Optimal Scheduling of Utility Electric Vehicle Fleet Offering Ancillary Services

Aleksandar Janjic and Lazar Zoran Velimirovic

Vehicle-to-grid presents a mechanism to meet the key requirements of an electric power system, using electric vehicles (EVs) when they are parked. The most economic ancillary service is that of frequency regulation, which imposes some constraints regarding the period and duration of time the vehicles have to be connected to the grid. The majority of research explores the profitability of the aggregator, while the perspective of the EV fleet owner, in terms of their need for usage of their fleet, remains neglected. In this paper, the optimal allocation of available vehicles on a day-ahead basis using queuing theory and fuzzy multi-criteria methodology has been determined. The proposed methodology is illustrated on the daily scheduling of EVs in an electricity distribution company.

Keywords: Electric vehicles, grid, frequency regulation, fuzzy multi-criteria decision making, queuing theory, analytic hierarchy process.

Manuscript received July 28, 2014; revised Dec. 16, 2014; accepted Jan. 2, 2015.

This work was supported by the Ministry of Education, Science and Technological Development of the Rep. of Serbia under Grant III 42006 and Grant III 44006.

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I. Introduction

Vehicle-to-grid (V2G) can be defined as a system in which there is the capability of controllable, bi-directional electrical energy flow between a vehicle and a power grid. Integrating large numbers of electric vehicles (EVs) into a power grid while simultaneously reducing their impacts is a major goal of V2G systems [1]–[2]. This task is primarily performed by an aggregator — an intermediary inserted between the vehicles performing ancillary services and the grid system operator. This aggregator receives ancillary service requests from the grid system operator and issues power commands to contracted vehicles that are both available and willing to perform the required services [3]–[9].

The most valuable ancillary service is that of regulation, which plays a significant role in maintaining the stable frequency of the grid [10]. The regulation control signal can call for either a positive or negative correction, often referred to in the industry as “regulation up” and “regulation down,” respectively. If load exceeds generation, then frequency and voltage drop; the system operator then relays a signal to generators requesting regulation up. When generation exceeds load and frequency increases, the operator requests regulation down and asks generators to reduce generation.

The aggregation for regulation services has been proposed and explored in [11], with an optimal charging sequence for EVs selling only regulation. This formulation does not consider bulk discharging for a source of income and bids symmetric capacities of regulation up and down. It also assumes that periods of charging are decoupled from periods of performing regulation. The preferred operation point is always zero when performing regulation. In the previous paper, [11], a unidirectional V2G has been explored. In [12], this approach has been extended to a bidirectional V2G, and in [13], it has been further extended to a combined provision of regulation and reserve. In [14], smart-charging optimization without V2G and optimized V2G with only regulation is formulated. This formulation did not consider the change in a battery's state of charge (SOC) from dispatch of regulating power through symmetric bidding of regulation up and down. It also did not consider the bulk discharge of a battery during peak prices.

These approaches focus on primary regulation and are mostly based on premises such as the global SOC of the aggregator's EV battery portfolio can be predicted (the corresponding prediction error is bounded); that the EV population's daily energy requirement can also be well predicted; and that the EV population, on average, is able to remain in the scheduled modes of aggregated operation for the entirety of each scheduled period of the optimization horizon [15]. This formulation takes into account unplanned EV departures during the contract periods and compensates accordingly, with each hour of EV availability having an associated unplanned departure probability.

The perspective of the EV fleet owner, in terms of their concern for the availability of their fleet, is quite different. Many firms and public organizations operate their fleets of EVs in accordance with the various needs of the population; that is, they are given over to emergency vehicles, commercial delivery vehicles, taxis, courier fleets, and so on. The impact of the size of the electricity distribution company's EV fleet in relation to its service quality is described in [16]. Some of these fleets have to perform tasks that may be known well in advance or that are sometimes repetitive, while many of them operate essentially in a demand-responsive mode. The demands for services are not known beforehand; thus, the fleets have to be deployed and managed in real time in an as effective manner as possible [17]. The requirements of the aggregator and of the EV fleet owner are, therefore, quite the opposite. While the aggregator needs as many vehicles as possible connected to the network, the EV fleet owner has to maintain a balance between service quality and revenue from ancillary services offered by EVs.

In [18], a system that enables remote reservations of charging slots and provides route planning assistance has been proposed. This system can be very helpful to the aggregator, as they are obliged to know the driving behavior of EVs and have to deal with unexpected departures during scheduling periods. However, in our approach, we adopted a fixed contract period of 8h and an obligation toward the aggregator not to depart unexpectedly, to increase revenues for regulation services.

