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An Optimal Charge Framework Using Multivariate Copula for Day-ahead Scheduling of Electric Vehicle in Parking Lot Providing Power Markets

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Abstract

With the increase of electric vehicles (EVs), forecasting and modeling charging load in parking lots and charging stations have become more important than ever. one of the most challenging problems in the optimal charging process is modeling EV owners' behavior. By estimating EV parameters charging stations can buy and sell energy in power markets. In this article, an optimal charging framework for electric vehicles in charging parking lots is presented, which reduces the cost of charging electric vehicles. In this study, real-time and day-ahead markets are considered simultaneously, for estimating EV's behavior the copula distribution is used as a more accurate distribution to model the electric vehicles data. In the optimal charging process, V2G and G2V processes and battery degradation are also considered. The simulation results show that by accurately modeling the behavior of EVs, the parking lot can participate in both markets and perform the optimal charging process and pay less than other ways.

Keywords: Electric vehicles, Day-ahead scheduling, Optimal charging, Power markets, Copula
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1. Introduction

Rising greenhouse gases, fluctuations in fossil fuel prices, declining oil reserves, global warming concerns, etc. are very compelling reasons to expand the use of electric vehicles [1]. An increase without control of electric vehicles in the distribution system can cause many problems for the grid. Therefore, it is necessary to charge electric vehicles in a managed manner, considering the profits of the owners of parking lots, the network, and the owner of the EVs [2].

To manage the charge of EVs, it is necessary to first model the parameters of the vehicles correctly. Modelling vehicle behaviour is the first major challenge in managing the charge of electric vehicles [3]. Electric cars spend most of their time parked in different places such as offices, shopping malls, homes, etc. Parking lots are very useful for this reason. EVs parked in certain parking lots (such as offices, shopping malls, etc.) have a uniform behaviour. But publicly available parking lots have EVs with very random behaviour due to the uncertaint arrival and departure time of vehicles [4].

So far, many statistical and non-statistical methods have been introduced to model vehicle behaviour. In [4] based on real data, a probability distribution function is considered for the behaviour of EVs. A probability distribution function is independently defined for the arrival time, departure time, load required to charge the vehicle, as well as other parameters. In [5] with the assumptions about the load ratio in different residential areas, the number of EVs is estimated. This assumption is not necessarily correct. Also, many scenarios for arrival time, departure time, and also the initial SOC are generated by the normal distribution methods and then scenario reduction has been done by the Roulette wheel. Coordinated charging of electric vehicles has been studied in [6] by considering the different charge levels in a multi-objective optimization algorithm from the perspective of the distribution network operator. In this study, for each of EV's travel parameters, a normal distribution function using Florida transportation data is considered, which is a high approximation; Then a load of cars is randomly generated. [7] was one of the first papers to introduce the Copula method for modelling electric vehicle parameters. In this paper, by presenting the distribution of Copula and generating a scenario by the Monte Carlo method, the effect of charging electric vehicles in the electricity network has been investigated. In this article, the use of day-ahead and real-time markets has not been studied and the optimal use of markets and increasing the profit of the owner of the parking lot or charging station has not been studied. Copula distribution is used in [8] for modelling the traffic behaviour of Iranian cars. In this paper, the considered charge management functions are optimized by generating a scenario with the Copula distribution method. In this article, the exploitation of markets is not investigated.

In all the mentioned articles, different methods for modelling the parameters of the vehicles have been explored and the optimal charging of the vehicles has been done. But the processes of charging, discharging, and battery degradation are not considered simultaneously. As mentioned, in the first step, it is necessary to model the parameters of EVs. A suitable way to do this is to be able to consider the correlation between these parameters as well. Therefore, the Copula distribution method is a very suitable method for this purpose due to considering the relationship between the parameters. Therefore, if it is possible to estimate the parking load by modelling the parameters of EVs in parking lots (arrival time, departure time, and required charging) considering the optimal charge, then we can use day-ahead and real-time markets and minimize the charging cost or maximize parking profits. In this paper, considering the distribution of Copula to model the random parameters of cars in charging parking lots, the optimal charging and discharging in day-ahead and real-time markets, considering the cost of battery degradation, is discussed.

