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Optimal Charging of Plug-in Electric Vehicles for a Car Park Infrastructure

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Abstract—**This paper proposes an intelligent workplace parking garage for plug-in hybrid electric vehicles (PHEVs). The system involves a developed smart power charging controller, a 75 kW photovoltaic (PV) panel, a DC distribution bus and the AC utility grid. Stochastic models of the power demanded by PHEVs in the parking garage and output power of PV are presented. In order to limit the impact of PHEV's charging on the utility AC grid, a fuzzy logic power flow controller was designed. Based on their power requirements, PHEVs were classified into five charging priorities with different rates according to the developed controller. The charging rates depend on the predicted PV output power, the power demand by the PHEVs, and the price of energy from the utility grid. The developed system can dramatically limit the impacts of PHEVs on the utility grid and reduce the charging cost. The system structure and the developed PHEVs smart charging algorithm are described. Moreover, a comparison between the impacts of the charging process of the PHEVs on the grid with/without the developed smart charging technique is presented and analyzed.**

Index Terms—**Charging priority levels, fuzzy logic, hybrid DC distribution system, plug-in hybrid electric vehicles, solar energy, impacts limitation.**

I. Introduction

PLUG-IN hybrid electric vehicles (PHEVs) are gaining popularity due to several reasons; they are convenient, visually appealing, quiet, and produce less pollution in the environment. PHEVs have the potential to reduce fossil energy consumption, green-house gas emissions and increase the penetration of sustainable energy sources such as solar energy and wind energy into our daily lives [1]-[3]. Furthermore, most personal vehicles in the United States are parked more than 95% of the day and generally follow the same daily schedule [4]. Therefore, PHEVs can be used as mobile energy storage devices in the future. More than 75% of drivers in the United States travel less than 45 miles in their daily commute and since many of today's PHEVs can go up to 100 miles on a single charge, their implementation can be widespread. Battery technology continues to advance with batteries becoming smaller in size while storing more energy. It is forecasted that in North America PHEVs will be on the roads in large numbers in the very near future [5].

The increasing number of PHEVs can have a huge impact on the electric utility if properly designed smart charging techniques are not utilized. Uncoordinated and random charging activities could greatly stress the distribution system, causing several kinds of technical and economic issues such as suboptimal generation dispatches, huge voltage fluctuations, degraded system efficiency and economy, as well as increasing the likelihood of blackouts because of network overloads. In order to maximize the usage of renewable energy sources and limit the impacts of PHEVs' charging to the utility AC grid, a smart power flow charging algorithm and controller should be designed. Moreover, accurate PV output power and PHEV's power requirement forecasting models should be built. PHEVs need to participate in vehicle-to-grid (V2G) and vehicle-to-vehicle (V2V) power transactions during the charging process. Fully controlled bidirectional AC-DC and DC-DC converters are needed in this system.

In [6], [7], load management solutions for coordinating the charging process of multiple PHEVs in a smart grid system based on real-time minimization of total cost of generating the energy plus the associated grid energy losses were proposed and developed. However, they did not consider the inclusion of a renewable energy source in the system, which holds the implementation of these algorithms back since the concept of PHEVs involves obtaining the power to charge them from renewable energy sources. In addition, the control strategy did consider charging priority level, but the level is based on how much the owner of the PHEV is willing to pay, not the state of charge (SOC) of the PHEV's batteries therefore the efficiency of V2V and V2G service is low.

In [8], [9], an intelligent method for scheduling the use of available energy storage capacity from PHEVs is proposed. The batteries in these PHEVs can either provide power to the grid or take power from the grid to charge the batteries on the vehicles. However, the detail about the energy dispatch during charging and V2G process is not given. Also, the SOCs of the PHEV's batteries are not considered during the process.

A fully controlled bi-directional AC-DC converter has been designed and implemented in [10]. This converter has the capability of controlling the power flow between the AC and DC sides of the systems in both directions while operating at unity power factor and within acceptable limits of time harmonic distortion (THD) for the current drawn from the grid. Hence, the amount of power flowing in either direction can be set to a certain pre-set value while a controlled rectifier, working as a voltage rectifier, maintains the power balance as it is free to supply any power needed in the DC grid. In addition, a controlled DC-DC boost converter and a bidirectional DC-DC converter are proposed and tested in [11] - [13].

In this work, a hybrid DC PHEVs' workspace parking garage charging system is established and tested. A 318V

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TABLE I
PARAMETERS FOR PHEVS IN DIFFERENT SIZE

PHEVs model	Percentage	Battery capacity (kWh)	Energy consumption per mile (kWh/mile)
compact sedan	32.5%	10-20	0.2
full-size sedan	37.5%	20-30	0.3
mid-size SUV or pickup	20%	30-40	0.45
full-size SUV or pickup	10%	40-50	0.6

grid-connected DC power distribution network combined with PV and PHEVs parking garage is designed. Accurate PV and PHEVs power stochastic models based on statistical theory are studied. A fuzzy logic power flow controller is also designed.