In this paper, we are exploring a hypothetical problem that is put to a company owning a fleet of EVs. The company's fleet of EVs operates to serve the different needs of its respective clients, and in this paper, we assume that each prospective vehicle mission requires some time to be fulfilled (service time). If the service time increases, then the company will suffer losses due to a reduction in its service quality. However, at the same time, when its vehicles are parked, the company is offering regulating services to the electricity network operator using V2G technology. Revenues from selling these services are directly related to the number of vehicles parked. Therefore, the optimization of vehicle daily scheduling is essential to increase the company's revenue and reduce costs relating to service quality.

A new, practical multi-criteria decision-making methodology for the daily scheduling of an EV fleet is proposed in this paper. The criteria (which are to be simultaneously fulfilled) for the new, practical multi-criteria decision-making methodology include the minimization of the service waiting time; the maximization of ancillary service revenue; and the minimization of costs incurred by vehicle charging. The number of client requests and service waiting times are modeled by queuing theory.

The contribution of this paper lies firmly in its introduction of a practical EV scheduling methodology that takes into account the interests of both the clients and the aggregator. The methodology offers a more flexible way of priority assessment using the Bellman–Zadeh approach for multiobjective allocation of these vehicles. Queuing theory has been used for the determination of the time required for the service provision.

This paper is organized as follows. After the introduction and literature review, details of the model parameters and the fuzzy multi-criteria decision-making technique are explained. In the next section, for the sake of illustration, the model is applied to an EV fleet belonging to a medium-sized power distribution company serving 50,000 consumers. Finally, we end this paper with some conclusions about the possibilities of the model's application and suggest our further research intentions.

II. Problem Formulation

V2G and regulation contributions of each EV are facilitated by an aggregator. The aggregator signals each plugged-in EV, indicating to them the mode they should be in so that the aggregated EV fleet meets the aggregator's energy and reserves day-ahead market positions. As stated in the previous section, the problem of optimization of V2G assets, or vehicle scheduling [9]–[15], has been exclusively treated as a one-dimensional problem, with the maximization of aggregator revenue as the sole objective. The sources of aggregator revenue are energy delivered to the EV; the revenues from selling regulation and spinning reserve capacity; and the

http://dx.doi.org/10.4218/etrij.15.2314.0046

revenues from selling energy. On the other hand, the sources of EV fleet owner revenue are the regulation and reserve services and energy sold to the spot market by the aggregator.

The relations between EV fleet owner and aggregator are, however, much more complex regarding, above all, the vehicle availability. An unexpected early departure would cause serious problems for the aggregator, in terms of them being able to provide the contracted amount of power; therefore, it is mandatory that drivers actively notify the aggregator of an expected departure time upon plugging in. A driver would sign a contract that states they are to keep their vehicle connected to the grid for a certain amount of time in return for incentives, such as a life-time battery warranty [14].

On the other hand, many utility companies require the usage of vehicles for long periods of time, without the possibility of vehicle charging (for example, when repairing faults). Therefore, the EV fleet owner needs to be able to schedule the number of vehicles required for fulfilling customers' daily activities, in advance, without decreasing the commercial quality of its services.

Finally, the EV fleet owner requires that its vehicles be fully charged and ready to use in the most economically viable way possible; this is what makes the aggregator ultimately responsible for purchasing cheap power from the grid for the purposes of vehicle battery charging.

For all these reasons, the problem of optimal allocation of vehicles requires a different approach; that is, one that incorporates multiple-criteria decision analysis. Multiple-criteria decision-making refers to making decisions in the presence of multiple, usually conflicting, criteria. In our case, the criteria that have to be treated simultaneously are: minimization of total service time, maximization of expected ancillary service revenues, and the minimization of charging costs. All of the aforementioned criteria will be explained in the following subsections.

1. Service Waiting Time

For any utility company, the matter of its own commercial quality is a crucial issue. For example, in the case of an electricity company, commercial quality is directly associated with the transactions between the company and its customers and covers not only the supply and sale of electricity, but also the various forms of contacts established between the company and its customers [19]–[21]. There are several services that can be requested or expected by customers, such as new connections; increase in connection capacity; disconnection upon customer's request; meter reading and verification; repairs and elimination of voltage quality problems; and so on. Each of these services is a transaction that involves both the extensive usage of vehicles and an aspect of commercial quality. The most frequent commercial quality aspect is the timeliness of services requested by customers. Guaranteed standards refer to service quality levels, which must be met in each individual case. If the company fails to provide the level of service required by the standard, then it must compensate accordingly.

According to [19], for some aspects of commercial quality, such as the time until the start of the restoration of supply following failure of fuse of distribution network operator, the guaranteed service time varies from 3h for customers dependent on medical equipment to 12h for settlements with less than 5,000 inhabitants, at weekends and on the periphery of municipalities.

