OPTIMIZATION OF PHEV CHARGING STATION

by

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ABSTRACT

OPTIMIZATION OF PHEV CHARGING STATION

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Plug-in hybrid vehicles are the most feasible approach towards significantly lowering the consumption of oil and improve fuel economy with today's existing technology. In Electric Power Research Institute and the Natural Resources Defense Council (EPRI-NRDC) 2007 study already proved that PHEVs will reduce emissions if they are broadly adopted. However, the charging infrastructures/station become key factor in the success of prevail of PHEVs.

The research of this paper is focusing the operation of the PHEV charging station with battery storage units. The battery units conserve the low price clean energy and discharge when demanded. The on-site installed photovoltaic (PV) and off-site (virtual) wind farm are the main supply of charging station to charge the battery units. The grid electricity plays an auxiliary role in the station when the renewable sources are unavailable. The drastically changing market clearing price (MCP) in the deregulation market make it possible that station participates the power trade as storage device. The paper examines the PHEVs charging trend, forecasts wind power with artificial neural network (ANN) model and MCP with the statistical model, and proposes an optimized operation for the battery storage schedule and strategy of power trading to minimize the cost of station. Analysis based on level of forecast uncertainty is utilized to

evaluate the optimization.

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CHAPTER 1

INTRODUCTION

1.1 Background

The environmental issues, the economic situations, and energy security have reshaped the way people think about energy. Looking for the alternative energy sources that are both sustainable and clean will be substantial and fundamental for the generations to come.

On the environment side, as the evidence of climate change is getting more and more apparent, it becomes a global consent that actions must be taken to curbing greenhouse gas emission. The United States government pledged to reduce greenhouse gas emissions by approximately 17 percent by 2020 [1]. According to the report from Energy Information Administration (Figure 1.1), the transportation sector alone takes up to 33.1 percent of all energy-related emissions and is the largest producer of carbon dioxide emission in US [2]. This presents the urgent needs for the transportation sector in the U.S. to act on emissions abatement.

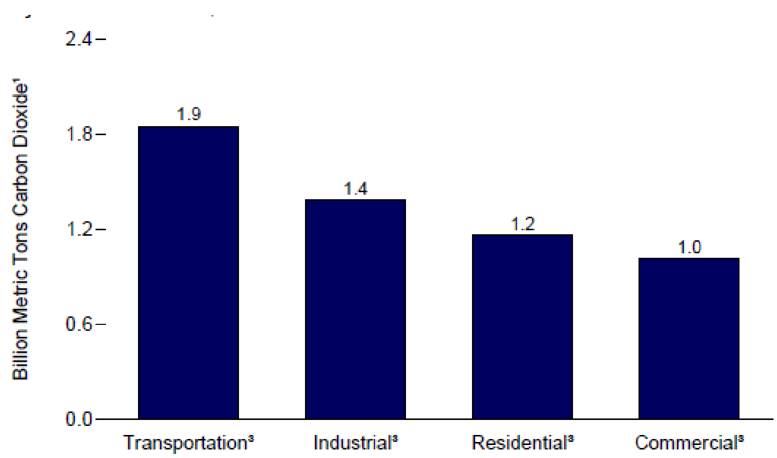


Figure 1.1 U.S. energy-related Carbon Dioxide Emission by End User, 2009

Meanwhile, the energy power the transportation sector is still derived almost exclusively from fossil fuel, making U.S. the world's largest consumer of crude oil and petroleum products.

Each day, Americans consume nearly 20 million barrels of petroleum, and more than half of this consumption is imported. It is not only that the available oil is harder and more dangerous to attain, but also volatility of the oil price is threatening both the energy security and economy. If this trend of heavily reliance on petroleum continues, as projected data in figure 2, the gap between oil consumption and production is going to be even wider [3]. Eventually, the cost of oil dependence with both national security and economy will be too high to afford.

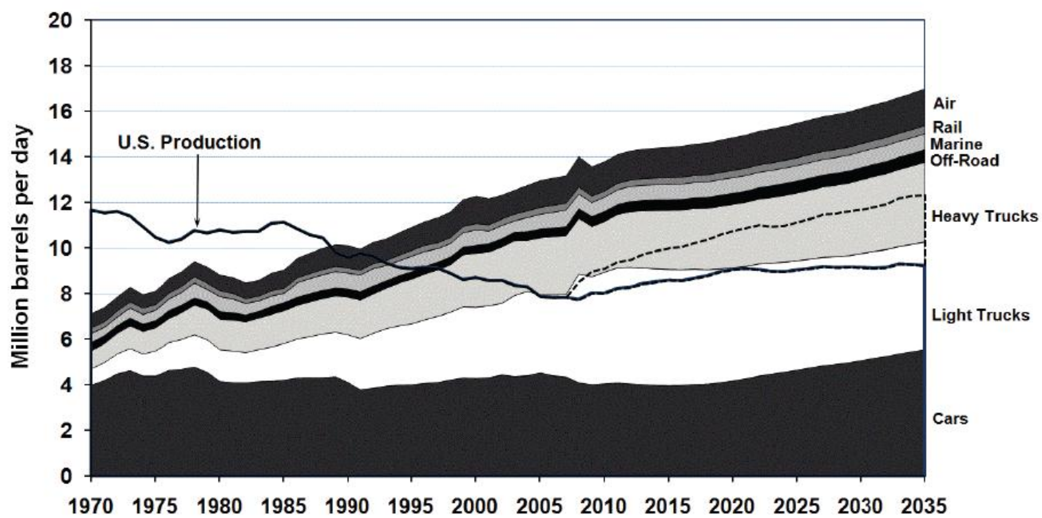


Figure 1.2 U.S. Petroleum Production vs. the Consumption in the Transportation Sector

Thus, the United States must find the solution to heavily dependence on petroleum-based energy sources. Energy independence needs to be accomplished through conservation, alternate renewable energy sources, conversion of current energy infrastructure, especially in the transportation industry.

1.2 Electrification of Transportation

There is a solution is emerging in this critical situation: a fundamental transformation is evolving that shifts from traditional oil based fleets to electrical power vehicular technologies. This embracing the new propulsion technology will allow the transportation sector take advantages from the electric power sector.

Unlike transportation sector, the fuel type in electric power sector is much more domestically diverse, including: coal, uranium, natural gas, flowing water, wind, geothermal heat, the solar, landfill gas, and so on [4]. The average price of electricity is stable. Moreover, the network is fully built up in through the country, surpassing other alternative substitution for petroleum, like biomass and hydrogen, etc.

Plug-in hybrid vehicles (PHEVs) take important role in this transformation, since it is the most feasible approach towards significantly lowering the consumption of oil and improve fuel economy with today's existing technologies. In order to achieve the spread of the PHEVs, the reliable access to charging infrastructure is one of the key factors. [5]

1.3 Approach

The thesis researches into the Plug-in Hybrid Electric Vehicles (PHEVs) charging infrastructure. It examines the three charging level in standard. The fast charging station with battery storage unit is chosen to best performance to both vehicle and power grid. The charging station uses photovoltaic (PV) and wind farm as the main supply to charge the battery units. When the renewable sources are unavailable, the grid electricity plays an auxiliary role in the station. Moreover, the charging station participates in the power trade as a storage device.

The steps of participation in the market are following:

1) Acquire real-time market clearing price (MCP) from system

2) Forecast the future MCP

3) Forecast the wind power output

4) Optimize the electricity storage for battery unit

5) Optimize the electricity selling schedule

1.4 Contributions

In the thesis, the idea of utilizing battery storage unit for PHEV charging is proposed. It solves the impact from intermittence of wind/solar energy. The battery storage also enables the station participate in the power market to reduce the operation cost. The participant schedule into the power grid is directed by the trading strategy “Buy Low, Sell High” in power market. To follow up the “Buy Low, Sell High” strategy, an accurate forecast of wind power and MCP is required. An artificial neural network (ANN) model [6] is discussed to forecast wind power, and autoregressive model [7] for the MCP forecasting. The analysis based on the different level of uncertain is utilized in the linear programming optimization. It lists battery storage schedule and sell/buy decision for power trading and is evaluated by operating electrical cost.

1.5 Organization of the Thesis

This chapter is the introduction which provides background of PHEV charging station. The rest of the thesis is organized as follows:

Chapter 2 reviews the plug-in hybrid vehicle and the standards of charging infrastructure. Chapter 3 looks for the conceptual design of proposed charging station. Based on forecasting in Chapter 4, the optimization algorithm of linear programming is developed to minimize the electricity cost. Chapter 5 concludes the thesis and provides the possible topics of future research.