This paper is organized as follows; the system description and problem formulations are given in section II. The stochastic models of the PHEV's parking system and PV are given in section III. The details of the developed real-time fuzzy logical power flow controller are given in section IV. The method to classify PHEVs into five priority levels and adjust their charging rates is given in section V. Results and discussion are given in section VI. Concluding remarks are provided in section VII.

II. SYSTEM DESCRIPTION AND PROBLEM FORMULATION

Consider a workplace parking garage DC hybrid power system equipped with a PV farm. Each workday various vehicles will park in the garage during their owner's working hours. The vehicles all differ in size, battery capacity, and energy consumption per mile. The specific details are shown in Table I. Whenever a PHEV is connected to the parking garage, the owner of it will set the departure time and the system will make a record of this time. Usually at the departure time, the SOC of the batteries is expected to be at least 80% of its full capacity. In order to take battery protection into consideration, the SOC of the PHEV's battery shouldn't go below a certain limit. If this limitation is reached, the PHEV will stop using electric energy and begin consuming gas from its combustion engine.

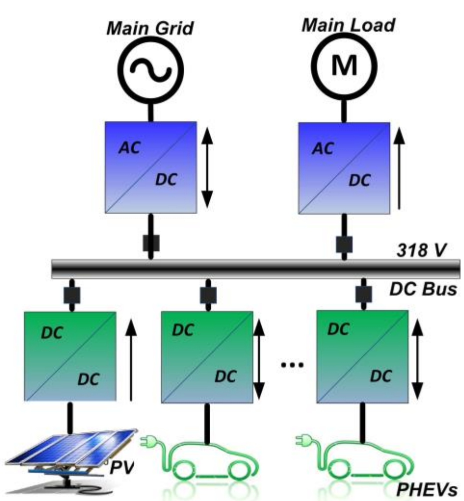

Fig. 1 Schematic diagram of the investigated system

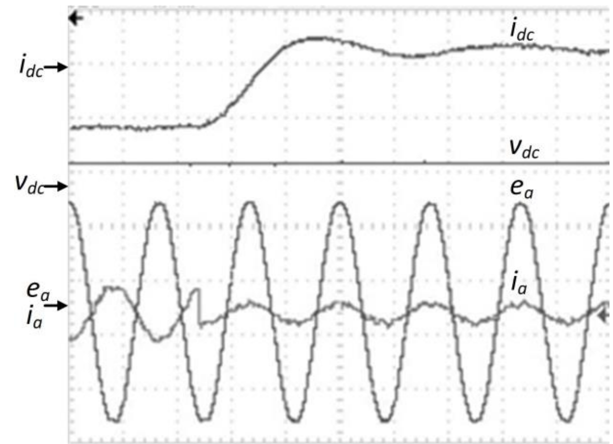

Fig. 2. Bi-directional converter response to a step change in the DC current reference from -4 to 1 A. (a) DC current, i_{dc}(4 A/div, 10 ms); (b) DC voltage, v_{dc}(1000 V/div, 10 ms); (c) AC phase voltage, e_a(30 V/div, 10 ms); (d) AC current, i_a(5 A/div, 10 ms).

The schematic diagram of the system under study is shown in Fig.1. As can be seen, the PHEVs, with their bi-directional DC-DC chargers, and the PV source, with its DC-DC regulating interface, share a common DC bus. Hence, the charging parking garage acts as a DC micro-grid that has the ability to send or receive power from the utility AC grid. The amount of power transferred between the AC and DC sides is determined according to the decisions from the developed energy management algorithm. Fig. 2 shows the response of this converter to a step change in the DC current reference from -4 A to 1 A; the current will reverse its direction, sending power from the DC micro-grid to the AC side so it can receive power. Also, the active and reactive power flow is controlled separately by using the active and reactive power decoupling technique. More simulation and experimental results on this converter as well as the controlled rectifier were illustrated in [1]-[2].

In order to limit the impact of PHEVs' charging to the utility AC grid while letting the PHEVs participate in the V2V and V2G power transactions, the parking garage should have a smart charging algorithm that can adjust the charging rates for PHEVs under different utility AC energy prices (E_{price}) and different power flow estimations (P_{grid}). Since the hourly energy price is assumed to be known beforehand, it is essential to estimate P_{grid}, which is given by (1).

$$P_{grid} = P_{PV} - P_{total} - \hat{P}_{upcoming} \tag{1}$$

where

- P_{PV} is the estimated PV output power for the next period T;
- P_{total} is the power needed by the PHEVs that are already parked in the parking garage;
- $\hat{P}_{upcoming}$ is the estimated power requirements by the upcoming PHEVs which will connect to the parking garage in the next period T.