2. EVs Charging Parameters Modelling

To model an EV charging process at a charging station or parking lot, we need to know a few important parameters such as when the car is connected to the charger (or Arrival Time), when the car is disconnected from the charger (or Departure Time), and also the amount of charge required (or SOC if battery capacity is available). The behavior of EVs is independent of each other, but there are a series of general rules for the charging parameters of an EV. For example, most EVs that require a high amount of charge, spend more time in the parking lot (difference in arrival and departure times). But a review of the actual data shows that the behavior of cars for charging in the parking lot is very random. For example, some EVs have a very large amount of charge in a short time and vice versa. Some EVs needed a small charge for a very long time. The existence of such random behavior in EVs charging indicates that in addition to considering the correlation between the parameters, random behavior of EVs should be considered by default. There are several ways to do this called "Synthesis Data Methods"[9,10,11]. One of the most efficient methods that can consider the relationship between different parameters of a trip is the Copula distribution, which can provide appropriate modeling and generate similar data by considering the relationship between several variables. The equation of Copula distribution function as follows [12]:

$$C^m(u_1,u_2,\dots,u_m) = \Pr(U_1 \le u_1, U_2 \le u_2, \dots, U_m \le u_m) \tag{1}$$

where u_m represents a sample of standard uniform random variables $u_1(q=1,\dots,m)$. for t C, two parameters ρ (correlation coefficient) and v (degree-of-free) are defined. Equation of t Copula as follows [12]:

$$C^t_{\rho,v}(u_i,u_j) = t_{\rho,v}\left(t_v^{-1}(u_i), t_v^{-1}(u_j)\right) = \int_{-\infty}^{t_v^{-1}(u_i)} \int_{-\infty}^{t_v^{-1}(u_j)} \frac{1}{2\pi\sqrt{1-\rho^2}} \times (1+\frac{s^2-2\rho st+t^2}{v(1-\rho^2)})^{-(v+2)/2} ds dt \tag{2}$$

Therefore, using the Copula distribution, the parameters of electric vehicles in parking lots or charging stations can be modelled (Figures 1). Then, by modelling them, similar data can be generated that have both the property of being random and the correlation between the parameters.

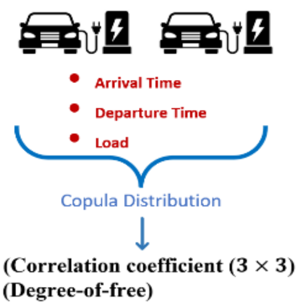

Fig. 1. EVs charging parameters modelling with Copula

3. DA & RT Power Market

The electricity market includes the real-time market and the day-ahead market, as well as ancillary services. In this market, electricity is purchased and sold to meet consumption [13].

Parking lots and charging stations can take advantage of the DA market by estimating day-ahead load and buying the amount of electricity they need at an optimal price from the DA market. They can also buy from the RT market at a time when the market offers a lower price (less than the DA market - this article assumes that the RT market price is already known and the parking lot accepts the price). With optimal charging based on DA and RT market prices, the parking lot can increase its profit. In addition to the issue of charging(G2V), because the parking lot has estimated its load, it can do the discharge process(V2G) for EVs at times when the market price is high and increases its profit from the previous situation or reduce the cost of EVs.

Prices in RTM are very different from prices in DAM. The price in RTM usually changes momentarily (for example, every five minutes) and these changes may be very sharp, but in the DAM market the prices change hourly, and the price change is not sharp [14]. Therefore, the parking lot must be able to correctly decide which market to choose.

4. EVs Scheduling Strategy

In this section, the mathematical modeling of the EVs and charging/discharging processes scheduling strategy is proposed. The objective function is formulated as follows:

$$Min_{\,p^+,p^-} \quad J_1 - J_2 + J_3$$

$$J_1 = \sum_{t=1}^{T}\sum_{i=1}^{N}(p_{i,t}^{+})\Delta T \rho_t^{buy} \tag{3}$$

$$J_2 = \sum_{t=1}^{T}\sum_{i=1}^{N}(p_{i,t}^{-})\Delta T \rho_t^{sell} \tag{4}$$