The problem of service time minimization is usually solved through the use of queuing theory and queuing models as an abstraction of Markov chain models. In [22]–[25], an ambulance system using the "hypercube" model is studied to evaluate the extent to which an urban ambulance service should be decentralized. Green and Kolesar [26] assess its empirical validity to assign patrols to New York City police stations. They conclude that queuing theory provides good approximations of the system behavior. Singer and others [27]–[28] configure a fleet whose vehicles receive calls while on route. The objective is to minimize operating costs subject to several constraints, including a maximum waiting time for customers, modeled using queuing formulas.

In our model, the recommended vehicle parameters are obtained from different probability distribution models defined in queuing theory [29]. The M/M/s model assumes that all times between different service requests (inter-arrival times) are independently and identically distributed according to an exponential distribution and that all service times are independently and identically distributed according to another exponential distribution; in this model, the number of servers (crews or vehicles) is denoted by s.

In the system with s vehicles, the probability that all vehicles are available is given by

$$P_0 = \left[\sum_{m=0}^{s-1} \frac{(\lambda/\mu)^m}{m!} + \left(\frac{(\lambda/\mu)^s}{s!} \right) \left(\frac{1}{1-\rho} \right) \right]^{-1}, \tag{1}$$

where s is the number of vehicles, λ is the expected number of interventions per time unit, μ is the expected number of completed interventions per time unit, ρ is the utilization factor ($\rho = \lambda/s\mu$), and m is the number of service requests.

The probability that m service requests exist in the system is given by

$$P_m = \frac{(\lambda/\mu)^m}{s!s^{m-s}} P_0. \tag{2}$$

The average waiting time for an intervention is obtained from the previous equations and is as follows:

$$W=\frac{(\lambda/\mu)^s}{\lambda s!(1-\rho)^2}P_0+\frac{1}{\mu}. \tag{3}$$

Introducing $\alpha=\lambda/\mu$, the probability distribution of waiting times (t) becomes

$$P\{W<t\}=1-\frac{\alpha^s P_0}{s!(1-\rho)}e^{-s\mu(1-\rho)t}. \tag{4}$$

When the service consists of essentially the same routine task, there is little variation in the service time required. The M/D/s model provides a representation of this situation because it assumes that all service times actually equal some fixed constant, with the Poisson input process having a fixed mean arrival time, λ.

The M/D/s model assumes zero variation in the service times, and the exponential service time distribution assumes a very large variation. The Erlang distribution for the service time (M/E$_k$/s model) lies between these two extremes, with the following probability density function for the service time:

$$f(t)=t^{\beta-1}e^{-\frac{t\alpha^\beta\Gamma(\beta)}{\alpha}}. \tag{5}$$

In this model, both the M/M/s and the M/E$_k$/s models are evaluated for different values of expected number of interventions per time unit and expected number of completed interventions per time unit. Concerning the multi-criteria model for the vehicle scheduling, the consumer service waiting time represents one of three considered criteria in the model.

For the sake of illustration, the simulation results for two queuing models are represented in Fig. 1. The parameters of these models are as follows:

- The M/M/s model with $\lambda=9$ requests/day, $\mu=2$ interventions/day.

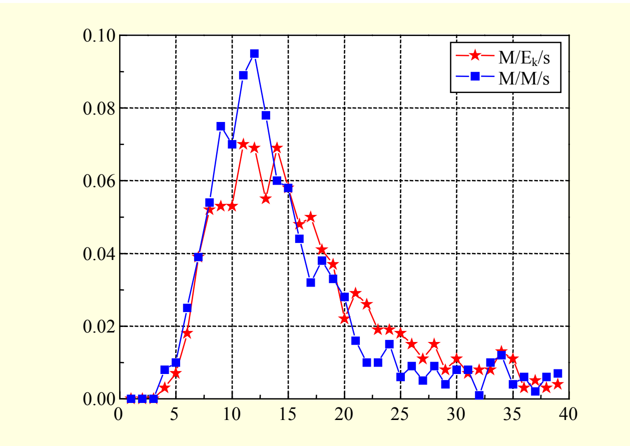

Fig. 1. Probability distribution densities for n clients in the system with 5 vehicles.

Table 1. Average service waiting times for different queuing models.

Number of vehicles	W (min) for M/M/s model	W (min) for M/E$_k$/s model
5	132, 9	360
6	34, 17	38, 4
7	10, 80	9, 6

- The M/E$_k$/s model with the same parameters for the service requests, with the parameters of gamma distribution ($\alpha=8, \beta=0.5$).

The average waiting times for service for both models are represented in Table 1.