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TABLE II
ARRIVAL AND DEPARTURE TIMES DISTRIBUTION PARAMETERS

	Arrival		Departure	
Parameter	Weekday	Weekend	Weekday	Weekend
$\mu_T[h]$	9	11	18	15
$(\sigma_T)^2[h]$	1.2	1.5	1.2	1.5

In order to design the smart charging control algorithm, an accurate power requirement forecasting model is needed to estimate P_{grid}.

For the power flow control for the next period *T*, the charging rates for different PHEVs should be adjusted based on E_{price} and P_{grid}. Because the system is highly nonlinear, a fuzzy logic controller is a good choice for solving this issue.

Often times the PHEVs in the parking garage will have different SOCs and different departure times so their average constant power requirements will differ. Some PHEVs may need a huge amount of energy within a short period of time. These kinds of PHEVs should be classified into the high priority level. Other PHEVs' SOCs are already high with departure times several hours later. These kinds of PHEVs should be classified into the lower priority level. Therefore, a priority classification should be designed for the PHEVs.

The objective of this paper is to design a grid-connected hybrid DC PHEV charging parking garage system with fuzzy logic power flow control and PV panels. The goal is to limit the impact of PHEV's charging to the utility AC grid and maximize the utilization of power generated from PV panels.

III. MODELING THE STOCHASTIC PHEVS' PARKING SYSTEM

A. PV Output Power Forecasting Model

In order to manage the energy in the PHEVs' parking park in a real-time manner, the power available from the PV source should be predicted and considered. Accuracy of the decision made by an algorithm is affected by the accuracy of the predictive models used to emulate the uncertainties in the system, i.e. PV power in this case. Hence, we count on real data to forecast the PV output power. The data forecasting process was based on PV data collected over 15 years on an hourly basis for an example PV system in the state of Texas. The output power data is used as the output to be forecasted, whereas the day of the year (1-365) and the hour of the day (1-24) were used as inputs. Different model evaluation indices were used to validate the developed mathematical models. The forecasting model used to predict the PV output in this paper is regenerated from the model derived in [14] using the historical PV data described in the previous subsection.

B. PHEVs' Power Requirement Forecasting Model

In order to develop an accurate PHEVs parking system model, it is essential to estimate the probability density function (PDF: a function that describes the relative likelihood for this

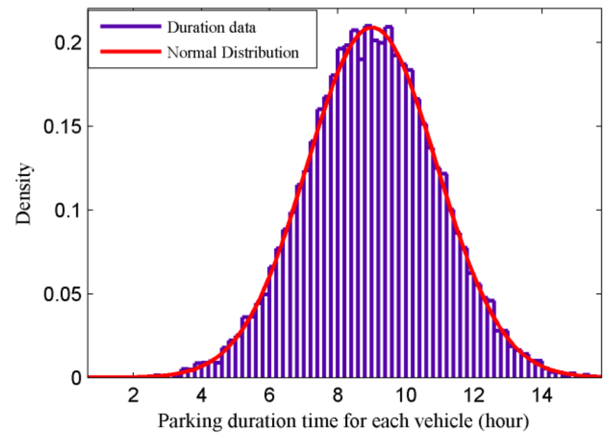

Fig. 3. The PDF of the daily parking duration.

random variable to take on a given value [15]) of the power needed by each PHEV when it is connected to the parking lot, $\hat{P}_{PHEV}$. This variable is based on the PHEV models, parking duration times, and daily travel distances.

In order to avoid serious damage, the batteries of the PHEVs should not be over discharged. PHEVs have the capability of using both electric energy and fossil fuel energy. The PHEV stops using electric energy when the SOC of its battery is below 10%. Therefore, the electric energy of a PHEV that can be used before its next charge is 70% of the total battery capacity. If the energy consumption is more than this value, the PHEV will use gas. If the total energy consumption for a certain PHEV before the next charge is less than 70% of its battery capacity, the energy needed by it for the next charge is $M \times E_m$. Otherwise, the energy needed by it is 70% of its battery capacity. The constant charging power needed by this PHEV is given below (2) and (3). In order to find $\hat{P}_{PHEV}$, the distribution of daily travel distance and daily parking duration time need to be obtained first.

If total energy consumption is less than 70% of the battery capacity:

$$\hat{P}_{PHEV} = \frac{M_d \times E_m}{D_t - A_t} \tag{2}$$

If total energy consumption is equal or more than 70% of the battery capacity:

$$\hat{P}_{PHEV} = \frac{70\% \times B_c}{D_t - A_t} \tag{3}$$

where

- M_d is the driver's daily travel distance;
- A_t is the PHEV's arrival time;
- D_t is the PHEV's departure time;
- E_m is the PHEV's energy consumption per mile;
- B_c is the PHEV's battery capacity.