CHAPTER 2

PLUG IN HYBRID ELECTRIC VEHICLES AND CHARGING INFRASTRUCTURES

2.1 Introduction to PHEV

Long before Plug-in hybrid electric vehicle (PHEV), the technology of Hybrid electric vehicle (HEV) was emerging in the late 1990s. The vehicles still rely on a conventional internal combustion engine, but supplement power assist, regenerative braking and some other additional functions from an on-board battery to improve the fuel efficiency. Nowadays, HEVs have already achieved familiarity and acceptance by both private consumers and fleets. Their sales have grown from 9,036 in 2000 to 324,318 through 2007 in the U.S. [8]. This great commercial success is the result of both government incentives and high oil prices. However, HEV has its own limitations since it still depends mostly on a combustion engine for propulsion. In other words, HEV simply increases the efficiency of conventional vehicles.

2.1.1 PHEV configuration

The next stage in the electrification of the transportation sector is the developing of PHEV. Technically, PHEVs are one step forward from HEV. By extending the size of the battery, adding a plug, the vehicle can draw power from electric grid via charging. Thus, PHEVs are able to solely use electric drivetrain to run the vehicle over substantial distances at all speed before the need of gasoline. The drivetrain of a PHEV can be configured in parallel or series format: A series drivetrain powers the vehicle strictly using the electric motor, which derives power from the battery. The battery is charged either with power from the grid (through the plug) or with power from the internal combustion engine via a generator. The parallel hybrid configuration simply adds a direct connection between the engine and the wheels. This allows the internal combustion engine to power the vehicle in conjunction with the electric motor or independently. Figure 1.3 shows the configuration diagram of a parallel plug-in hybrid vehicle [9].

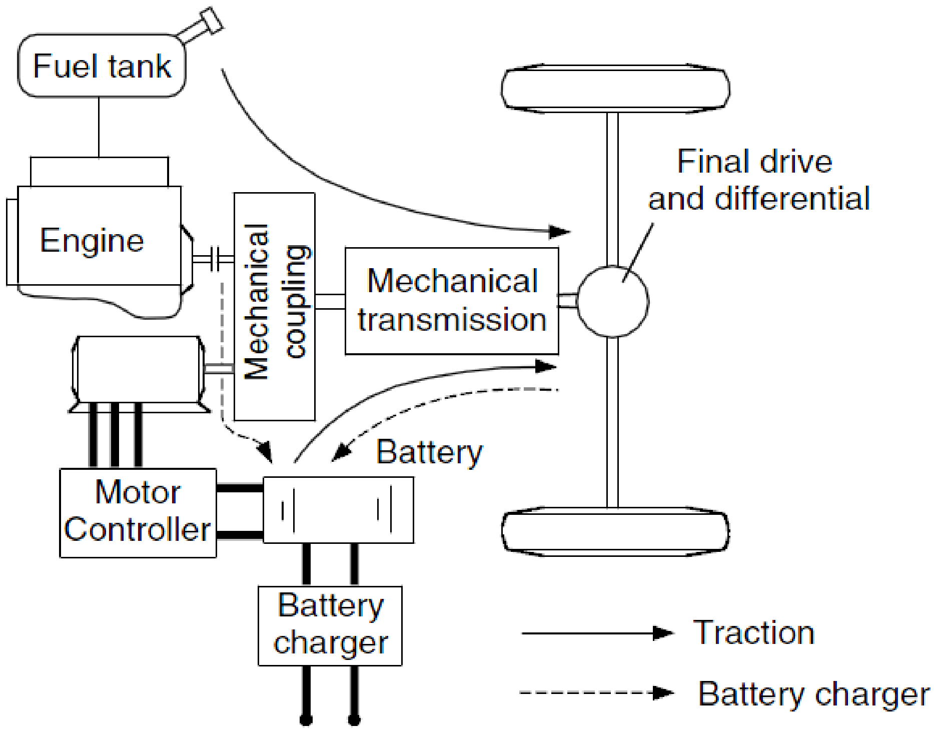


Figure 2.1 Configuration diagram of parallel Plug-in Hybrid Vehicle

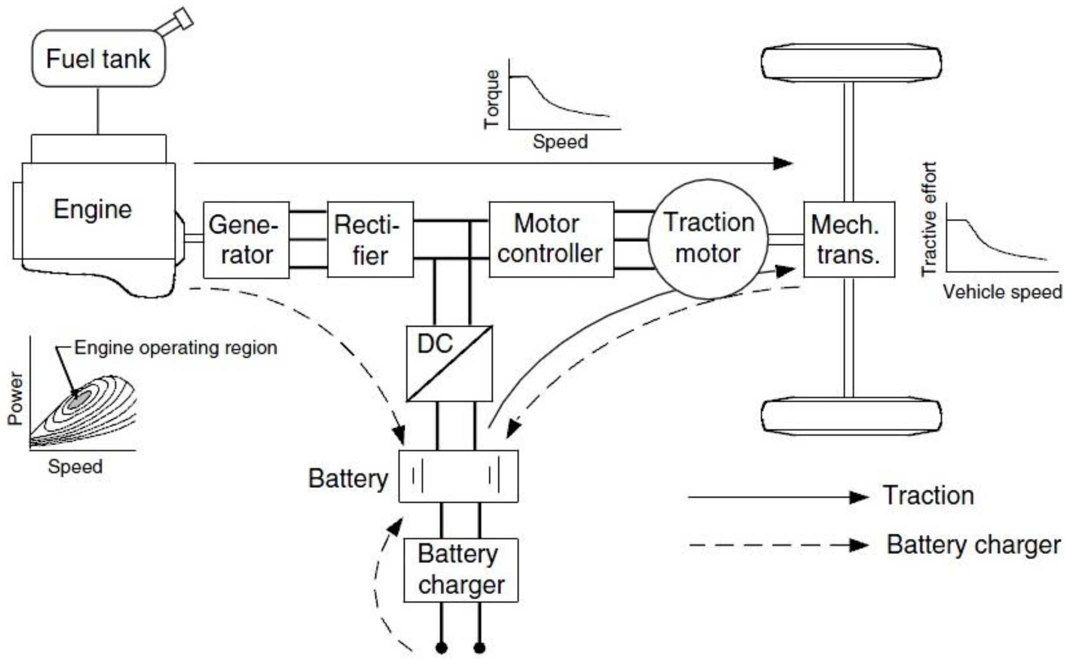


Figure 2.2 Configuration diagram of series Plug-in Hybrid Vehicle

2.1.2 PHEV emission

A PHEV has lower emissions compared to conventional gasoline internal combustion vehicles, even in the area that electricity is majorly relied on coal plant. California Air Resources Board studies show that battery electric vehicles emit at least 67% lower greenhouse gases than gasoline cars [10]. Another study from Carnegie Mellon University [11] assesses life cycle greenhouse gas (GHG) emissions from PHEVs, including energy use plus greenhouse gas emissions from battery production. Figure 1.4 indicates that the type of generation options determine greenhouse gas emission intensities to PHEVs. So PHEV gets cleaner when the electric sector gets cleaner.

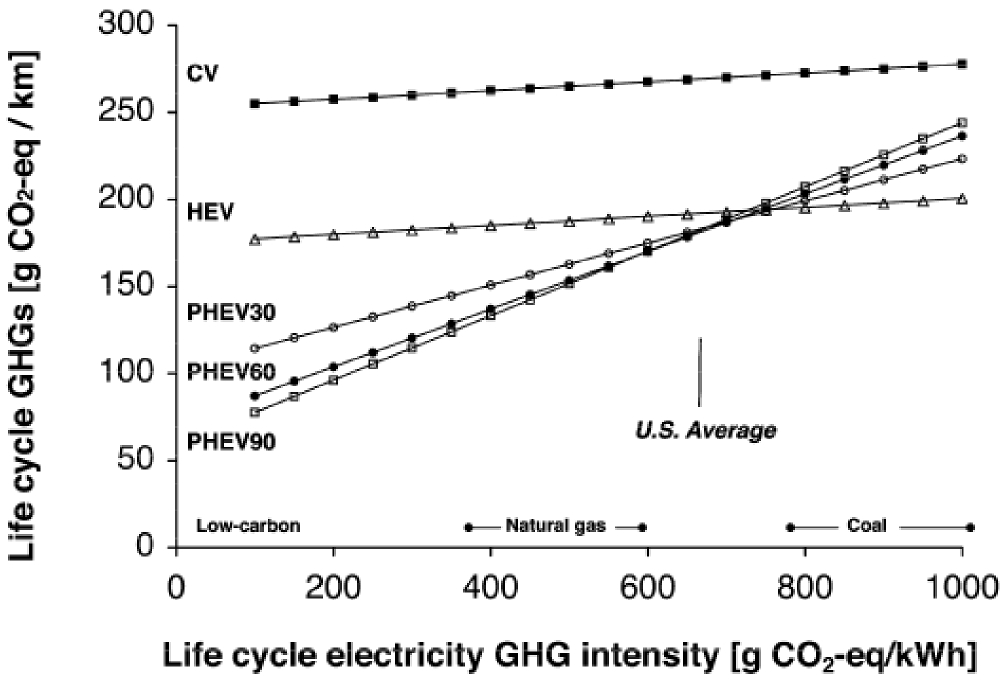


Figure 2.3 Life cycle GHG emissions of vehicle as intensity of electricity generation [11]