The first part of the objective functions J1 and J2 are the cost of purchasing/selling electricity from/to the power market. $p_{i,t}^{+}$, $p_{i,t}^{-}$ are the charging and discharging power of EVs. ΔT is the duration of each time interval. $\rho_t^{buy}/\rho_t^{sell}$ are optimal prices for buying/selling power from/to the power market. The optimal price equations are formulated as follows:

$$\rho_t^{buy} = \min(\rho_t^{DAM}, \rho_t^{RTM}) \tag{5}$$

$$\rho_t^{Sell} = \max(\rho_t^{DAM}, \rho_t^{RTM}) \tag{6}$$

where $\rho_t^{DAM}, \rho_t^{RTM}$ are prices of DAM and RTM respectively. Equations [5-6] indicate that the optimal price for buying/selling electricity is the minimum/maximum of DAM and RTM respectively. Also, J3 is the cost of battery degradation that is formulated as follows [15]:

$$dw_n = k_b(p_n^{+} + 2p_n^{-}) \quad (kW.h)/day \tag{7}$$

$$N_n^{life} = \frac{0.2C_n}{dw_n} \tag{8}$$

$$J_3 = \frac{i_d(CC^B(1+i_d)^{N_n^{life}} - SV)}{(1+i_d)^{N_n^{life}} - 1} \quad US\$/day \tag{9}$$

where k_b is the wear of battery capacity per charge/discharge; which is equal to 0.00015 (kWh/kWh) according to [16]. In equation (8), N_n^{life} is lifespan of the battery, C_n is battery capacity. In equation (9) i_d is the inflation rate, CC^B is the initial purchase price of the EV battery ($), SV is the battery salvage value at the end of its life cycle ($).

5. Dataset

This article uses the CAISO dataset for electricity market prices. In the CAISO market, corporations in the DA market are required to submit their offers the next day, in the RT market. In this article, the prices of the PGAE zone for the day-ahead market and the TH-NP15 zone for the real-time market are considered [17]. The chart of DAM and RTM prices on an example day is shown in Figure 2.

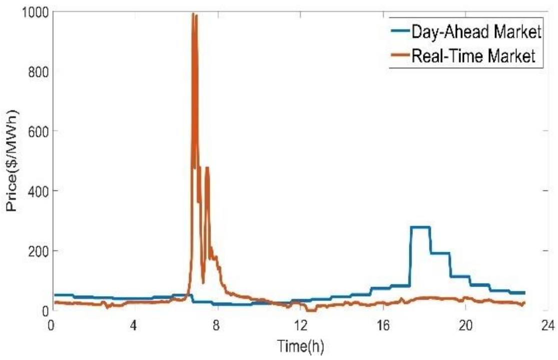

Fig. 2. Caiso DAM&RTM price for example day (September 8th 2020)

Also, for considering the data associated with electric vehicles, the dataset collected by Caltech has been considered. This dataset includes charging session data for electric vehicles in three parking lots. The ACN on the Caltech campus is in a parking garage and has 54 Electric Vehicle Supply Equipment or charging stations (EVSEs) along with a 50-kW dc fast charger. Caltech is open to the public and is often used by non-Caltech drivers. The second parking lot is JPL's ACN includes 52 EVSEs in a parking garage. Only employees are able to use the JPL campus. the third parking lot is the Office with a capacity of 8 EVs in the Silicon Valley area, which is for employees only. This dataset includes 3 parameters of charging sessions. these parameters are arrival time, departure time, and the amount of EV's load in the parking lot. In Figures 3-5 charts of the normal distribution function for each of these parameters for Caltech site are shown.