In this work, the parking garage is located by the workplace of a company whose office hours are from 9:00 am to 6:00 pm. Based on the Central Limit Theorem (the conditions under which the mean of a sufficiently large number of independent

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random variables, each with finite mean and variance, will be approximately normally distributed [16]), the distribution of the PHEVs arrival and departure time is shown in Table II. With the PDFs of A_t and D_t, the joint probability density function of D_t - A_t can be found, which is the daily parking duration time. It is a normally distributed random variable with μ_d and $\sigma_d = 1.92a$.The PDF of the daily parking duration is shown in Fig. 3.

Based on known driving pattern statistics, the average yearly total miles driven in the United States is 12,000 miles with 50% of drivers driving 25 miles per day or less, and 80% of drivers driving 40 miles or less. A log normal distribution with $\mu_m=3.37$, $\sigma_m=0.5$ is selected to approximate the PDF of M_d, which shows that the total yearly driving distance average is 12,018 miles, 48% of the vehicles drive 25 miles or less each day, and 83% of the vehicles drive 45 miles or less each day, which closely approximates the driving performance results from [1]. The distribution function for M_d is given in (4).

$$f_X(x;\mu_m,\sigma_m) = \frac{1}{x\sigma_m\sqrt{2\pi}}\exp\{-\frac{(\ln x-\mu_m)^2}{2\sigma_m^{\ 2}}\} \quad (4)$$

With the PDF of daily duration time, PDF of daily travel distance, and power consumptions of each class of PHEVs, by using MATLAB's statistic distribution fitting toolbox and Monte Carlo simulation with 30000 samples, the PDF of constant power needed by each PHEV when it is connected to the parking lot, $\hat{P}_{PHEV}$, is finally found as an inverse Gaussian distribution with $\mu_p=1.573$ and $\lambda_p=3.652$. The distribution function for $\hat{P}_{PHEV}$ is given in equation (5). The PDFs of the M_d and $\hat{P}_{PHEV}$ are shown in Fig. 4 and Fig. 5, respectively.

$$f_X(x,\mu_p,\lambda_p) = \sqrt{\frac{\lambda_p}{2\pi x^3}}\exp\{-\frac{\lambda_p}{2\mu_p^{\ 2}x}(x-\mu_p)^2\} \quad (5)$$

After getting the probability distribution function of $\hat{P}_{PHEV}$, the forecasting model of power needed by PHEVs in the parking system is built. Together with the forecasting model of the power generated by renewable energy sources and hourly price of the energy from the utility grid, a real-time smart parking system is established. For instance, at a certain time t, the SOC of the PHEVs already parked in the parking lot and their power requirements are already known. In order to forecast the power needed by the PHEVs that will arrive during the upcoming period T, the following equation can be used.

$$\hat{P}_{upcoming} = \int_t^{t+T} f_{A_t}(x,\mu_{A_t},\sigma_{A_t})dt \times NP \times \hat{p}_{PHEV\_avg} \quad (6)$$

where

- NP is the total number of PHEVs that will park in the parking lot this day;
- $f_{A_t}(x,\mu_{A_t},\sigma_{A_t})$ is the PDF of the arriving time A_t;
- $\hat{P}_{PHEV\_avg}$ is the average constant power requirement for all PHEVs when they are connected to the parking lot. $\hat{P}_{PHEV\_avg}$ can be calculated from the PDF of $\hat{P}_{PHEV}$.

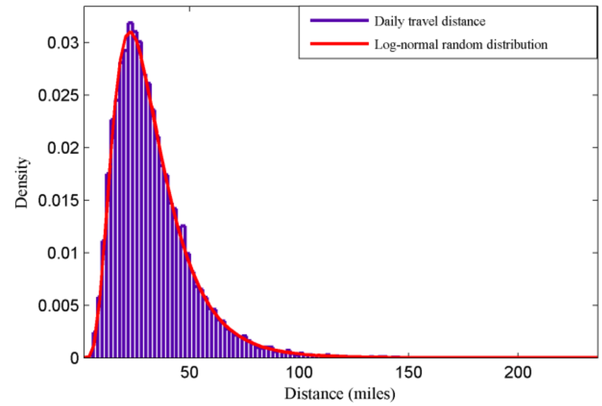

Fig. 4. The PDF of the daily travel distance.

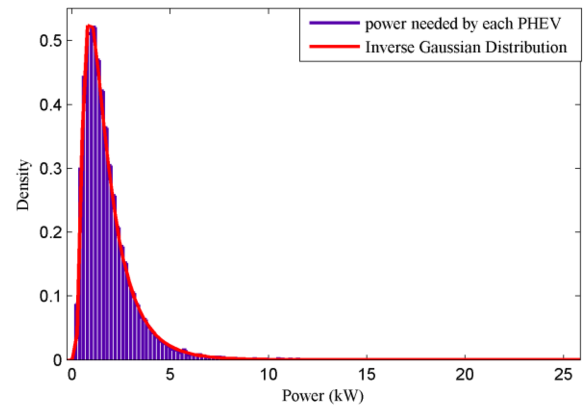

Fig. 5. Power needed by each PHEV when connected to the parking garage.

