Charging Load from Large-scale Plug-in Hybrid Electric Vehicles: Impact and Optimization

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Abstract – **In this paper, a stochastic model of large-scale plug-in hybrid electric vehicles' (PHEV) charging loads is developed in Matlab to investigate its impact on power grid. In this model, two main types of PHEVs are defined: public transportation vehicles and private vehicles. Different charging time schedule, charging speed and battery capacity are considered for each type of vehicles. The simulation results reveal that there are two huge load peaks (at noon and in evening) when the penetration level of PHEVs increase continuously to 30% in 2030. Therefore, optimization is introduced to shift peak loads. This optimization process is based on real time regional pricing and wind power output data, so as to make better use of surplus wind power. With the help of smart grid, power that is allocated to each vehicle could be controlled. As a result, this optimization process could fulfill the goal to shift peak loads to valley areas where real time price is low or wind output is high depending on system operator's preference.**

Index Terms – Plug-in hybrid electric vehicle, stochastic model, optimization, demand side response, renewable energy

I. INTRODUCTION

After a new round of petroleum price increase, almost every aspect of our daily life is affected. For instance, the traveling cost of automobile and plane grows apparently. Consequently, cost of all kinds of merchandise increases. For every vehicle owner, more attention is paid to fuel efficiency to save money. As a result, the MPG (miles per gallon) value becomes an important criterion for customers who plan to purchase a new vehicle. Commonly, for internal combustion engine vehicles, high MPG value usually means lower engine displacement, slower acceleration or compact size. To better utilize power from internal combustion engine, extra battery packs and electric motor are installed in hybrid electric vehicles (HEV). Less gasoline consumption also means less pollution to environment. This type of vehicles possesses two engines, combustion engine and electric motor. But, all power comes from gasoline. In recent years, engineers are trying to install more battery packs in hybrid electric vehicles and let these batteries be charged from the grid with the help of on/off board charger. This new type of hybrid electric vehicle is called Plug-in Hybrid Electric Vehicle (PHEV). In next two decades, it is hoped that automobiles will continuously become independent of petroleum, and PHEVs will replace conventional combustion engine vehicles gradually.

There have been many studies about PHEVs' impacts on operation of bulk power grid. These can be classified as vehicle performance studies, supply adequacy, Vehicle to Grid (V2G) studies and distribution system impact studies. This paper is primarily focused on large-scale PHEVs' integration into power grid as charging loads, potential effects for the operation of the grid, and optimization of the charging load to reduce the negative impact.

Even if studies about PHEVs are popular, there are still two main drawbacks in PHEVs' popularization: cost of large capacity battery and lack of charging station. They are only suitable for short-distance commuting. Besides, their retail price is much higher than that of normal compact vehicles. So, the only way to analyze long-distance pure electric vehicles' impact on the grid is simulation. Stochastic modeling method is introduced to simulate PHEV's load to the grid under different penetration levels. In stochastic approach, charging characteristics should be generated by probabilistic distribution of variables, such as State of Charge (SOC), vehicle arrival and departure time and battery full-charge time.

II. STOCHASTIC MODELING FOR PHEVS

Charging patterns for PHEVs are affected by many factors. So, it is better to define different charging patterns according to vehicle's function. In this paper, all PHEVs are divided into two parts: public transportation vehicles and private vehicles.

A. *Public transportation vehicles*

Public transportation plays a more and more indispensible role in transportation system. Therefore, this portion of traffic system should not be omitted even though public buses do not constitute significant share of all vehicles in many cities in United States.

BYD electric bus is selected as the model because its electric driving capacity (EDC) is suitable for daily public bus operation. EDC is the miles that a PHEV could drive only from battery electricity, when its battery's state of charge is 100% percent. EDC of BYD electric bus is 155 miles in urban condition. Average daily mileage for normal transportation bus is about 90 to 125 miles [1]. So, Electric bus is capable for a whole day operation with one charging. However, safety factor must be taken into consideration. Deeply charging the battery would harm its life. So, charging 2 times a day is essential. The first charging period begins at about 10 am and ends at 4:30 pm between two commuting-hour periods. Since the charging time is quite limited, C100D, a three phase charger, is used for this charging period. The power for C100D is 100 kW. It takes 3 hours for the on-board batteries to be fully charged [2]. Another charging period begins at 11 pm and ends at 5:30 am. One hour is reserved for daily preparation and dispatch. There is enough charging time at night. C60, 60 kW three phase charger is used instead of C100D. The full-charge time is extended to 5 hours. [2]