2.1.3 The PHEV energy requirements

PHEV technology is applicable to all light duty vehicles (comprised of passenger vehicles, light trucks under 8,500lbs, vans and SUVs) and can be easily adopted from the conversions of current HEVs. The energy requirements per mile for selected light duty vehicle classes are adopted from Electric Power Research Institute's (EPRI's) Hybrid Electric Working Group [12] as listed in Table 2.1.

Table 2.1 Specific Energy and Energy Storage Requirements by Vehicle Classes

Vehicle Class	Specific Energy Requirements [kWh/mile]	Size of Battery for PHEV33 [kWh]
Compact sedan	0.26	8.6
Mid-size sedan	0.30	9.9
Mid-size SUV	0.38	12.5
Full-size SUV	0.46	15.2

2.1.4 Disadvantage of PHEV

In bringing PHEVs to market, the biggest obstacles that manufacturers face are battery cost and performance. According to a 2010 study by the National Research Council, currently the cost of a lithium-ion battery pack is about USD 1,700/kW·h of usable energy, and considering that a first generation of the PHEV-10 (the number represents the distance the vehicle can travel on battery power alone, so here it means the vehicle can travel 10 miles without using its combustion engine) requires about 2.0 kWh, the manufacturer cost of the battery pack for a PHEV-10 is more than $3,000 and it can go up to $14,000 for a PHEV-40 [13]. However, with technology improvement, it is believed that the cost could drop to as little as $420 per kWh by 2015 with better performance (Figure 1.5).

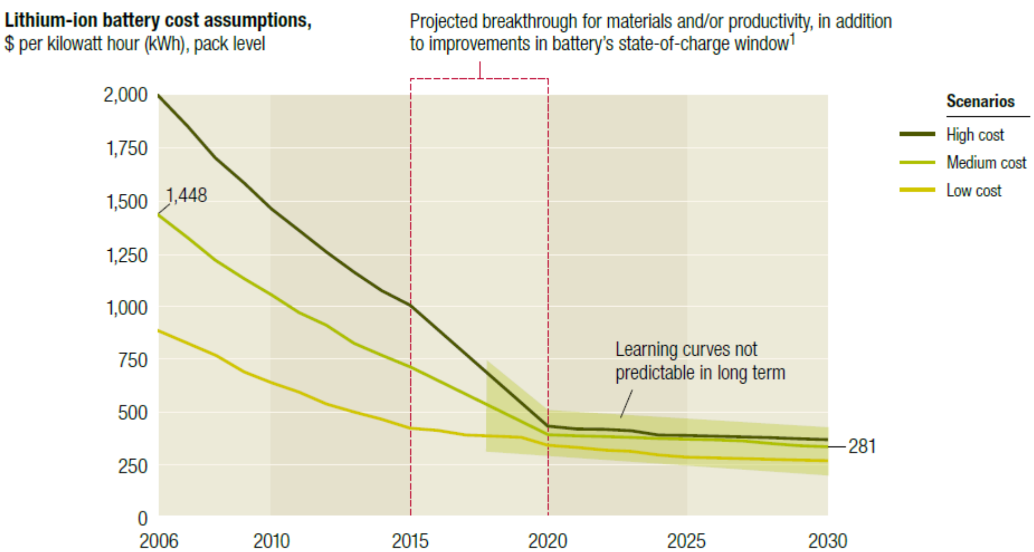


Figure 2.4 Projected Lithium-ion battery cost based on learning curve [14]

These vehicles account for over 93% of the total fleet. Additionally, light duty vehicles have an average vehicle life of 15 years, as opposed to 28 years for heavy duty vehicle [15]. All of these factors make PHEV a feasible and efficient approach towards electrification of transportation sector.

2.2 PHEV charging infrastructure

Deploying PHEV at scale will require the construction of a network of charging infrastructure, both public and private (home). Unlike filling station of petroleum based fuels, PHEV charging infrastructure requires much less construction because of existing ubiquitous network of electricity infrastructure. Only upgrades to the last few feet of electric grid are required to set up for chargers infrastructure in mass. Although a substantial portion of charging can be done overnight at home, public charging options are needed to add more flexibility, better fuel economy as well as to increase consumer confidence. The Department of Energy's grant to companies to deploy public charging site in several regions shows the importance of the situation [16] [17].

In order to design a proper PHEV charging station, investigation in the infrastructure and need for the infrastructure must comes in first place.

PHEV infrastructure is defined as structures, machinery, and equipment necessary and integral to support a PHEV, including battery charging stations and/or battery exchange stations. Infrastructure must meet or exceed any applicable standards, codes, and regulations.

A charging station, also called electric recharging point, supplies electricity for the charging of electric vehicles. There are different levels of charging based on the power available. Back in 1998, levels of charging power was firstly defined by the California Air Resources Board in Title 13 of the California Code of Regulations. It was then defined by the Electric Power Research Institute and codified in the National Electric Code (NEC) section 625 (1999).

Currently, the charging levels in the United States are governed by a specification published by the Society of Automotive Engineers (SAE), a standards development organization that is responsible for the engineering of powered vehicles of all kinds, including cars, trucks, boats, aircraft, and others. The specification, entitled J1772, defines levels of charging as well as the interface between the vehicle and the electric vehicle supply equipment (EVSE).

2.3 Charging level Standard

In the initial standard of J1772, two charging levels are defined [18]. And usually, An additional approach, Fast Charge DC charging, is referred to as level 3 charging, which has multiple standards currently. The detail explanation of basic charging levels is in the following subsections.

2.3.1 AC level 1

AC level 1 uses a standard 120V, single phase power, comes with 15A of branch circuit breaker rating and 12A of continuous maximum current or 20A of branch circuit breaker rating and 16A of continuous maximum current. This method uses the lowest common voltage level which can be found both in residential and commercial buildings in the U.S., allows a PHEV to be connected to the National Electrical Manufacturers Association 5-15 and 5-20 outlet -- the traditional home plug. Because only a small amount of power can be provided as for AC level 1 charging (maximum of 1.44/1.92 kW), the charging time can extend up to 8- 15 hours depending on the size of the battery.

AC level 1 is an entry level voltage charging during the introduction of battery electric vehicles and not the ultimate charging solution. The importance of this charging level is due to the availability of 120 VAC outlets, charging is still accessible during emergency situations.

Figure 2.1 gives an example of level 1 onboard charger. An Onboard charger is a charger located on the vehicle. In most typical configuration, the AC level 1 charger is installed on the vehicle and the 120V power is brought through a plug and cord set.

Figure 2.5 Example of an AC level 1 onboard charger

Figure 2.5 shows the charging plug on a PHEV, and figure 2.3 illustrates the charging scenario with a plug and cord set connected to the 120V wall socket.

Figure 2.6 Charging plug in NEMA 5-20P configuration shows up by opening the gas filler door [19]

Figure 2.7 Plugging the PHEV on the wall socket with plug and cord set [19]

2.3.2 AC level 2

AC level 2 specifies 240V, single-phase power, and charging current of 12 A to 80 A. The voltage it applied can be found in many homes for electric clothes driers, electric ovens, or pool pumps. Thus, AC level 2 is considered as the preferred option for a PHEV charger at home. Because AC level 2 works on a higher voltage, a dedicated electric vehicle supply equipment to provide a high level of safety is required. Figure 2.4 presents an example of conductive offboard electric vehicle service equipment.