IV. Real Time Fuzzy Logical Power Flow Controller

In the previous section, the details of how to build the model of the parking garage and find the PDF of the $\hat{P}_{PHEV}$ are given. Together with the stochastic model of PV and hourly energy price of the AC utility grid, a smart charging algorithm with a fuzzy logic power flow controller is designed. The flowchart is shown in Fig. 6.

The charging rates of PHEVs at different priority levels for the next period varies based on the forecasting of the power generated by the PV panel, the forecasting of the power needed by the upcoming PHEVs, the price of the utility energy grid, and the power needed by the current PHEVs. Without the V2V and V2G services, the power flow in the next period between the utility AC grid and the hybrid parking system can be calculated by using equation(1).

The price of energy for the next period, E_{price}, and the next period forecasting power flow, P_{grid}, are used as the two inputs of the real time Mamdani-type fuzzy logic power flow controller to determine the charging index δ_p, which will determine the charging rates of PHEVs at different priority levels. The power flow between the utility AC grid and the DC system, P_{grid}, is described as "negative", "positive small", "positive medium", "positive" and "positive big". Similarly, the energy price, E_{price}, is described as "very cheap", "cheap", "normal", "expensive", and "very expensive". The method implemented for defuzzification is centroid based. Within the

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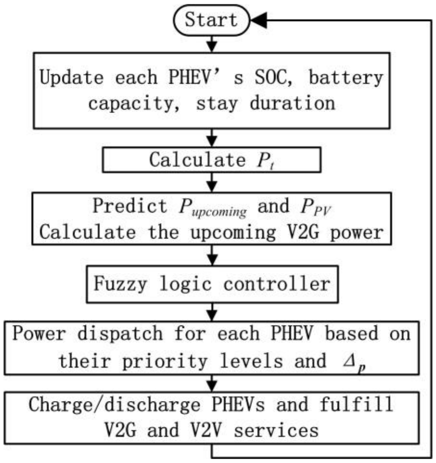

Fig. 6. The flow chart of the developed real time fuzzy logical charging controller.

model, minimum and maximum are used for "AND" and "OR" operators, respectively. The output of the fuzzy controller is the index δ_p, which is used for adjusting the charging rates for PHEVs in different priority levels. The parameter δ_P is described as "NB", "N", "Z", "P" and "PB", which stand for negative big, negative, zero, positive and positive big. The Mamdani-type model based fuzzy rules of the fuzzy logic power flow controller is given in Table III. The membership functions of E_{price}, P_{grid}, and δ_p and the surface of the fuzzy logic controller's rules are shown in Fig. 7 and Fig. 8.

With the charging index, δ_p, which varies from -1.0 to 1.0, the charging rates for PHEVs in different priority levels will be obtained.

V. Classification of PHEVs into Five Priority Levels

The charging rates of different PHEVs with different SOCs and power requirements should apparently be charged at different rates. For example, a PHEV is connected to the parking lot at 9:00 am with a departure time of 6:00 pm and the SOC of charge is 65%. The average constant power required by this PHEV is small. At the same time, another PHEV is connected to the parking lot also at 9:00 am but will leave at 10:30 am and the SOC is only 10%. This PHEV's average constant power requirement is larger than the previous one, which means its charging condition is also more emergent. So in order to reduce the impact of the PHEVs' charging to the utility AC grid, at a certain time, different PHEVs should be charged at different rates. Furthermore, since the former PHEV will stay in the parking lot for more than 8 hours, it can be viewed as an energy storage device during this period. For instance, at a certain time the energy price is below the daily average price and PV generates more power than the total PHEV's requirements. The extra power can be saved in this PHEV as backup energy. By doing so, the priority level of this PHEV decreases. At another time during this period, the price of the utility grid energy could be high and the power generated by the PV can't meet the total load and PHEV's power requirement, so instead of buying power with a high price from the utility grid, the parking system can get the backup energy from this PHEV. By doing so, the priority of this PHEV will increase. During the entire day, all the PHEV's priorities are