The starting state of charge (SOC) is assumed to follow a statistical normal distribution. SOC indicates the percentage of energy that remains in the battery. For example, Cap is the capacity for vehicle's battery. The remaining energy is SOC *Cap. The battery capacity needed to be charged is Cap*(1-SOC). For electric busses, when they come back to charging station, their SOC is generated according to equation (1). The expected average state of charge is set to 50% considering safety factor and life of battery. The standard deviation is set to be 10%.

$$\begin{aligned} SOC_{Bus}^{m} &= random('norm', \mu, \sigma) \\ \mu_{Bus} &= 0.5 \\ \sigma_{Bus} &= 0.1 \end{aligned} \qquad (1)$$

The arrival and departure time are also assumed to follow normal distribution. And the standard deviation is set to 45 minutes considering different arrival and departure times for different bus lines. Note that in one day, there are 1440 minutes. AT_{am}^{m} means the arrival time in am for the *m*-th electric bus in array. AT_{am}^{m} follows normal distribution, with a mean value of 600, corresponding to the 600th minute in 1440 minutes within a day. In other words, the average arrival time is 10:00 (600/60) am after morning commuting hour. Standard deviation is assumed to be 45 minutes. DT_{am}^{m} is the departure time for *m*-th bus in am Similarly, AT_{pm}^{m} and DT_{pm}^{m} are arrival and departure times in pm.

$$AT_{am}^{m} = random('norm', 600, 45) \qquad (3)$$

$$DT_{am}^{m} = random('norm', 990, 45) \qquad (4)$$

$$AT_{pm}^{m} = random('norm', 1380, 45) \qquad (5)$$

$$DT_{pm}^{m} = random('norm', 1440+330, 45) \qquad (6)$$

In the morning, *m*-th electric bus needs Tc_{am}^{m} minutes for its battery to be fully charged. In the afternoon, Tc_{pm}^{m} minutes are needed. CS_{100kW} and CS_{60kW} are the charging speed for 100kW and 60 kW charger respectively. The unit for charging speed is percents per minute.

$$Tc_{am}^{m} = (1 - SoC^{m}) / CS_{100kW} \qquad (7)$$

$$Tc_{pm}^{m} = (1 - SoC^{m}) / CS_{60kW} \qquad (8)$$

The maximum charging time for *m*-th electric bus in day or night time is the time period between arrival and departure time. If *m*-th battery is fully charged before departure, the actual charging time is Tc^{m} (full-charge time for *m*-th battery). On the hand, if the battery could not get fully charged before departure, the actual charging time would be $DT^{m} - At^{m}$ (time period between arrival and departure time). Therefore, the actual charging time for *m*-th electric bus is the minor value between full-charge time and maximum charging time.

$$\text{Actual charging time} = \min[Tc^{m}, (DT^{m} - AT^{m})] \qquad (9)$$

Other simulation requirements are

1. State of charge (SOC) >= 0
2. Departure time > Arrival time

The small-scale simulation size is 200 buses. Simulation results are plotted in Fig 2.1.2, the night time peak is 11.58 MW at 00:08 am. The day time peak is 14.3 MW at 10:49 am. Daytime peak is higher than night one by 2720 kW.

Taxis are also a considerable part in urban transportation system, especially in highly-developed modern city, because parking is always the difficult problem in downtown area. Taxi becomes the first choice for many people if they do not want to spend too much time in finding a parking lot or spend too much on parking fee. Taxis' daily mileage is from 217 to 310 miles [3]. Operation time for most of taxis is 24 hours. But driver may change shifts. BYD e6 has been operated as taxi in Shenzhen, China, in small scale. So, it is chosen as the model of taxi. Its EDC is 186.4 miles [4].