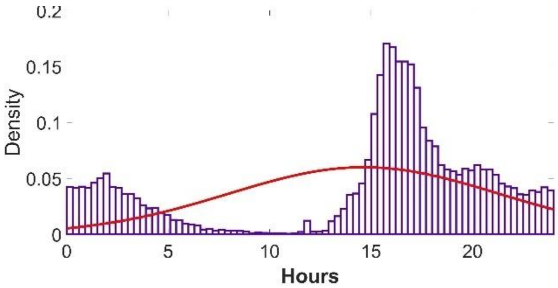

Fig. 3. Arrival time of EVs at Caltech site

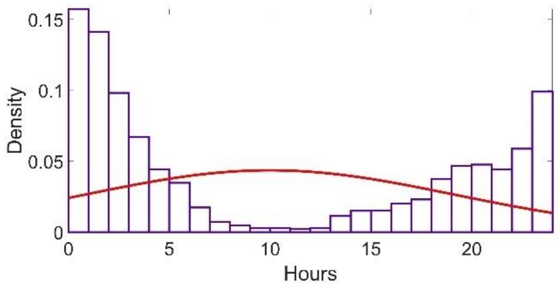

Fig. 4. Departure time of EVs at Caltech site

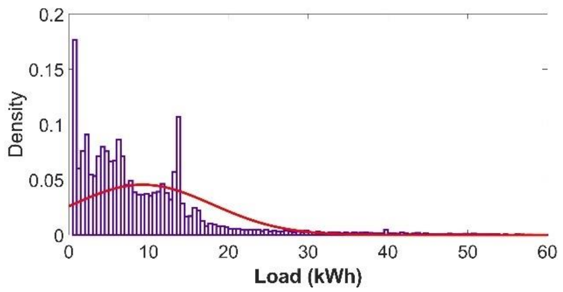

Fig. 5. kWh delivered of EVs at Caltech site

As can be seen in the above figures, EVs usually arrive at the parking lot at two different time intervals. Times 0 to 5, and 13 to 24 are the peak times for arrival time. The peak time of departure time is from 0 to 7 and from 13 to 24 hours. The charge load is often less than 20 kWh and has an average of 10 kWh.

6. Simulation Results

In this section, multiple scenarios are considered to estimate the parameters of electric vehicles and optimal charge in RTM and DAM. In EV's parameters estimation, Monte Carlo (MC) is considered. For the MC method in this article best distribution is non-parametric distribution because of the large variance. In this regard, 1000 scenario is generated, and then scenario reduction is performed to achieve the best accuracy.

There are two types of optimal prices for the charging schedule. The first type is the optimal price for the V2G process, and the second type is for the G2V process. In V2G process optimal price is high and it's reasonable for selling energy to the grid. In contrast In the G2V process, the price is low and the parking lot should buy energy from the grid and charge EVs. The optimal price is shown in Figure 6.

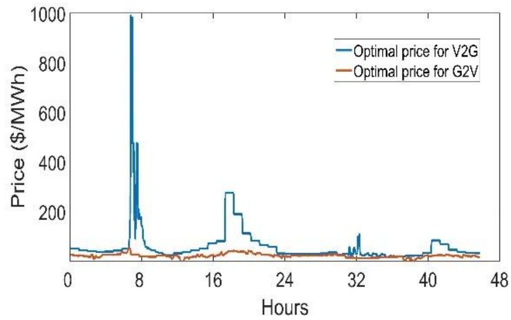

Fig. 6. Optimal price for V2G & G2V process

In simulation two days are considered, because most EVs leave the parking lot the next day morning. Also, 48 hours are divided into 5 min for every time interval. It is assumed that the parking lot has 100 EV capacity for the charging process. For optimization, the PSO algorithm is used because the wear cost of the batteries is non-linear. All parameter is shown in Table 1. The optimal charge for real data (Caltech parking lot) is shown in Figure 7. The parking load will be zero after about 450-time intervals because all the EVs that arrived at the parking lot on the specified day have departed.

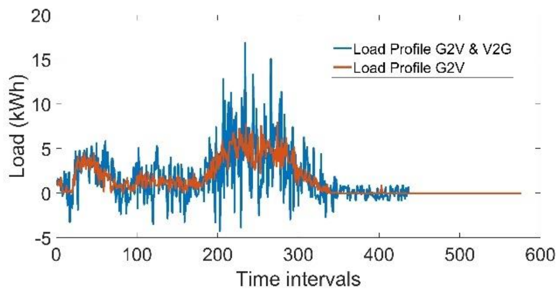

Fig. 7. Optimal charge for real data Caltech parking lot

In another scenario the parking lot uses Copula method to model EV parameters.

As can be seen in Figure 8, the Copula method can model the original data more accurately. Because the Monte Carlo method does not consider the correlation between features, it is less accurate than the Copula method. Now, in different scenarios where the parking lot considers different methods for optimal charging, the charging cost is listed in Table 1.