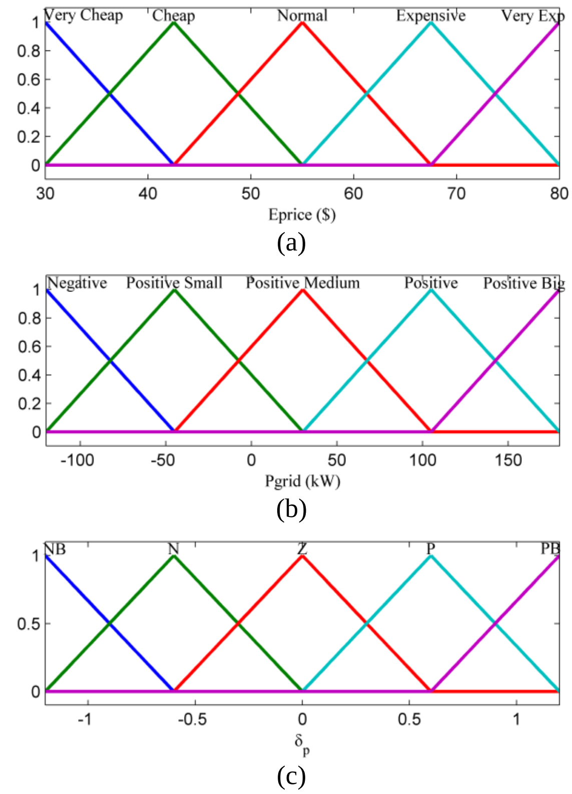

Fig. 7. Membership functions. (a) Power flow; (b) Energy price; (c) Power flow control index.

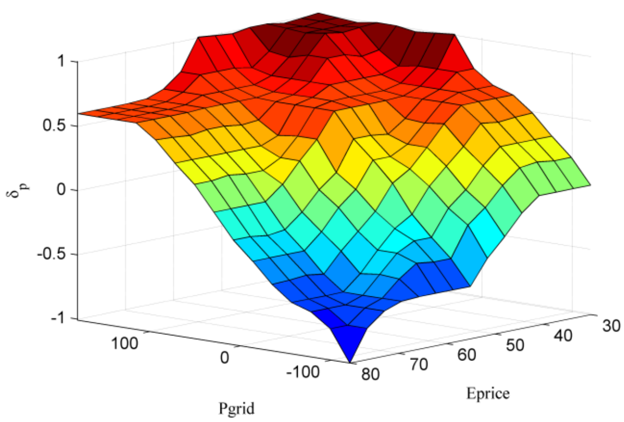

Fig. 8 The surface of the fuzzy logic controller's rules.

varying with their SOCs thus energy can be delivered between V2G and V2V. The five charging priorities are shown in Table IV.

The PHEV's charging priority levels are only dependent on their power requirements. Also, because of the bi-directional power flow converter, PHEVs can be charged and discharged, so their charging priority levels are varying with time. PHEVs in levels 1, 2, and 3 can only be charged. Those PHEVs either need a lot of energy (such as having an SOC of only 10% when connected to the parking station) or will leave in a short time but still have not met the owner's charging requirement (such as having an SOC of only 65% and departing in half an hour). PHEVs in level 4 and 5 can be discharged to fulfill the V2G and V2V services. These PHEVs will continue staying in the parking lot for longer durations. The various SOCs of the PHEVs will change over time thus PHEVs in lower priority

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TABLE IV
CHARGING RATES FOR DIFFERENT CHARGING LEVELS

Priority level	Power requirement	Maximum charging rate	Minimum charging rate
Level 1	$p \geq 15kW$	12kW	12kW
Level 2	$10kW \leq p < 15kW$	12kW	6kW
Level 3	$5kW \leq p < 10kW$	8kW	0kW
Level 4	$2kW \leq p < 5kW$	5kW	-5kW
Level 5	$p < 2kW$	2kW	-8kW

levels can jump to the higher levels of priority and vice versa.

With the charging index, δ_p, the charging rates of PHEVs in levels 1-5 are given in (7)-(11).

$$p_{charging\_rate} = 12, \tag{7}$$

$$p_{charging\_rate} = 9 + 3 \times \delta_p, \tag{8}$$

$$p_{charging\_rate} = 4 + 4 \times \delta_p, \tag{9}$$

$$p_{charging\_rate} = 0 + 5 \times \delta_p, \tag{10}$$

$$p_{charging\_rate} = -3 + 5 \times \delta_p. \tag{11}$$

VI. RESULTS AND DISCUSSION

In this section, a 318 V DC workplace parking garage hybrid power system equipped with a 75 kW photovoltaic (PV) panel has 350 parking positions, and each work day around 300 vehicles will park in the garage during the work hours from 9:00 am to 6:00 pm. Of the 300 vehicles, around 60% of them are PHEVs. The battery capacities and energy consumptions per mile of PHEVs in different sizes are given in Table I. The parking garage will upgrade all the information every 6 minutes and generate a new charging index, δ_p, to adjust the charging rates for the PHEVs parking in it. All the PHEVs are assumed to be only charged at this workplace parking garage, and the state of charge (SOC) of the batteries are expected to be over 80% at their departure times. The PHEVs' SOC of the batteries shouldn't go below 10%.

Two experiments are done both in MATLAB simulation and hardware test. The first simulation represent the power flow between the utility grid and the DC hybrid PHEVs parking garage without real-time charging optimal control and the second simulation contains real-time fuzzy logic charging optimal control. Both experiments are under the same conditions: same number and types of PHEVs, same departure and arrival times, same hourly energy price, and same power generated by the PV panels.