Considering taxi's long daily mileage, two times of charging in one day is necessary. Since the difference between commuting hour and normal hour is not quite obvious for taxi drivers, they may choose to charge battery when they have lunch break or they make shifts at mid night. Charger for both time periods must be three phase fast charger. Parameters for taxi charging load simulation are listed in Table 2.1.1

Taxi		
Average daily mileage	217-310 miles	
Operation time	24 hours	
Mileage capacity	186 miles	
Charging times	2 times a day	Take safety factor into consideration
Charging periods	11:30 am-14:00 pm	Day time
	2:00 am-4:00 am	Night time
Starting SOC	Normal distribution N (0.3, 0.1)	

Table 2.1.1 Parameters of electric taxi load simulation

Compared to electric bus's load curve, taxi load peaks are located at around 2:30 am and 11:00 am. The peak load is 19.4 MW. Taxi is the only type of vehicles with their batteries charged in a large scale at night. The subtotal loads of public transportation vehicles are illustrated in Fig 2.1.1. The subtotal load peak is 27.1 MW at 11:42 am.

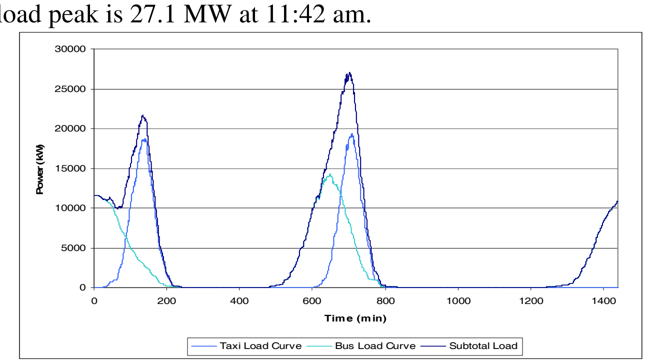


Fig 2.1.1 Load curve of public transportation vehicles in small scale

B. Private vehicles

Average daily mileage for private car is only about 42 miles a day [5] for commuting to and from work or school. The mileage is much fewer than that of bus and taxi. In this study, BYD e6 is still chosen as the model of main stream family sedan. Taking safety factor into consideration, owner of PHEV should charge battery every two days at home or in workplace.

Private vehicle's main function is commuting. So, charging periods starts when they arrive at working place or arrive home. It can be easily figured out that there is comparatively abundant charging time for private car. Therefore, for both periods, slow charging mode is the first option. In the United States, the ratio for sedan and SUV is about 6:4. Thus, SUV also accounts for a considerable share in private vehicles. BYD S6DM is selected as the model for SUV. In consideration of output power and mileage capacity, S6DM is designed as a dual mode hybrid vehicle. It also relies on gasoline to some extent. So, its charging loads would be much fewer than that of BYDe6 compact sedan. BYDe6 is pure electric vehicle.

The modeling and simulation method is that same as that used in public transportation vehicle simulation. But parameters for charging schedule and battery charger need to be adjusted.

Private car		
Average daily mileage	42 miles	
Mileage capacity	190 miles	
Charging times	once every two days	Take safety factor into consideration
Charging periods	8:00-17:00	Day time
	19:00-7:00	Night time
Starting SOC	Normal distribution N (0.5, 0.1)	

Table 2.2.1 Parameters of private vehicles load simulation

C. Small-scale charging pattern for all types of PHEVs

Loads for all types of PHEVs are summarized in Fig 2.3.1. In small-scale simulation, 200 buses, 500 taxis, 10,000 private sedans and 6000 private SUVs are included. Loads of private vehicles take the largest part of all types of electric vehicles. In subtotal, the load peak is at 11:35 a.m. The peak value is about 31.6 MW. Load grows continuously before the peak and drops suddenly after the peak. That means there is a lot of potential to shift the peak backwards to relieve the pressure to grid.