2. Revenues from Ancillary Services

The active power markets of V2G can be divided into four general groups [30]. These four groups are as follows: base load power — the bulk power generation that is running most of the time; peak shaving — during the hours of predicted highest power demand; spinning reserves — supplied by fast generators ready to respond in case of equipment or power supplier failures; and active regulation — used to keep the frequency and voltage steady. Typically, spinning reserves are called upon around 20 times a year. The duration of supply provided by a spin reserve is typically around 10 min, but the source must be able to last for up to 1h. Regulation is called upon for only a few minutes at a time, but the number of times can be from anywhere between 400 and 500 times per day. The utility supplier pays for spinning reserves and regulation sources, in part, on a per hourly basis as and when is necessary; however, base load and peak shaving are paid per kilowatt hour generated.

The formulas for calculating revenues depend on the market that the V2G power is sold into and the number of services the EV fleet owner contracts with the aggregator. This study assumes that a V2G vehicle performs frequency regulation service only, which previous studies have shown is the most lucrative and realizable ancillary service for V2G [1]. A further assumption is that a V2G vehicle contracting and performing both regulation-up and regulation-down services results in a net-zero energy transaction, avoiding capacity issues related to vehicle SOC.

For regulation services, revenue is derived from the payment for the maximum capacity contracted for in a given time duration and the payment for the actual kilowatt hour produced. For regulation services, there can be up to 400 dispatches per day, varying in power (P_{disp}). For planning and scheduling purposes, to estimate revenue, we approximate the sum of P_{disp}

http://dx.doi.org/10.4218/etrij.15.2314.0046

by using the average dispatch-to-contract ratio ($R_{\text{d-c}}$) defined in [1]. The actual energy dispatched for regulation is some fraction of both the total power available and total power contracted for

$$R_{\text{d-c}} = E_{\text{disp}} / P_{\text{contr}} t_{\text{contr}}, \tag{6}$$

where E_{disp} is the total energy dispatched over the contract period (MWh), P_{contr} is the contracted capacity (MW), and t_{contr} is the duration of the contract (h).

For regulation up, the vehicle owners get paid for both the contracted power and energy delivered by spot market prices. For regulation down, it's assumed that V2G owners will receive payment for the contractible power, minus the sum for the vehicle charging energy sold by the aggregator (no "free charge" policy). In this model, the general case of different time-of-use tariffs for the charging of batteries is analyzed.

The total revenue for the period consisting of n segments is given by

$$\sum_{i}^{n} r_i = \sum_{i}^{n} p_{\text{cap}_i} P_i t_i + \alpha p_{\text{e}_i} E_{\text{up}_i}, \tag{7}$$

where n is the number of time segments, r_i is the revenue in the ith time period, p_{cap_i} is the capacity price in dollars per kilowatt hour in the ith time period, P_i is the contracted capacity in the ith time period, t_i is the duration of the ith time period, p_{e_i} is the spot market price of energy, and α is the aggregator factor. In the previous expression, the aggregator's services for selling the energy to the EV owner are calculated through the aggregator factor α ($\alpha \leq 1$). The total dispatched energy for the regulation up is, therefore, given by

$$E_{\text{up}_i} = P_i t_i R_{\text{dc-up}}. \tag{8}$$

In this study, it is supposed that EV offers both regulation-up and regulation-down services, which is encompassed by the sole price p_{cap_i} in (7). Another premise is that the measurement of energy is bidirectional; this is necessary to register separately the energy used for battery charging from the energy withdrawn from a battery.

3. Costs of Regulation

Costs of regulation encompass the following two expressions: $C_{\text{reg-up}_i}$ — cost of regulation up (9) and $C_{\text{reg-d}_i}$ — cost of regulation down (10). The aggregator price of energy has to account for the differences in energy delivered to and taken from the battery compared to what is measured at the meter.

$$C_{\text{reg-up}_i} = E_{\text{up}_i} c_{\text{en}_i} / \eta_{\text{conv}}, \tag{9}$$

$$C_{\text{reg-d}_i} = E_{\text{d}_i} c_{\text{en}_i}, \tag{10}$$

$$E_{\text{d}_i} = P_i t_i R_{\text{dc-d}}. \tag{11}$$

The costs per unit energy at time segment i, (c_{en_i}), presented in (12), is a function of the electrical purchase price (c_{pe_i}), efficiency of the charger (η_{conv}), and battery degradation (c_{d}). The battery degradation, calculated in (13), is a function of the total energy storage of the battery (E_{s}); battery cost per kilowatt hour (c_{b}); battery replacement labor and time (c_{l}); and the number of cycles during the battery life (L_{c}) based on battery depth of discharge.

$$c_{\text{en}_i} = c_{\text{pe}_i} / \eta + c_{\text{d}}, \tag{12}$$

$$c_{\text{d}} = \frac{E_{\text{s}} c_{\text{b}} + c_{\text{l}}}{3 L_{\text{c}} E_{\text{s}} D_0 D}. \tag{13}$$

The total regulation costs are, therefore, calculated as the sum of the individual regulation costs (14).

$$C = \sum_{i=1}^{n} \left(C_{\text{reg-up}_i} + C_{\text{reg-d}_i} \right). \tag{14}$$

Although it is possible to treat the total income as a net value; that is, the difference between the revenues (7) and costs (8), in the general case, these two values can be treated separately, as two independent criteria. This approach is adopted in this study, which will be explained in the next section.

