumed to be fixed at 10 cents/kW h. Fig. 8 shows the scheduled *POP* for the deterministic and fuzzy optimal solutions when the charging efficiency is 90%. In comparison with Fig. 3, it can be seen that the scheduled *POP* is slightly higher now in order to compensate for the losses due to charging efficiency. The corresponding expected profits in that case are $86.23 for the deterministic case and $78.69 for the fuzzy case. Table 7 shows expected profits comparison between the two cases 100% and 90% efficiency. From the table, it can be seen that when the efficiency is considered, the profits of the PLO has increased. This comes from the fact that the PLO, in the case of reduced efficiency, has to push more energy to charge the battery to the final required SOC and to compensate for the losses. Therefore, the EV owners pay more, and hence the profits of the PLO increase.

To realize the actual profits in real time, MCS simulation is used to generate random scenario to investigate the case when the efficiency is 90%. The realized profits are $84.0 using the deterministic schedules and $87.5 using the fuzzy-based schedules. The fuzzy formulation gives rise to more realized profits, which indicates that it can handle the uncertainties effectively.

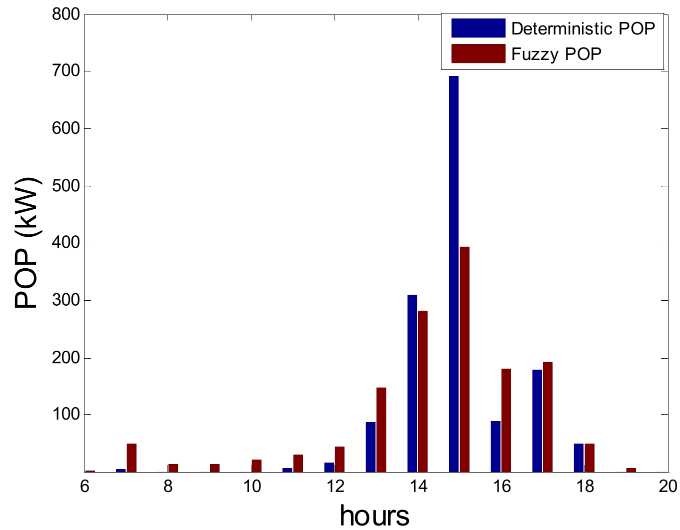

Fig. 8. Charging schedules of the deterministic and fuzzy formulations with 90% charging efficiency 90%.

Table 7
Expected profits in ($) in day ahead for different charging efficiencies.

Schedule Used	100% efficiency	90% efficiency
Deterministic	78.1	86.22
Fuzzy	72	78.69

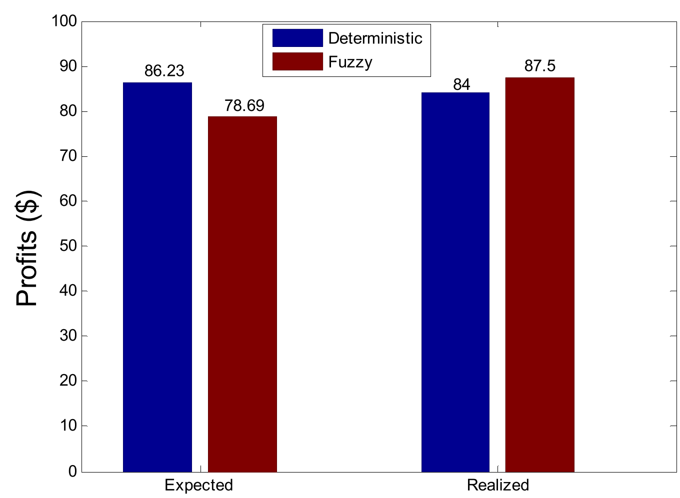

Fig. 9. Expected and realized profits with charging efficiency 90%.

Fig. 9 shows both the expected and realized profits for the deterministic and fuzzy-based schedules considering 90% charging efficiency. It can be seen that although the deterministic schedules result in higher expected profits, it results in less realized profits than the fuzzy-based schedules.

7. Conclusion

In this paper, a new fuzzy formulation of EV charge optimization for a parking lot considering market and EVs mobility uncertainties is proposed. The uncertainties of the market and EVs mobility are modeled using fuzzy sets. These include uncertainties in battery initial state of charge, required final state of charge, battery capacity, maximum charging rate, market prices, and departure time. Unlike other works reported in the literature, the proposed fuzzy approach fuzzifies the problem constraints rather than each of the problem uncertain parameters. This reduces substantially the complexity of the optimization problem. Although the solution obtained by the proposed fuzzy approach has a lower expected profit in the day-ahead market, higher realized profits, which take into account both day-ahead and spot markets, are achieved. The sensitivity of the proposed fuzzy solution to the PLO decisions of the fuzzy parameters is investigated. The results confirm the robustness and effectiveness of the fuzzy approach to handle high level of uncertainties. The comparison with the deterministic case demonstrates the superiority of the proposed fuzzy approach in achieving higher realized profits for the PLO.

The proposed fuzzy approach will be extended in future work to allow the PLO to participate in ancillary service markets. This will require modeling the uncertainties associated with ancillary market prices and deployment signals. Coordination of bidding in energy and ancillary service markets in this case will be of special interest.

Acknowledgments

This work was supported by King Fahd University of Petroleum & Minerals (KFUPM) and King Abdulaziz City of Science and Technology under NSTIP project no. 14-ENE2897-04.

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