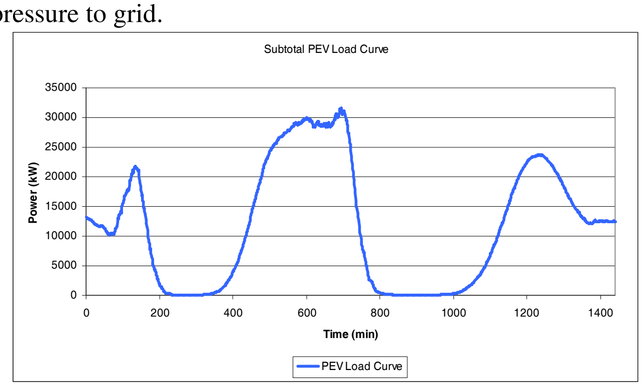


Fig 2.3.1 Subtotal plug-in electric vehicles load curve

D. Outlook of large-scale charging pattern for all types of PHEVs

To analyze the impact of large-scale PHEVs, firstly, the amount of each type of PHEVs in next two decades should be predicted. As for private vehicles, the growth rate would be evenly distributed in next two decades. Although electric vehicles saves a lot in gasoline consumption, owners of private vehicles might not change their car immediately due to high price of PHEV and worry about lack of charging station. So, this replacement of older combustion engine vehicles would be a continuous process.

PHEVs might have a bright future. But, the beginning for PHEVs seems not smooth. Referring to the latest forecast from Pike Research, a clean tech analyst, the United States will lag behind of President Obama's goal of having one million plug-in electric vehicles on roads by 2015. This goal would be filled in 2017 [7]. It took ten years for sale of conventional hybrids to reach about 2% of auto sales. In contrast, plug-in hybrids would reach that market share in seven years. And the growth would be even faster in next ten years. Referring to the US Bureau of Transit Statistics for 2004, there are 243,023,485 registered passenger vehicles in the United States. About 136 million of them were normal 2-axle, 4-tire vehicles, such as sedan and compact car. They accounted for 56.13% share of total amount. 91 million (37.79%) were other 2-axle, 4-tire vehicles. For example, SUVs and busses are included in this type. Not every registered vehicle is still on road. Many of them are just sitting idle or waiting for total loss. So, there are approximately 250 million vehicles on road in 2012. About 16 million brand new cars are sold annually. Considerable amount of old cars whose mileage is over 100,000 miles are also scraped annually, the number of all types of vehicles in 2017 would be about 320 million [5]. In contrast, only one million plug-in electric vehicles will be on the road in 2017. However, if the amount of PHEVs increases at this rate continuously, PHEVs will account for more and more share in the market. The detailed amount for each type of electric vehicle is listed in Table 2.5.1.

Amount of Plug-in Electric Vehicles (million)					
	Public bus	Taxi	Sedan	SUV	Total amount
2017	0.017	0.04	0.718	0.484	1.259
2020	0.047	0.11	1.97	1.328	3.455
2030	0.291	0.68	27.158	18.308	46.437

Table 2.4.1 Amount of plug-in electric vehicles

The annual growth rate for public bus and taxi is assumed to be 40% between 2017 and 2020. From 2020 to 2030, the average growth rate is reduced to 20%. With government's subsidy, the replacement of conventional combustion engine vehicles with new generation plug-in electric vehicle would be smooth. However, when the generation change is over, growth rate should decrease evidently. In contrast, for private owners, they may set plug-in vehicles as their first choice for next car. But, they are not willing to buy them immediately considering

PHEV's high retail price. So, growth rate of private PHEVs is predicted to be more evenly distributed in next two decades.

In next twenty years, the total amount for PHEVs would increase rapidly. Therefore, the small-scale simulation method is no longer suitable. Matlab is not able to handle this large amount of calculation, since every parameter is generated in loop. Loop sentence decrease the calculation efficiency significantly. As a result, Monte Carlo simulation method is introduced to save computation time. To further save computing time, time step is increased from 1 min to 10 min. After modification, the basic simulation method does not change. The amount of each type of PHEVs predicted in Table 2.4.1 is input into modified simulation model, subtotal load curve for all PHEVs in 2017, 2020 and 2030 could be obtained. Results are illustrated in Fig 2.4.1 and 2.4.2