Figure 2.8 AC level 2 conductive electric vehicle service equipment with a five-pin connector [20]

Although the maximum current for AC level 2 is 80 A, most vehicles are being designed to accept a Level 2 charge at no more than 30 A, due to the smaller onboard charging system in the car. The onboard charger in the vehicle converts power from 120V or 240V AC to the DC voltage that actually controls the charging rate. This limits the level 2 charging a maximum power of 7.2kW.

SAE establish the standard connector for AC level 2 in SAE J1772 in January 14, 2010. It specifies five pins, a Yazaki design as shown in Figure 2.5 [21]. The function of each pin of the connector are: 2 pins for AC power (line 1 and line 2), 1 pin for ground, 1 pin for signals related to the amount of current allowed for the particular vehicle model being charged (control pilot), and 1 pin for preventing the car from being moved while charging is under way (proximity detection). Figure 2.6 shows the scenario the PHEV with SAE J1772 standard receptacle about to plug in and charge.

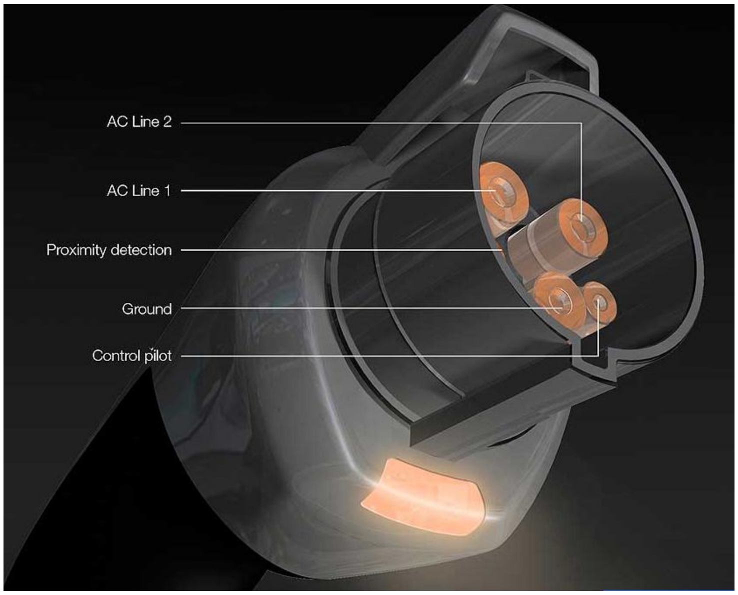


Figure 2.9 SAE J1772 specifies a five-pin connector for delivering 120 or 240V [21]

Figure 2.10 PHEV with SAE J1772 standard receptacle about to plug in and charge [22]

2.3.3 Level 3

Level 3 usually refers to DC charging, or "fast charging". It is designated to have the similar performance as a commercial gasoline filling station. It requires very high levels of voltage and current, thus bring a very high speed of charging. There are currently no

International standards for fast charging established yet. However, as for commercial application for public use, some common idea is shared. The fast charging will also have an offboard charger system as AC level 2, but it should be supply a DC current directly feeding to the plug-in vehicle high voltage battery bus. Actual charge rate is limited by battery chemistry, infrastructure and some other factors. Table 2.2 Shows the current three different fast charging standard.

Table 2.2 Specification of Three Fast Charging Standards

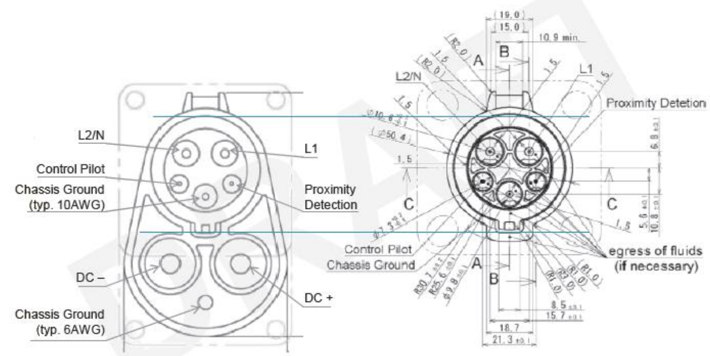
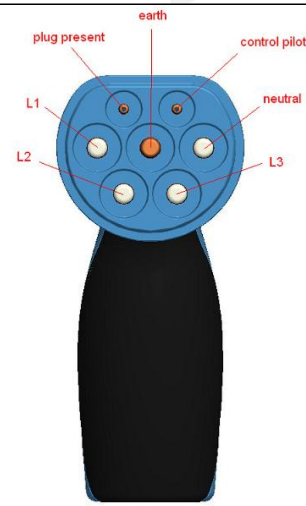
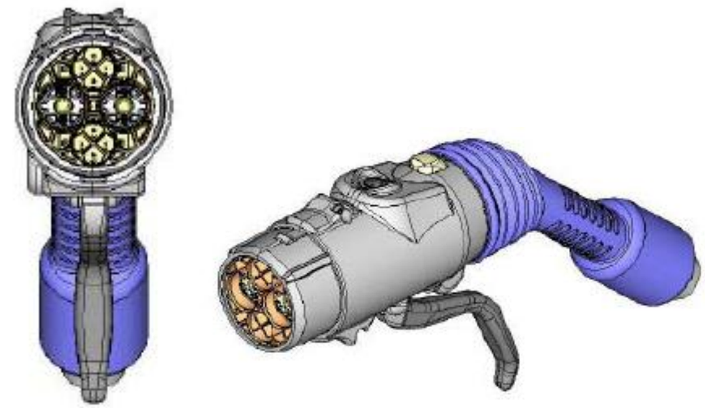
Standard Name	location	Charging parameter	Connector
SAE fast charging [23]	North American	Voltage rating:300-600V DC 3-phase Current rating: 80 - 400A Power output rating: 90-240kW (Not finalized)	
IEC 62196 standard[24]	Europe	AC Standard: Maximum AC Power output: 172.5kW Voltage: 690V, 50-60Hz Maximum AC current: 250A DC Standard: Maximum DC Power output: 240kW Voltage: 600V Maximum AC current: 400A	

Table 2.2 – *Continued*

TEPCO level 3 charging standard [25]	Japan	Input: 3-phase 200V Maximum DC output power: 50kW Maximum DC output Voltage: 500V Maximum DC output Current: 100A	

Conclusively, each charging level has its own designated utilization: level 1 charging is merely for emergency situations; level 2 is the solution to hour-lasting over night home charging; the fast level 3 charging is designed for public charging. Thus, the level 3 charging is chosen for the charging station design.

CHAPTER 3

PHEVS CHARGING STATION DESIGN

3.1 Basic configuration

The goal of design is to build a fast charging station that uses solar and wind energy to simultaneously fast charge multiple vehicles in the way current gasoline or diesel stations simultaneously refuel multiple vehicles. However, there will be some issues happening in the system:

1) The mismatch of the solar and wind energy supply with station charging demand

2) The large mount of PHEVs charging will bring a lot of load strain in the system.

Thus, the deployment of energy storage technology is proposed to mitigate the issues. It can store the excessive solar and wind energy and release when there are charging demand in the station. It can also become energy buffer for charging station when system is at peak load. The last but not least, it enables the station to joint the power market to reduce the operating cost.

3.2 Energy sources of PHEV charging station

The basis of the design is to make PHEV cleaner, and maximum utilize the renewable energy. Two natural resource, solar power and wind power, are main energy supply for system stored in battery unit, while the intermittence of wind power and PV output can be compensated by grid electricity.

3.2.1 Wind power

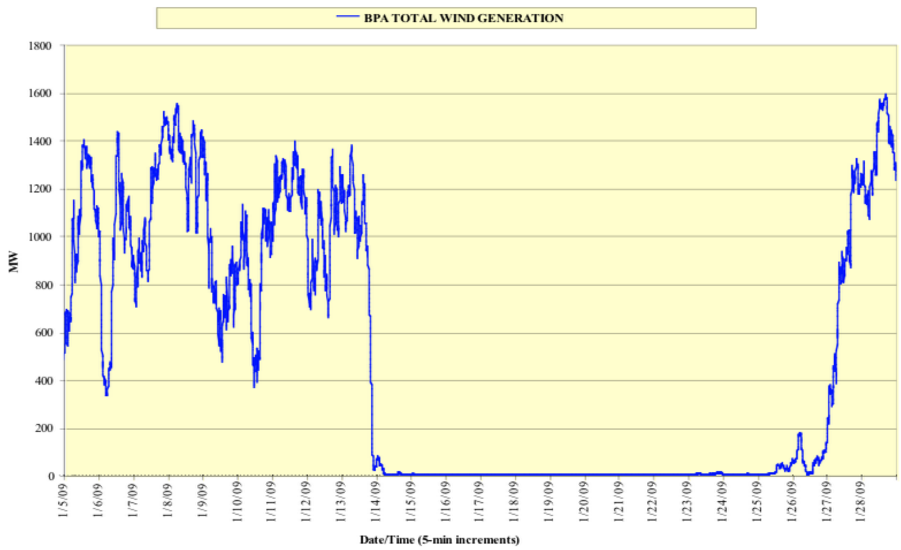
3.2.1.1 Introduction of wind power

There are technologies to convert wind energy into other useful form of energy, such as using wind turbines to make electricity, wind mills for mechanical power, wind pumps for pumping water or drainage, or sails to propel ships.