The simulation of the power flow during the daytime and the PHEV's SOCs at departure times for the parking garage without an optimal charging method is shown in Figs.9 and 10.

Whenever a PHEV is connected to the parking garage, it will be charged with a constant rate of 10 kW. It will not stop charging until the SOC of its battery reaches 80%. From the simulation it is clear that the peak happens around 9:00 am because most of the PHEVs arrive around this time every day. The peak is near 700 kW and the power flow above 300 kW lasts from 7:30 am to 11:20 am, more than three and a half

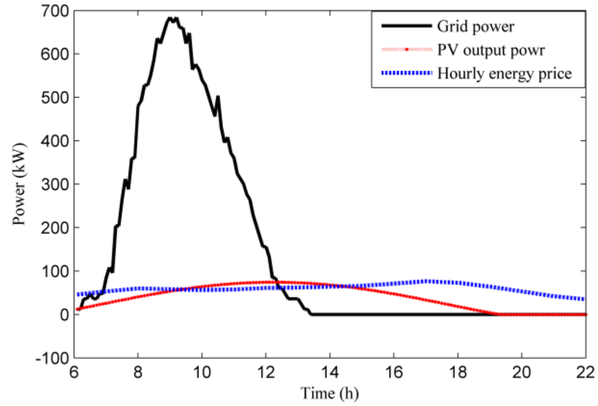

Fig. 9. Hourly power flow from AC grid without optimal controller.

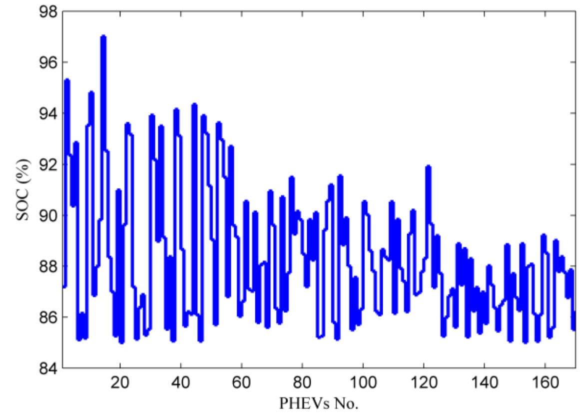

Fig. 10. PHEVs' SOCs at their departure time without optimal controller.

hours. After 1:30 pm, the charging stops because all the PHEVs that are parked in the garage at that time already meet the charging requirement. After 1:30 pm there is no power flow between the utility AC grid and the parking garage because there aren't any new PHEVs connected to the parking garage. But at that time, the PV's output power is still high while the energy price is cheap. It's not a good time to sell power to the AC grid but the parking garage without optimal charging control doesn't have any other option other than selling power. From Fig. 10 it is clear that all the PHEV's SOCs are above 80% at their departure times since all of them are charged with the same charging rates.

The simulation of the power flow during the daytime and the departure PHEVs' SOC for the parking garage with an optimal fuzzy logic charging controller is shown in Figs 11 and 12. From Fig.11 it is clear that the peak of the power flow from the AC utility grid to the smart parking garage is limited to 300kW and the power flow, which is above 250 kW, only lasts from 9:30 am to 11:20 am and partly in the afternoon around 4:00pm, all together no more than two and half hours.

Furthermore, when the energy price is high, the power flow from the AC side will decrease apparently, which happens around 17:00 PM. Also, when the PV output power is above a certain amount, power flow from the AC grid to the smart charging garage will decrease because more PHEVs will be charged by the power generated by the PV. From Fig. 10 we can see all the PHEVs' SOCs are above 80% at their departure

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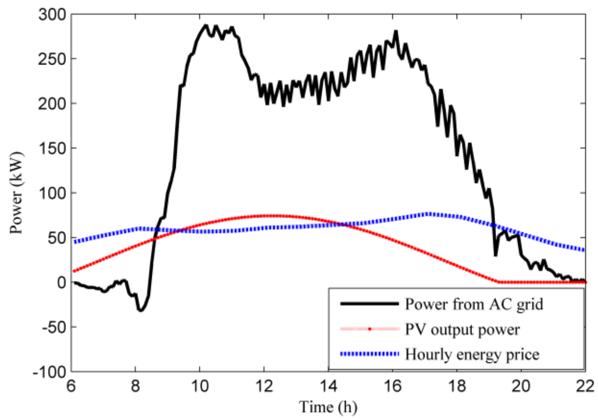

Fig.11. Hourly power flow from the AC grid with optimal controller

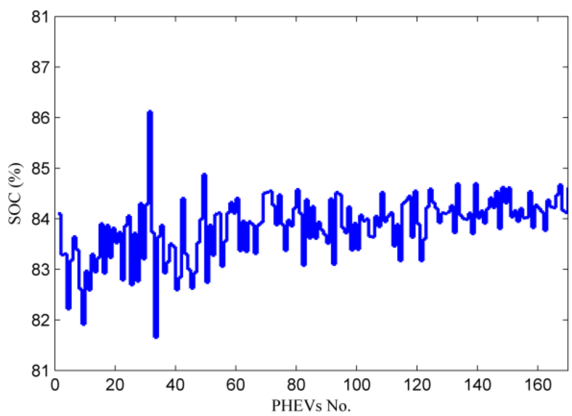

Fig. 12. PHEVs' SOCs at their departure time with optimal controller.

times, which also meets the charging requirements.