III. Methodology

Multi-criteria risk assessment is based on multiple-criteria decision analysis — a scientific discipline that deals with methods and procedures for solving problems with several, often conflicting, criteria [30]. The following model encompasses several aspects of decision-making in the absence of certainty. The decision maker first chooses an action (x_i) from a set of available actions or alternatives (**X**). Let $\mathbf{X} = \{x_1, x_2, \ldots, x_m\}$ be a set of alternatives and $G = \{g_1, g_2, \ldots, g_n\}$ a set of goals (criteria) to be attained. A set of objective functions $G(\mathbf{X}) = \{g_1(\mathbf{X}), \ldots, g_n(\mathbf{X})\}$ is considered, and the problem consists of how best to simultaneously optimize all objective functions. When applying decision-making in a fuzzy environment, each objective function $g_j(\mathbf{X})$ is replaced by a fuzzy objective function or a fuzzy set $\bar{G}_j$ for $j = 1, 2, \ldots, k$. The importance (weight) of a goal j is expressed by w_j. The attainment of goal j by alternative i is illustrated by the membership function of x_i in fuzzy set $\bar{G}_j$; that is,

$$\bar{G}_j = \left(x_i, \mu_{\bar{G}_j}(x_i) \right). \tag{15}$$

When applying the Bellman–Zadeh approach [31]–[32], the maximum degree of implementing goals serves as a criterion of optimality. This conforms to the principle of guaranteed result and provides constructive lines in obtaining harmonious solutions.

A "decision" is defined as the intersection of multiple fuzzy sets and can be represented as

$$\overline{D} = \overline{G}_1 \cap \overline{G}_2 \cap \cdots \cap \overline{G}_k, \tag{16}$$

with a membership function

$$\mu_{\overline{D}}(x) = \min_j \left(\mu_{\overline{G}_j}(\mathbf{X})\right), \quad j = 1, 2, \ldots, k. \tag{17}$$

The worst outcome of alternative k is then found using

$$\min \geq \left(\mu_{\overline{D}}(X_j)\right) = \min_j \min_i \left(\mu_{\overline{D}}(x_i)\right). \tag{18}$$

Using (19), it is possible to obtain the best outcome of alternative k as

$$\max\left(\mu_{\overline{D}}(X_j)\right) = \max_j \min_i \left(\mu_{\overline{D}}(x_i)\right). \tag{19}$$

The optimal alternative is then

$$X^O = \arg\left(\max_j \min_i \left(\mu_{\overline{D}}(x_i)\right)\right). \tag{20}$$

To obtain the solution to (20), it is necessary to build membership functions $\mu_G(x)$ reflecting a degree of achieving own optima by $g_i(\mathbf{X})$. This condition is satisfied by the use of membership functions, which for maximized objective functions, are given as

$$\mu_{G_i}(x) = \left[\frac{g_i(\mathbf{X}) - \min g_i(\mathbf{X})}{\max g_i(\mathbf{X}) - \min g_i(\mathbf{X})}\right]^{w_i}. \tag{21}$$

Or, it is given by membership functions, which for minimized objective functions, are given as

$$\mu_G(x) = \left[\frac{\max g_i(\mathbf{X}) - g_i(\mathbf{X})}{\max g_i(\mathbf{X}) - \min g_i(\mathbf{X})}\right]^{w_i}. \tag{22}$$

The alternatives are ranked in descending order of the above membership degree. This method provides a simple logic-driven procedure to aggregate attribute attainments of alternatives and to rank the alternatives on such an aggregation. Using the weights as exponents has the effect of making the membership function of decision set D more determinable by attributes that are more important. However, attribute weights are not considered as fuzzy sets, and they should be taken as *crisp* values.

In our methodology, the vector of alternatives, $\mathbf{X} = \{x_1, x_2, \ldots, x_m\}$, is composed of multiple combinations of parked vehicles, used by the aggregator, and vehicles used freely by the EV fleet owner. The number of fuzzy objective functions or fuzzy sets is reduced to three in this study (revenues, costs, and service time), but these sets can be enlarged by other criteria, such as those relating to environmental, social, or marketing conditions.