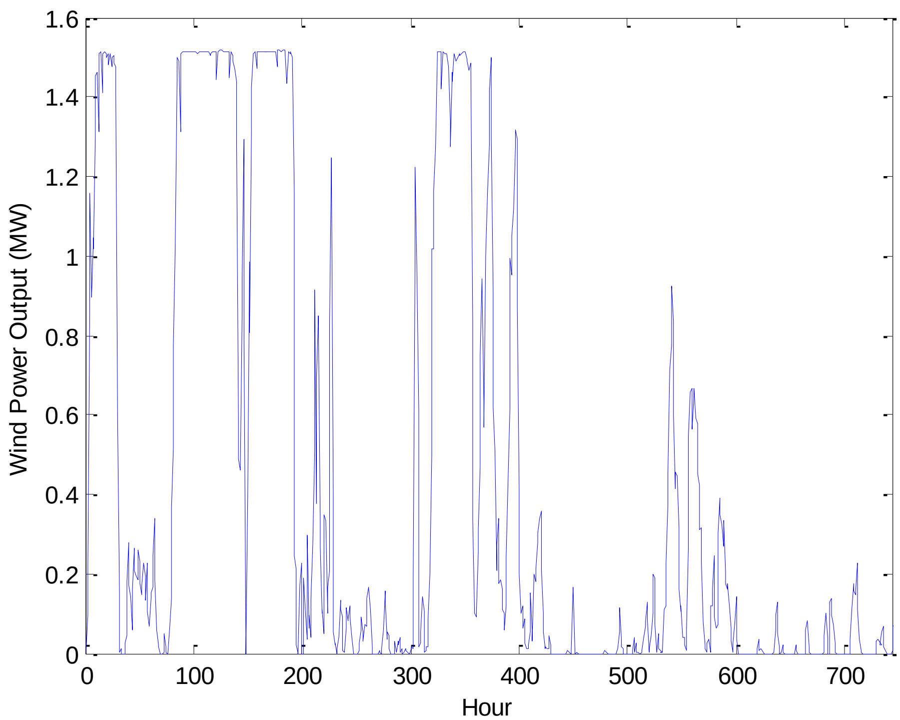
Wind generation is the most mature and cost effective renewable energy technology available today. In practices, large-scale wind farms are connected to the electric power transmission network; smaller facilities are used to provide electricity to isolated locations. Wind energy is plentiful, renewable, widely distributed, and clean, and does not produce greenhouse gases during operation.

With the advance of wind generator technologies, the cost of wind is getting even lower; between 3 to 5 cents per kWh depend on the particular projects. Thus, in the power market, wind power is becoming a very competitive energy source, comparing with traditional fossil fuel power plant.

However, wind power is non-dispatchable resource and they are intermittence in natural. Because in the power system, the demand and supply must always be balanced, this intermittence is the major challenge to largely introduce wind power into the power system. Figure 3.1 (a) shows an example of intermittence of wind power. And Figure 3.1(b) gives the wind power output data used in simulation.



(a)



(b)

Figure 3.1 Intermittence of Wind Power (a) example of intermittence of wind power [26] and (b) actual simulation wind output data

3.2.1.2 Wind power in U.S.

Figure 3.2 shows the annual capacity addition and cumulative capacity of wind power in United State from 1995 to 2009. In recent years, the U.S. has added substantial amounts of wind power generation capacity, growing from just over 6 GW at the end of 2004 to over 35 GW at the end of 2009. By the year 2008, U.S. took over the fist place in installed wind power capacity from Germany and becomes the world's leader in wind power generation capacity. In 2009, the country as a whole generates 2.4% of its electrical power from wind.

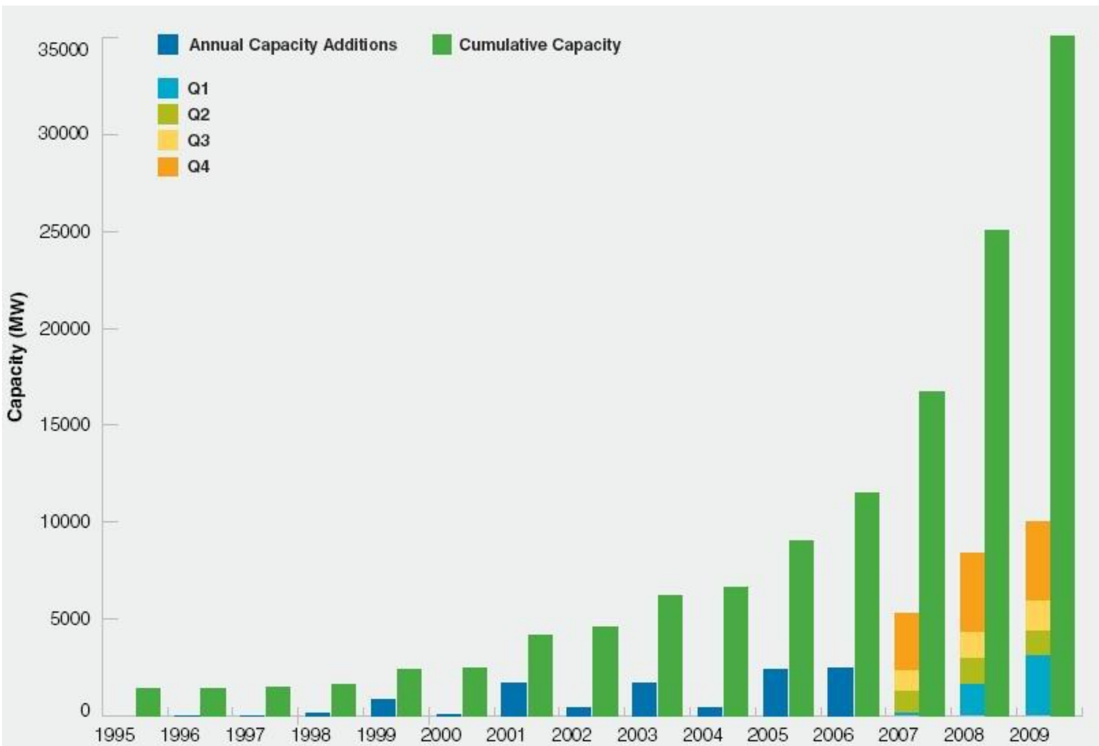


Figure 3.2 Historical cumulative wind generation installation capacity in the U.S. [27].

California was one of the incubators of the modern wind power industry, and led the U.S. in installed capacity for many years. Currently, Texas is the state with the largest amount of generation installed capacity and Iowa is the state with the highest percentage of wind generation [28]. As of July 2010, total installed wind generation capacity in the US Exceeds 36,300 MW. Figure 3.3 geographically demonstrates the wind power generation capacity in each state. The U.S. Department of Energy (DOE) is still working towards the goal of achieving 20% wind power in the United States by 2030.