Fig. 13 shows the variation of a randomly chosen PHEVs' SOC during the charging process with optimal fuzzy logic charging controller. This PHEV is connected to the parking garage at 8:18 AM, and the departure time is 17:12 PM. When this PHEV is connected to the parking garage, the SOC is around 28%, and the PHEV's owner enters the departure time 17:30 PM. So the charging system can calculate the real time average power required for this PHEV. The duration time is long at the beginning of the day from 8:00 am to 10:00 am so the PHEV's average power requirement is low with a classification of level 4 or 5. At this time the price of energy is high, therefore instead of buying power from the AC grid, the parking garage uses the energy stored in this PHEV to charge other PHEVs in the higher levels of priority. This is why the SOC of the PHEV is decreasing during this period. From 10:00 am to 1:30 pm, the AC grid energy price is low so more power is bought from the AC side and since δ_p is positive, this PHEV's charging rate is positive. However, the duration time is still long so the priority level is still low and the charging rate is low. The priority levels increase at around 2:00 pm, when its departure time is near. At this time the charging rate is higher than before. This charging rate is kept until 5:12 pm, when the SOC is already above 80% and the departure time is very close. This PHEV no longer participates in V2G or V2V power transactions and the SOC remains constant from then on.

Fig. 14 shows the comparison of the voltage variation on the AC bus corresponding to the PHEV's charging process

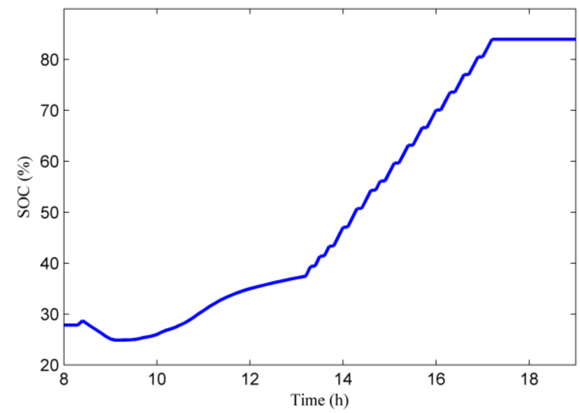

Fig. 13. Variation of PHEV's SOC during the charging process.

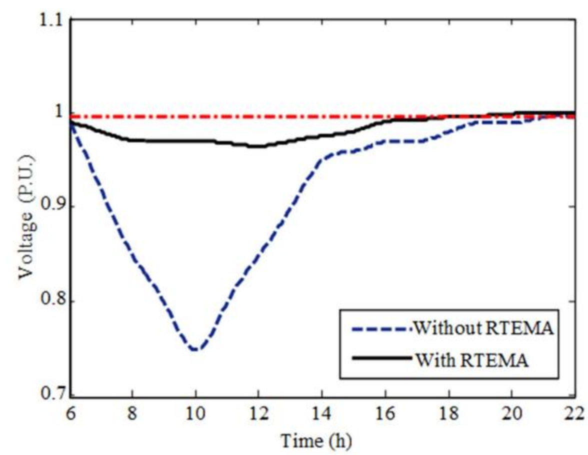

Fig. 14. The voltage on the AC bus corresponding to the PHEVs charging process with/without optimal fuzzy logic charging controller.

with/without an optimal fuzzy logic charging controller. It is clear that during the charging process without the optimal charging controller, the voltage on the AC bus will drop to around 0.75 P.U. of the rated voltage. Also, the voltage below 0.9 P.U. lasts longer than three hours. With the optimal charging controller, the voltage of the AC bus during the whole charging process is above 0.95P.U.

VII. Conclusion

This paper presented a model of PHEVs workplace car park charging infrastructure with a grid-connected hybrid DC power system involving renewable sources. To forecast next period power flow, accurate PHEVs and PV power stochastic models were developed. The fuzzy logic power flow controller was designed to control the real-time power flow. A new power dispatch method based on PHEVs priority levels and a real-time PHEV's charging algorithm was developed. Furthermore, bi-directional DC-DC and AC-DC converters were designed to let the PHEVs participate in the V2V and V2G services. The simulation results show that the optimal power flow control algorithm can maximize the utilization of PV output power for charging of PHEVs and simultaneously decrease the impacts on the grid greatly. At the same time, the PHEV's SOCs at their departure time are all above the charging requirement. The system presented in this paper benefits both the AC utility grid and PHEV's owners.

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