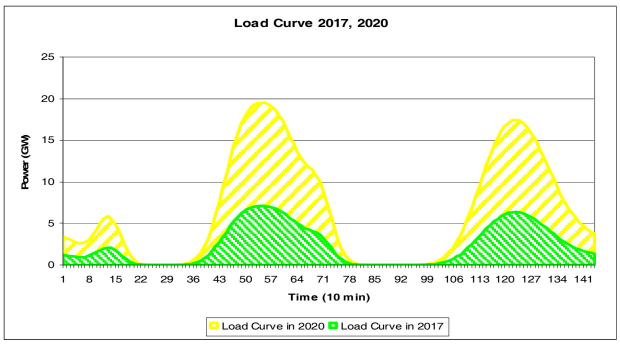


Fig 2.4.1 Subtotal load curve 2017, 2020

In 2017, the load peak at noon is expected to be 7.12 GW. This amount of loads from PHEVs' charging will not have huge effect on the grid in 2017. However, this peak grows really fast. After 3 years, in 2020, it will reach 19.49 GW. The load is almost tripled. Besides, two load peaks become more prominent, if owners are allowed to charge their vehicles freely with no introduction and regulation. After 10 years of development, PHEVs would take 30% share of all kinds of vehicles. That also means that its charging load will become a considerable part on the grid. Its peak at noon would be 263.56 GW. Compared to load curve in 2020, loads in the evening and morning after commuting hour increase evidently. That means loads from private vehicle become more and more important. In contrast, load peak in mid night become less significant.

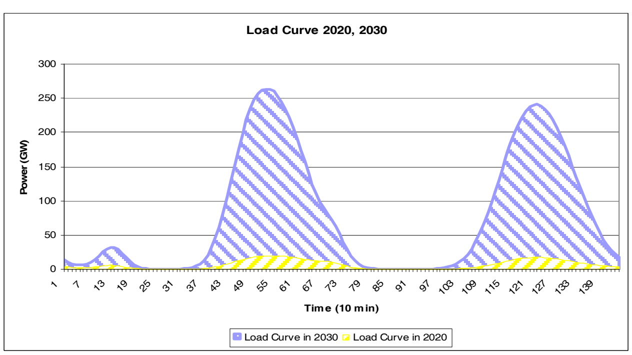


Fig 2.4.1 Subtotal load curve 2020, 2030

III PEAK LOAD SHIFTING OPTIMIZATION

A. Load optimization according to real-time price

In simulation conducted in previous sections, owners of PHEVs start charging their vehicles when batteries are plugged into the grid. In [10], this charging scheme is called uncoordinated direct charging. There is great potential to re-coordinate the charging scheme, so as to relieve its impact on the grid. Firstly, the charging loads are concentrated at two time point, 8:30 am and 8:30 pm. Secondly, the available charging time for private vehicles is abundant. Those two factors would make optimization process effective and could be conducted according to real-time electricity price and wind power output curve.

The reasons why real time pricing is selected as the criteria for optimization process are as follows: (1) Smart grid and smart meter make it possible that costumers could know real time electricity price before they use electricity. Consequently, this will give them a strong incentive to charge their PEV when price is low and finally save money on daily commuting cost. As for taxis, they might get notice from operation centre to suggest them to charge battery when price is low. For instance, they might bring forward a break to charge battery at low price to save money. Since their daily mileage is far more than that of private vehicle, the cumulative saving is considerable. (2) Time period of price peak commonly means there is a huge demand in this period. If charging in peak time period could be avoided wisely, the demand stress on the grid could be relieved.

A reference regional price curve in 7/8/2012 is shown in Fig 3.1.2 [11]. There are two obvious price peaks in the morning and evening. The morning peak is from 50 min to 65 min. The reference regional price is about $90 per MWh. The evening peak is quite short. It is from 107 min to 116 min. The peak value is about $95 per MWh.

General objective function

$$Cost = \sum_{m=1}^{m=N} \sum_{t=X_m}^{t=X_m+Tc_m} P[t] \qquad (9)$$

$$Tc_m = (1 - SOC_m) / CS_m$$

Constraints

$$X_m \geq At_m$$

$$0.2 \leq SOC_m \leq 1$$

P[t] is the regional reference price curve. X_m is the start charging time point for *m*-th vehicle. Tcm is the full-charge time for *m*-th vehicle. It is decided by SOC_m, the state of charge for *m*-th vehicle. CS_m is the charging speed for *m*-th vehicle. N is the subtotal amount for one type of vehicle. In this optimization process, all PHEVs consist of 200 buses, 500 taxis, 1000 private sedan and 600 private SUV. Its objective is to find minimum cost in the mean time vehicles also get charged as much as possible.