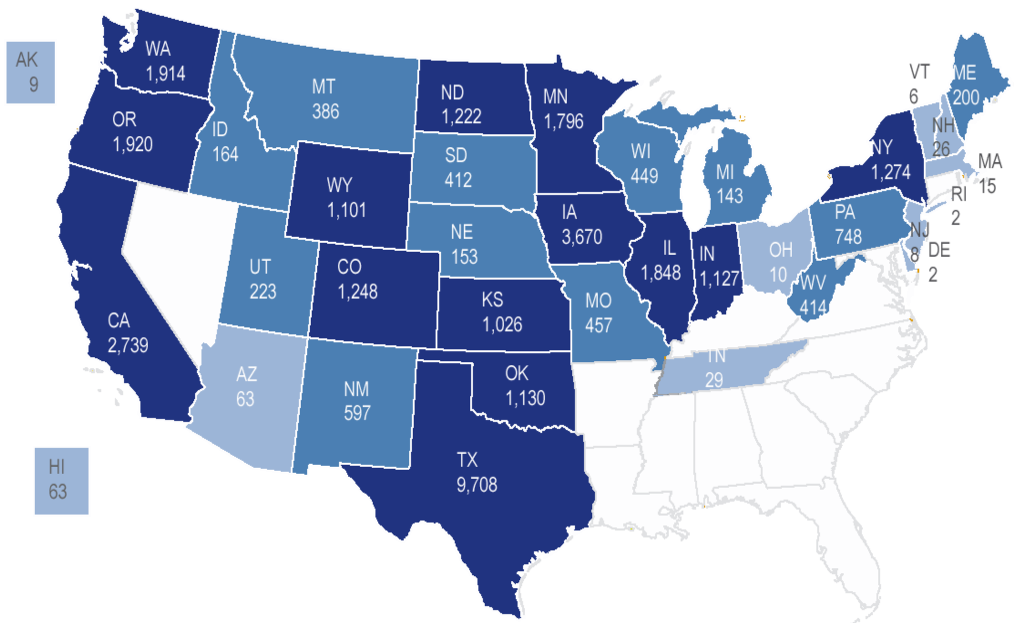


Figure 3.3 Current Installed Wind Capacity Map in U.S. [29]. (AWEA)

3.2.2 Solar power

3.2.2.1 Introduction to photovoltaic devices

Photovoltaics (PV) use semiconductor devices to convert solar radiation into direct current electricity. The principle of generating electricity is in the following three steps:

1) Photons in sunlight hit the solar panel and are absorbed by semiconducting materials, such as silicon.

2) Electrons (negatively charged) are knocked loose from their atoms, allowing them to flow through the material to produce electricity. Due to the special composition of solar cells, the electrons are only allowed to move in a single direction.

3) An array of solar cells converts solar energy into a usable amount of direct current (DC) electricity.

The principle is illustrated in Figure 3.4 [30].

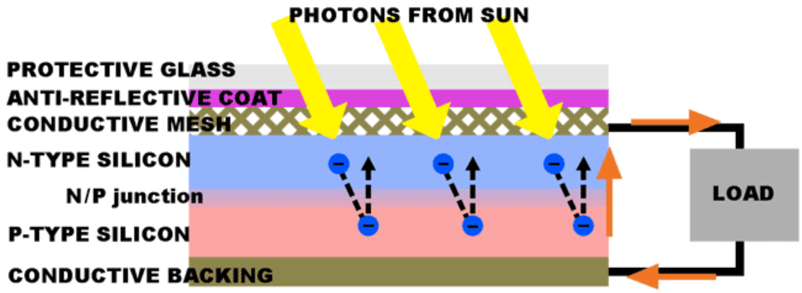


Figure 3.4 Operation of Photovoltaic

Materials presently used for photovoltaics include monocrystalline silicon, polycrystalline silicon, amorphous silicon, cadmium telluride, and copper indium selenide/sulfide [31]. Photovoltaic power capacity is measured as maximum power output under standardized test conditions. Most commercially available solar power systems are capable of producing electricity for at least twenty years without significant efficiency loss. The typical warranty given by panel manufacturers is for a period of 25 – 30 years, wherein the output shall not fall below 85% of the rated capacity [32].

There are two basic systems for utilizing the electricity generated by photovoltaics: stand-alone and grid connected. In the stand alone system, electricity will be stored and used on demand locally. The output of the PV array is connected to charge batteries for running small electrical applications. In grid connected systems, the array is directly connected to the electricity grid via an approved inverter and meter. The energy produced by the PV array can be used on-site when demand is sufficient, or exported to the grid and sold to utility company.

As a rule of thumb for monocrystalline arrays, an area of 8 to 9 m^2 will be required to produce a power output of 1kW. For the less efficient multicrystalline arrays are used an area of 10 to 12 m^2 for the same output and an area 20 to 22 m^2 will be required for the amorphous arrays [33].

Solar power is an intermittent energy source also. It is only available when there is solar radiation. Thus, normally solar power is supplemented by storage or another energy source such as wind power or traditional generators. .

3.2.2.2 Solar Array in U.S.

Photovoltaic production has been doubled every 2 years since 2002 and increased by 98% in 2008, making it the world's fastest-growing energy technology. At the end of 2008, the cumulative national grid-tied PV installations reached 1,256 MW, and off-grid installations likely totaled at 40-60 MW. [34].

3.2.3 Grid power

3.2.3.1 Deregulation in the power market

In the deregulation power market, the traditional vertically integrated monopoly structure is splitting generation, transmission and distribution. The motivation behind the deregulation is to promote efficiency gains in the long run [7].

3.2.3.1 Market Clearing Price for Energy (MCPE)

The deregulation of the power system has created a need for organized market at the wholesale level. The usual trading system is a daily double-sided auction for the certain time interval to match transactions at a single price and a fixed point in time.[35] The market participants, including generator, distributor and large consumer, submit their bids that how much they are prepared to sell or buy at their designated prices. For price determination, all the bids are collected and sorted according to the price and aggregated to get a market demand and supply curve for each bidding interval. The Market Clearing Price for Energy is establish through a intersection of the two curve at market clearing trade volume, as showed in figure 3.5. Based on the historical data, the MCPE is a variable rate and is much lower then a fixed price rate.

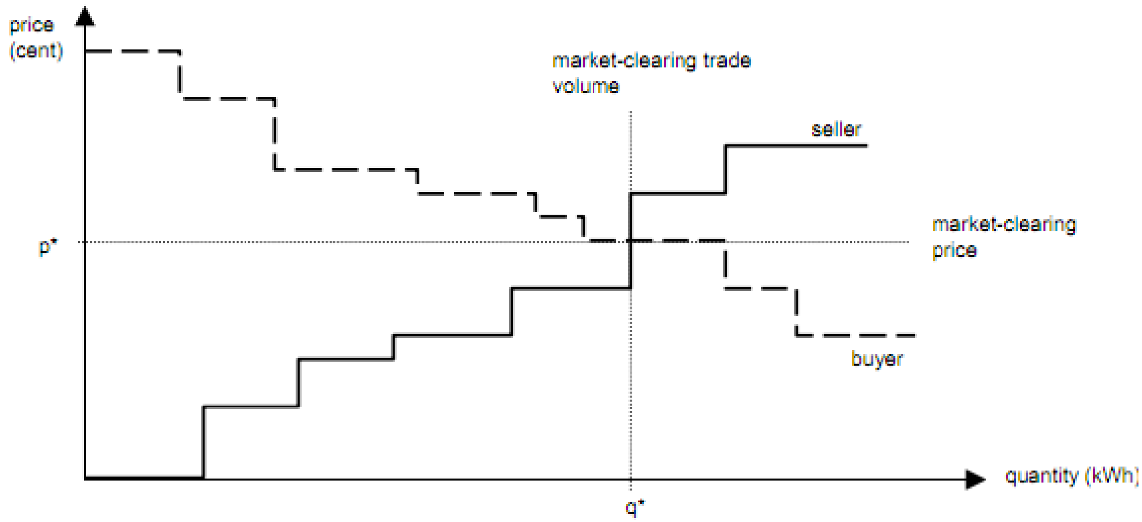


Figure 3.5 Mechanism of Power Exchange Price Formation [35]

3.3 Power storage battery unit

Power storage unit demands a tremendously large capacity and discharging rate battery. There are various types of energy storage technologies available today, including compressed air energy storage (CAES), lead-acid batteries, Lithium-ion battery, sodium sulfur and zinc-bromine, etc [36].

A sodium-sulfur battery is constructed from sodium (Na) and sulfur (S). This type of battery has a high energy density, high efficiency of charge/discharge (89–92%) and long cycle life, and is fabricated from inexpensive materials. However, because of the highly corrosive nature of the sodium polysulfides, such cells are primarily suitable for large-scale non-mobile applications such as grid energy storage.

The performance of the commercial NAS battery bank is as follows: [37]

1) 1MW per unit

2) 6 MWh/cycle

3) Efficiency of 87%

4) Lifetime of 2,500 cycles (at 100% DOD - depth of discharge), or 4,500 cycles (at 80% DOD)

Figure 3.6 1MW NAS Battery Installation in Charleston, W.V. [37]

3.4 The conceptual design

All the previous sections investigate energy sources and storage component in the PHEV charging station. The thesis proposes an active power storage charging station.