The best alternative for the aggregator is to dispose with vehicles (and contracted power) during the whole contracted period. Since an EV can depart unexpectedly during a scheduling period, it is necessary for the aggregator to compensate for this lost capacity by drawing more power for the remaining vehicles (that is, to over dispatch them). To do so, the aggregator must leave some reserve in existing vehicles (under schedule them). This compensation for the lost capacity can be estimated by the following compensation factor [12]:

$$\text{Comp}(t) = 1 + \frac{\text{probability\_of\_departure}}{1 - \text{probability\_of\_departure}}. \tag{23}$$

In our study, to reduce this compensation factor to zero, we adopt a fixed time period of vehicle leasing to the aggregator.

Weighting factor w_j, in expressions (21) and (22), is determined by the AHP method. The original AHP was developed by Thomas L. Saaty in the late 1970s [33]. In this method, a person's judgments are represented as crisp values. Terms such as "much more important," "more important," "equally important," "less important," and "much less important" are defined using Saaty's scale for pairwise comparisons [33].

The AHP method was developed to optimize decision-making when one is faced with a mix of qualitative, quantitative, and sometimes conflicting factors. AHP has been very effective in making complicated and often irreversible decisions. AHP uses the judgments of decision-makers to form a decomposition of problems into hierarchies. This method is primarily applied to the field of multi-criteria decision-making, where on the basis of every defined criterion set and attribute value of each alternative, the most acceptable solution is accepted; alternatively, the complete layout of the alternative importance in a model is shown.

In this particular case, a comparison scale of five points has been used. The elements of a weighting matrix, T, are defined as follows:

- If i is much more important than j, then $t_{ij} = 3$.
- If i is more important than j, then $t_{ij} = 2$.
- If i and j are equally important, then $t_{ij} = 1$.
- If i is less important than j, then $t_{ij} = 0.5$.
- If i is much less important than j, then $t_{ij} = 0.3$.
- The eigenvector of matrix T represents the weighting vector $\mathbf{w}$.

The Bellman–Zadeh approach permits one to realize an effective (from a computational standpoint) and rigorous (from the standpoint of obtaining solutions) method of analyzing multiobjective models. Finally, its use allows one to preserve a natural measure of uncertainty in decision-making and to take into account indices, criteria, and constraints of a qualitative nature. The methodology is utilized in the case of optimal distribution of vehicles to network missions and regulation services.

IV. Case Study

The case study in this paper is concerned with the scheduling of a nine-car-strong EV fleet supported by one electricity distribution utility. The EVs in this fleet serve an urban area and remain on standby for call-outs relating to repair faults within the urban area; the EVs are assumed to be available for three distinct periods during the day. The first of these periods is between midnight and 8 a.m. and is characterized by, on average, 7 reported faults ($\lambda = 7/8$h), with an average of 2.67h per intervention (three repaired faults per crew during this period $\mu = 3/8$h). The parameters of the second and more intensive period, which is from 8 a.m. to 4 p.m., are $\lambda = 10/8$h and $\mu = 4/8$h, while in the third period, which is between 4 p.m. and midnight, the parameters are $\lambda = 8/8$h and $\mu = 3/8$h (see Fig. 2). The values in Fig. 2 are simulated for illustration purposes.

The number of customer complaints or requests (denoted by λ) represents the total number of calls during the day. The average number of repaired faults is, however, not related to the total number of faults, but to the number of accomplished missions of one service crew (one vehicle). A slight increase in the number of repaired faults per crew during the second period (four repaired faults during this period versus three repaired faults during periods one and three) is explained by the more organized logistic service during the working hours. This company has a contract with an aggregator who is paying for the usage of EVs for regulation services, by the prices varying during the day (see Fig. 3). Day-ahead ancillary service prices are the actual prices used in the ERCOT system [34]. For each of the three periods, we have to find the optimal number of vehicles that should be parked and connected to the charger/

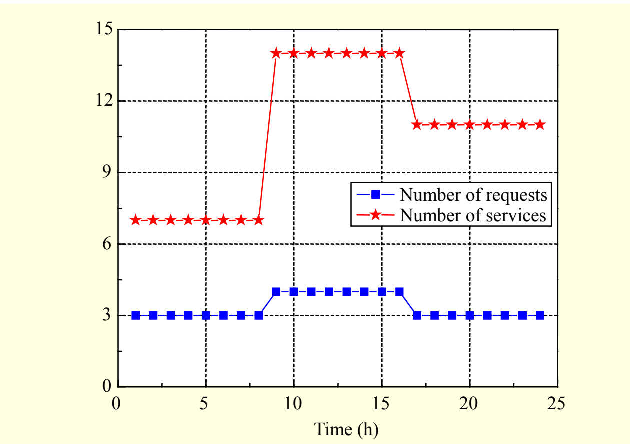

Fig. 2. Average values for the number of requests for service (blue line) and accomplished tasks (red line).