Optimized bus load curve is shown in Fig 3.1.1. Load peak at 11 am is clearly shifted rightwards. Recall the reference regional price curve, the peak period is from 9 am to 11 am. Load curve after optimization avoid peak period successfully. And, these loads are shifted to afternoon before departure. Charging for each vehicle is also guaranteed. Similar optimization method could also be applied to taxi charging pattern and private vehicle charging pattern.

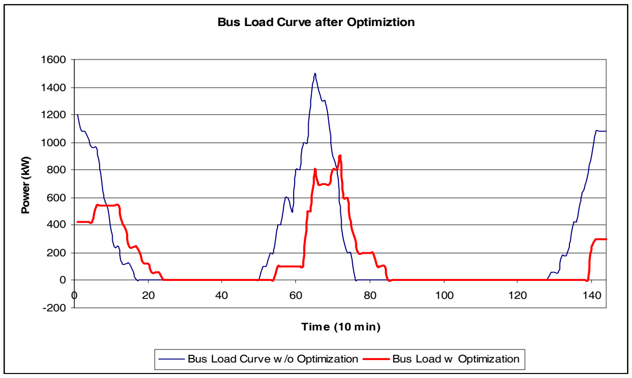
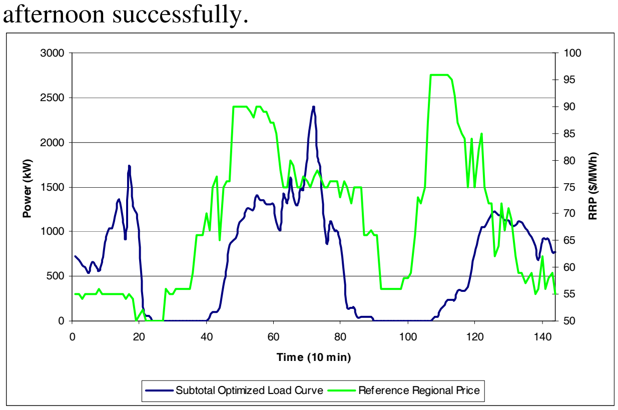


Fig 3.1.1 Bus load curve after optimization

The overall load pattern for three types of vehicles after optimization according to real-time pricing is shown in Figure 3.1.4. Recall the results from small scale simulation, loads suddenly drops to zero after 11:30. However, in optimized load curve, loads are allocated more evenly, and loads decrease to zero until 3:00 pm. That means loads were shifted to afternoon successfully.



3.1.2 Subtotal optimized load curve

B. Load optimization according to wind power output curve

Besides real-time pricing, if wind output curve is also considered in objective function, excess wind power could be better utilized. The reasons why wind power should be coordinated with PHEV charging are as follows: (1) as is known to all that it is hard to control wind power output. Wind farm may suddenly generate many mega watts of power or drop to zero output in ten minutes. That is always a risk for voltage and frequency stability. Normally, if wind farm output increases abruptly, operation centre will have to decrease generation from other power plants to maintain the balance. Now, charging loads join the grid and when to charge these loads could be controlled since their charging time is pretty ample. These loads could be utilized to pick up this increase from wind farm without shutting down other power plant. (2) A lot of wind power in midnight is just wasted, and charging loads in midnight is able to utilize this excess power. (3) PHEV is friendly to environment. If electricity is also from clean energy, that means there is no carbon dioxide emission from energy source to every vehicle terminal.

Wind power output curve on 1/1/2011 is illustrated in Figure 3.2.1 [18]. The variability for wind power output is considerably large. The output is at high level from 0:00 to 15:00 and suddenly drops to zero. Nowadays, there are many methods to predict wind power output. If the predicted load curve could be utilized in optimization, which would surely help to better take advantage of wind power.

Main objective function

$$J = P_1 \cdot \sum_{m=1}^{m=N} \sum_{t=X_m}^{t=X_m+Tc_m} p[t] + P_2 \cdot \sum_{m=1}^{m=N} \sum_{t=X_m}^{t=X_m+Tc_m} w[t] \qquad (10)$$

$$Tc_m = (1 - SOC_m) / CS_m$$

Constraints

$$X_m \geq At_m$$

$$0.2 \leq SOC_m \leq 1$$

$$p[t] = \frac{P[t] - Min\{P[t]\}}{Max\{P[t]\} - Min\{P[t]\}}$$

$$w[t] = \frac{W[t] - Min\{W[t]\}}{Max\{W[t]\} - Min\{W[t]\}}$$

w[t] is the wind power output curve. This output curve is from a 72 Mits Wind farm on 1/1/2011. P[t] is the reference regional price curve. Since regional reference price curve and wind power output curve are not on the same scale, all of them should be normalized in order to assign similar importance to each one. P_1 and P_2 are two constants. $P_1 + P_2 = 1$. Operator may assign different values for P_1 and P_2 to lay more emphasis on real-time pricing or wind power output.