Figure 3.7 depicts the operation diagram of the proposed charging station. Control Center does the optimal control over the whole system, which will be discussed in the next chapter. All the renewable energy will directly take into the storage unit. The charging station will buy electricity from grid if there is not enough energy stored in the battery unit and the market price is favorable. If there is any excess power, the station can be sold back to the system with right price.

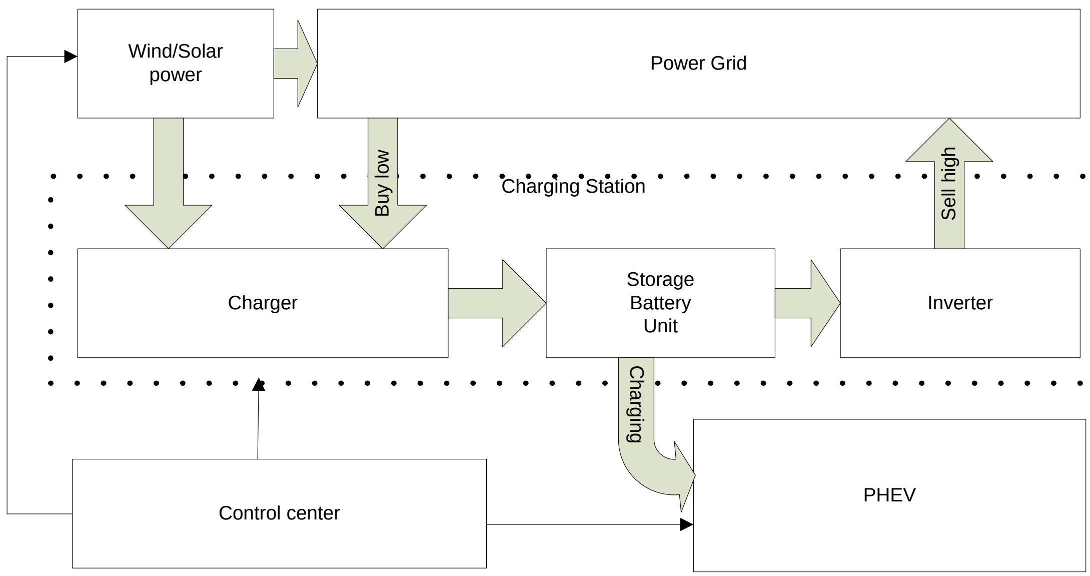


Figure 3.7 Operation diagram of the proposed charging station

Figure 3.8 illustrates one potential arrangement setting for the proposed charging station. The photovoltaic is installed upon the charging slot in the charging station to harvest solar energy, as well as function of roofing. The storage battery unit and control central can be place in the affiliate building. As for the wind part, the charging station can sign an agreement with wind farm owner to “purchase” the electricity from some of wind generation units to form “virtual off-site wind farm”. It should be noted that the charging station must have its own electrical transformer for distribution line to supply the massive energy demand from the fast charging PHEVs.

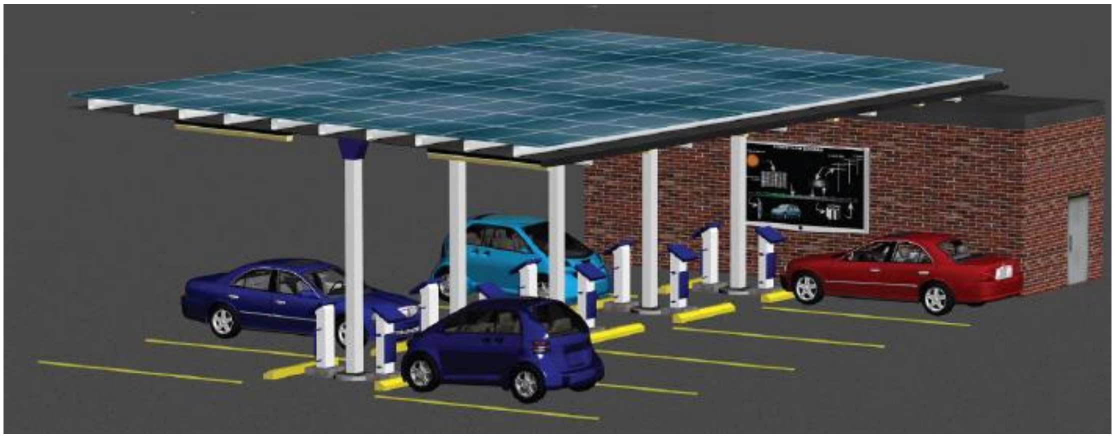


Figure 3.8 Setting for on-site solar panel and storage battery [38]

CHAPTER 4

OPTIMIZATION OF PHEV CHARGING STATION

4.1 Uncertain variables of the Sources and Demands

Four uncertain variables have to be determined in the station optimization operation: solar array output, wind power output, market clearing price, and the PHEV charging demand.

4.1.1 Photovoltaic (PV) output

Photovoltaic output is determined by the solar radiation which varies during the time of day and month. Figure 4.1 shows the monthly average daily solar radiation in Fort Worth, Texas from the recent thirty year historical data [39].

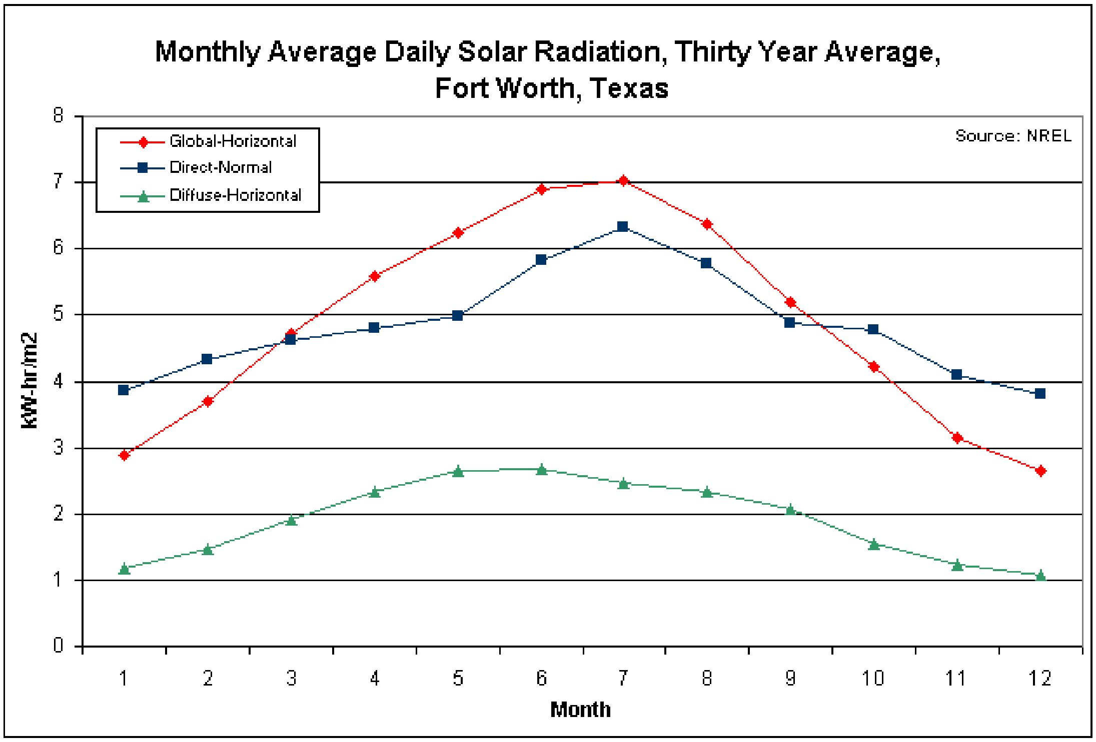


Figure 4.1 Statistical Solar Radiation Data at Fort Worth, Texas

Typical PV output is assumed in this thesis because the capacity of PV is very small compared to the overall capacity. Accounting the conversion efficiency for PV commercial module which ranges from 15% to 20%, the assumed profiles of PV output in size 50m*50m are shown in Table 4.1. Assuming each park space takes 6m*3m, that is 18 square meter, the charging station with 10 charging outlet will require 180 square meter space. PV is installed as the roof of charging slot, so the area for PV is also 180 square meter. Thus we get the PV output profile for the system. Moreover, the uncertainty of PV output will be considered in the evaluation of the optimization design.