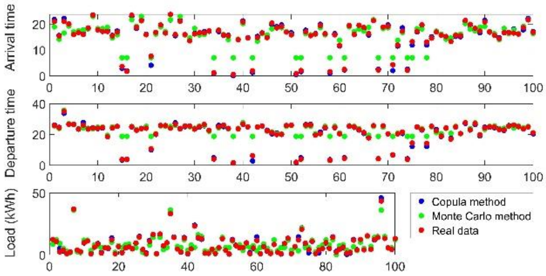

Fig. 8. Modelling data with MC and Copula methods

As shown in Table 1, if the V2G is considered for optimal charging, in at the optimal price (combination of RTM and DAM), EVs will receive a profit in addition to charging. This gain is considered by the degradation of batteries, and only at prices where the profit of the EV owners is greater than the degradation of the battery, the discharge process takes place. Also, the Copula distribution can be very similar to the real data and have very similar costs, and the parking lot can easily use this distribution to model the random behaviour of EVs.

In another scenario, if the parking lot participates only in the RTM and performs the optimal charging process, its costs will be indifferent methods according to Table 2.

As can be seen in Table 2, costs have increased relative to the optimal price way, which is reasonable. Also, because the cost function has a nonlinear part (battery degradation), the optimal global answer is not obtained and the best possible answer is obtained, so the cost of the process V2G may be higher than the process G2V. It should be noted that this optimal charging process costs less than unplanned charging. The cost of the various methods in the DAM market is also shown in Table 3. Due to the higher price of the DAM than the RTM, charging cost or even discharge profit has increased. Therefore, it can be concluded that in general, it is better to discharge cars with DAM prices and also to charge at RTM prices. In this article, the strategy of combining these two markets is presented. Also, because the Monte Carlo and Copula methods are using the generated data (fake data), therefore cannot perform optimal charge accurately compared with using the real data. The total power purchased more or less than the actual amount by the parking lot is shown in Figure 9.

Table 1

Cost of optimal charging in optimal price

	Optimal price	
	V2G&G2V	***G2V***
Real data	−82.82$	71.10$
MC	−94.09$	73.51$
Copula	−82.98$	71.05$

Table 2

Cost of optimal charging in RTM

	RTM	
	V2G&G2V	**G2V**
Real data	72.096$	75.81$
MC	81.67$	74.82$
Copula	74.06$	72.36$

Table 3

Cost of optimal charging in DAM

	DAM	
	V2G&G2V	**G2V**
Real data	−9.56$	119.85$
MC	−18.95$	126.28$
Copula	−15.05$	121.10$

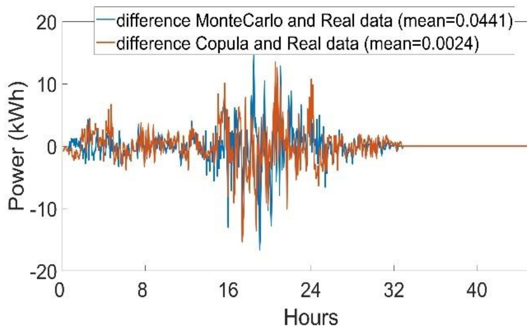

Fig. 9. Difference power

The power difference in the Copula method is less than the power difference in the Monte Carlo, which indicates that it is closer to the real condition. It can also be seen in Figure 9 that this difference is around zero and has an average of approximately zero, so the negative power difference is approximately equal to the positive, and it is useful to use a battery to compensate for this power difference.

7. Conclusion

This article presented an optimal charging framework for electric vehicles in parking lots. This framework has two levels. In the first level, the behaviour of electric vehicles is modelled by statistical methods, and then, according to the available markets for the optimal charge, charging is performed in the second level.

According to the simulation results, the Copula distribution method has a more accurate answer than other statistical methods and presents a more accurate model than the original data. Parking can also reduce the cost of charging EVs by making the best use of DAM and RTM. Simultaneous use of DAM and RTM reduced the cost of charging EVs.

As mentioned in the simulation results, the optimal charge process with the data produced by the Copula method differs from the optimal charge with the real data, and this difference can be compensated in future works by using the battery and examining the use of the battery with buying from the real-time market. In this paper, it is assumed that the parking lot is aware of the real-time market prices, while in real conditions this is not the real situation. However, the real-time market price can be estimated and used in research by time-series regression methods.

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