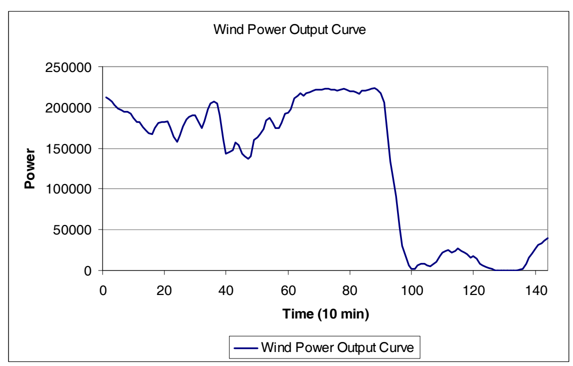


Fig 3.2.1 Wind power output curve on 1/1/2011

Considering wind power output curve, more vehicle charging loads were fulfilled when wind output is high. In Figure 3.2.1, the most productive area for wind power is from 60 min to 80 min. Compared to load curve without considering wind power, loads in this area increase to some extent clearly. In future work, besides wind power, solar power and other factor could also be taken into consideration. That would grant the operator more potential to optimize the charging pattern for PHEVs.

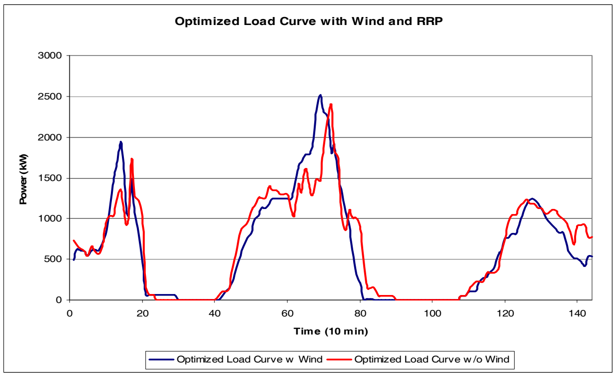


Fig 3.2.2 Optimized load curve with wind and reference regional price

IV CONCLUSION

With the growth of penetration level of PHEVs, charging load of PHEVs would surely present a great burden on the grid. As a result, the impact of PHEVs' penetration on grid operation should be estimated to prevent upcoming problems such as transformer aging and capacity for charging infrastructure in community. In distribution level, congestion problem may also appear due to this huge amount of loads in morning and night peak period.

To analyze PHEVs' impact, stochastic modeling is introduced to simulate its impact on the grid. All PHEVs consist of two types: public transportation vehicles and private vehicles. Different charging scheme and charging speed are applied for each of them. The small-scale simulation result shows that load peaks at day and night time are quite prominent. Besides, the charging time is sufficient for private vehicles' charging. These two factors indicate that there is enough potential and flexibility to better coordinate PHEVs' charging in smart grid.

Firstly, optimization process is conducted considering reference regional price. This optimization helps owners of PHEVs save electricity bills. On the other hand, charging load peaks are also shifted to relieve load demand pressure to the grid. The optimized result is promising. Charging load peaks in day and night time are shifted to time periods where real-time electricity price is comparatively low. Additionally, the charging completion rate is not affected, compared to direct uncoordinated method.

Secondly, wind power output curve is also taken into optimization process for following reason: Charging loads are considered as demand side response. Dispatching charging loads with excess wind power output could help maintain system's stability without affecting other power plants' output. This paper presents a stochastic modeling method to simulate PHEVs' charging loads and two optimization processes to better coordinate their charging scheme. In future study, other factors, such as solar power and congestion problem, could also be included in optimization process to make the charging scheme more grid-friendly and economical.

V ACKNOWLEDGEMENT

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