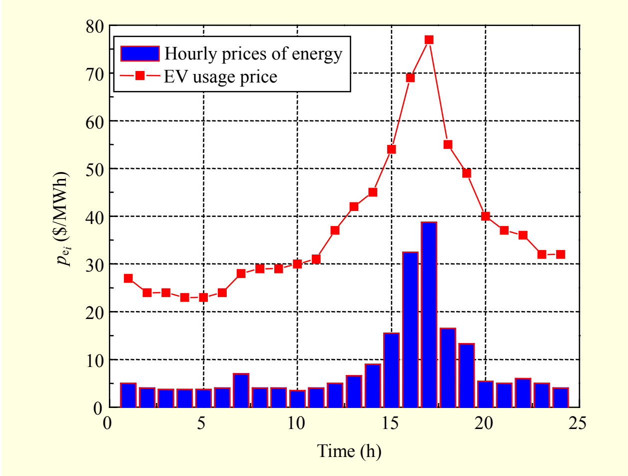

Fig. 3. Hourly energy and EV usage prices for July 7, 2013.

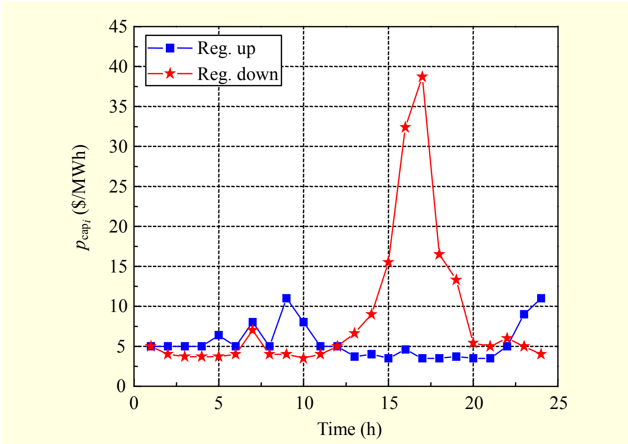

Fig. 4. Hourly prices for ancillary services on July 7, 2013.

inverter combination while simultaneously minimizing the service waiting time, maximizing expected revenues of ancillary services, and minimizing charging costs. In addition, the spot prices on the electricity market, p_{e_i} from (7), are represented in Fig. 3. Day-ahead energy prices are also the actual prices used in the ERCOT system [34]. Hourly ancillary service prices are shown in Fig. 4. Finally, the price that the EV fleet owner is paying the aggregator; that is, the cost for charging, including degradation costs (12), is presented in Fig. 5. Parameters inherent to the type of vehicles used in this calculation, together with the adopted values of dispatch-to-contract ratios and the period of the regulation services are presented in Table 2. Using (3), (7), and (14), values for different combinations of vehicles scheduled for regulation purposes (N_{reg}) and vehicles for regular daily activities (N_{serv}), for the three predefined time periods, are presented in Tables 3, 4, and 5. In the cases where N_{serv} is small, the resulting unstable situations, "stockpiling" of requests, are marked as "N.A." in the tables.

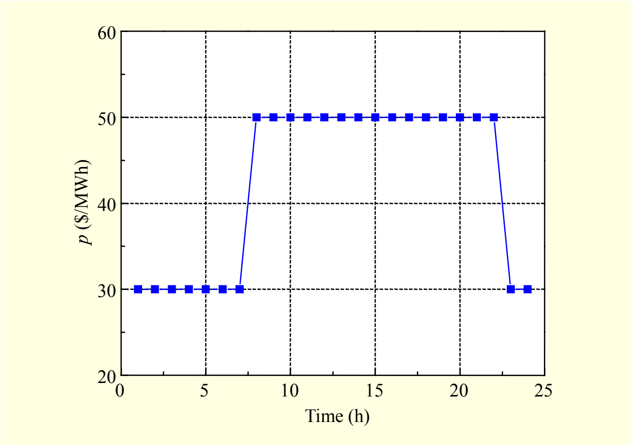

Fig. 5. Hourly prices for battery charging.

Table 2. Parameters of vehicles and regulation services.

Parameter	Value
P(kW)	20
$R_{\text{dc-up}}$	0.1
$R_{\text{dc-d}}$	0.1
η_{conv}	0.9
c_d($/kWh)	0.075
t(h)	8
N	9

Table 3. Criteria values for the period from midnight to 8 a.m.

N_{reg}	N_{serv}	r($)	C($)	t(min)
1	8	23.9	12.64	160
2	7	47.8	25.28	160
3	6	71.7	37.92	160
4	5	95.6	50.56	160
5	4	119.5	63.2	163
6	3	143.4	75.84	177
7	2	167.3	88.48	288
8	1	191.2	101.12	N.A.
9	0	215.1	113.76	N.A.

Table 4. Criteria values for the period from 8 a.m. to 4 p.m.

N_{reg}	N_{serv}	r($)	C($)	t(min)
1	8	21.64	12	120
2	7	43.28	24	120
3	6	64.92	36	121
4	5	86.56	48	126
5	4	108.2	60	145
6	3	129.84	72	288
7	2	151.48	84	N.A.
8	1	173.12	96	N.A.
9	0	194.76	108	N.A.

Table 5. Criteria values for the period from 4 p.m. to 12 p.m.

N_{reg}	N_{serv}	r($)	C($)	t(min)
1	8	57.70	19.04	160
2	7	115.4	38.08	160
3	6	173.1	57.12	162
4	5	230.8	76.16	171
5	4	288.5	95.20	205
6	3	346.2	114.24	542
7	2	403.9	133.28	N.A.
8	1	461.6	152.32	N.A.
9	0	519.3	171.36	N.A.

Table 6. Criteria membership values for different alternatives.

	Period I (0h–8h)			Period II (8h–16h)			Period III (16h–24h)		
	$\mu(r)^{w_1}$	$\mu(C)^{w_2}$	$\mu(t)^{w_3}$	$\mu(r)^{w_1}$	$\mu(C)^{w_2}$	$\mu(t)^{w_3}$	$\mu(r)^{w_1}$	$\mu(C)^{w_2}$	$\mu(t)^{w_3}$
1	**0.54**	1.00	1.00	**0.53**	1.00	1.00	**0.64**	1.00	1.00
2	**0.62**	0.96	1.00	**0.61**	0.96	1.00	**0.74**	0.96	1.00
3	**0.67**	0.91	1.00	**0.66**	0.92	0.99	**0.80**	0.92	1.00
4	**0.71**	0.87	1.00	**0.70**	0.87	0.96	***0.85***	0.87	0.99
5	**0.74**	0.81	0.98	***0.73***	0.81	0.83	0.89	**0.81**	0.94
6	0.77	***0.75***	0.90	0.76	0.75	**0.00**	0.92	0.74	**0.00**
7	0.80	0.65	**0.00**	0.78	0.66	**0.00**	0.95	0.66	**0.00**
8	0.82	0.53	**0.00**	0.80	0.54	**0.00**	0.98	0.53	**0.00**
9	0.84	0.00	**0.00**	0.82	0.00	**0.00**	1.00	0.00	**0.00**

In the next step, using expressions (21) and (22), the values presented in Table 6 are obtained. The weighting factors used in the examples for revenues, costs, and service waiting times are $w_1 = 0.2$, $w_2 = 0.3$, and $w_3 = 0.5$, respectively. The optimal alternative for each period using (20) is: six vehicles for ancillary services and three for customer services (first period); five vehicles for ancillary services (second period); and finally, four vehicles for ancillary services and five vehicles for customer services (third period). In Table 6, the first column represents the number of vehicles intended for the purpose of regulation (N_{reg}). Using (20), the minimal values given in the rows for each particular period are selected (values are marked

http://dx.doi.org/10.4218/etrij.15.2314.0046

bold in the table), and after that, maximal values denoting the optimal alternative are determined (marked bold and italic in the table). The optimal alternative for each period, using (20), is: six vehicles for ancillary services and three for customer services (first period); five vehicles for ancillary services (second period); and finally, four vehicles intended for regulation (third period).

Taking into account the low number of service calls during the night-time period, it seems entirely logical that there should be an increased number of vehicles that should be parked and connected to the grid for regulation purposes. However, in periods two and three, the high price for regulation services could be misleading when drawing such a conclusion. In this particular case, the decision-maker places customer satisfaction in first place, in comparison to costs and revenues. The result is that a smaller number of vehicles are required to power market services in comparison to the number required for customer services.

V. Conclusion

In this paper, the problem of optimally scheduling a fleet of EVs to successfully complete their daily activities, including the offering of frequency regulation services using V2G technology, has been considered. This paper contributes an optimal solution weighted more in favor of the EV fleet owner than the aggregator — one that is made possible through the use of queuing theory. Furthermore, the scheduling is treated as a multi-criteria optimization problem — one that includes revenues, costs, and commercial quality in its optimization criteria.

The use of the Bellman–Zadeh approach has served as a basis for solving this optimization problem, where the maximum degree of implementing goals serves as a criterion of optimality. The proposed methodology has been successfully implemented on the daily scheduling of an EV fleet served by an electricity distribution company. The elaborated case encompassed only three criterion and offering of regulation services, only. Further research will focus on an enlargement of both the criteria set and the ancillary services set.

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http://dx.doi.org/10.4218/etrij.15.2314.0046