Table 4.1 Assumption of PV (50m*50m) Output Profile

Time	Output (kW)	Time	Output (kW)
6:00 AM	94	1:00 PM	284
7:00 AM	188	2:00 PM	284
8:00 AM	284	3:00 PM	284
9:00 AM	284	4:00 PM	284
10:00 AM	284	5:00 PM	284
11:00 AM	284	6:00 PM	188
12:00 PM	284	7:00 PM	94

4.1.2 Wind Power Forecasting

Wind energy forecast is a complex as wind magnitude is influenced by many factors such as temperature, pressure variation, solar radiation, landscape, etc. Since the power generation from the wind turbine is theoretically proportional to a cube of wind speed, the large error in wind speed prediction can lead to a significant error of wind turbine generation, which in turn affects the power storage schedule and power trading decision of the station.

Artificial Neural Network has been used as a general mathematical tool in many applications. For the forecast application, a multi-layer feed forward perceptron (MLP) shown in Figure 4.2 is generally employed. ANN model of this type is well suited for function mapping problem, which is analogous to our forecast problem. The main benefit of ANN over other conventional statistical methods is that it has ability to extract system information by training process. In other words, the model is capable of recognizing the embedded dependency between a set of the inputs and outputs of the system without necessity to express this relationship explicitly, as usually does required in other statistical approaches.

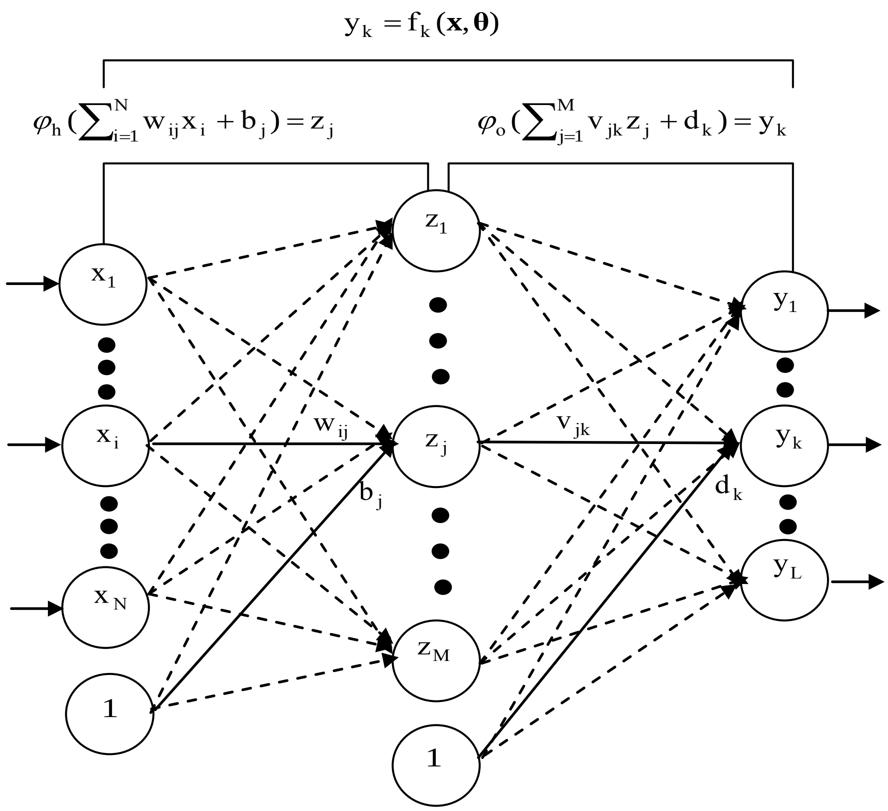


Figure 4.2 Multi-layer Feed Forward networks

Three-layer-feed-forward ANN networks [15] is proposed for real time wind power forecasting. The historical data of wind speed and wind power output is selected as the input parameters of the model, input neurons. The wind power output is the only one neuron. The hidden neurons are decided by the forward heuristic simulation. The Levenberg-Marquardt method is utilized to train the ANN model after the set up of the network structure.

The historical wind output data in the thesis is obtained from a Taiwan wind farm company. The capacity of the wind farm is 1.5MW. However, in this case, we only buy 0.5 MW capacity.

4.1.3 MCPE Forecasting

The market clearing price for energy (MCPE) is highly flexible under the competitive power market environment after deregulation. It exhibits extreme volatility (up to 50%) comparing with other commodities (less than 4% for stock market). Figure 4.3 show one day MCPE fluctuation in north Texas of March 13, 2009.

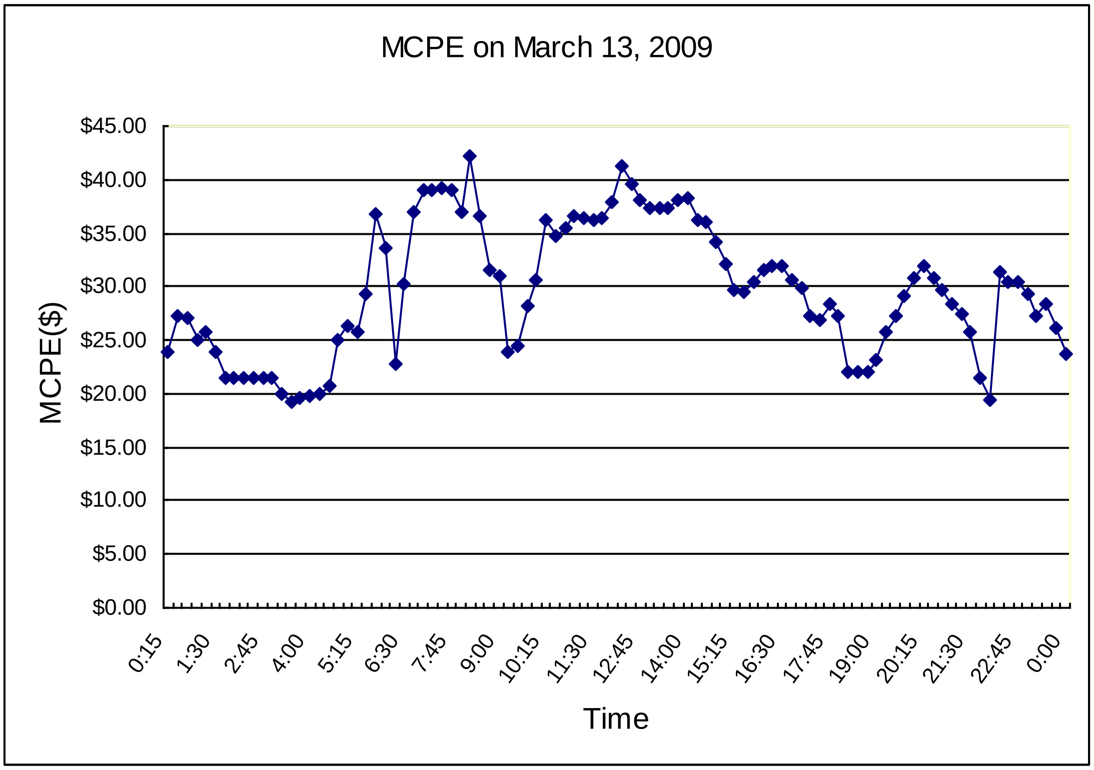


Figure 4.3 MCPE in north Texas on March 13, 2009 provided by ERCOT [40].

Many MCPE forecasting methods have been proposed after deregulation. They can be classified in two sets: simulation methods and statistical methods. The detailed physical data of the power system, including load forecasting, unit data, transmission data, has to be modeled in simulation methods. The power flow technique and economic dispatch have to be performed in simulation methods. Simulations method may achieve good forecasting results. However, it is not practical for the owner of charging station to build and maintenance such complicated system data. The statistical methods usually explore the historical MCPE and load data, which can be accessed on the ISO's website, to forecast the future MCPE. There are many statistical methods which have been applied to MCPE forecasting: ARMA-type methods, time series models with exogenous variables, autoregressive garch models, regime-switching models, threshold autoregressive models, markov regime-switching models etc [6].

The statistical model of Autoregressive model with exogenous/input variables (ARX) is examined for MCP real time forecasting in this research. The system load is used as the input variable.

The model structure of ARX [41] is:

$$\phi(B)p_t = \psi_l L_t + d_1 D_{Mon} + d_2 D_{Sat} + d_3 D_{Sun} + \varepsilon_t$$

Where:

p_t is the current price.

B is the backward shift operator.

$$\phi(B) = 1 - \phi_1 B - ... - \phi_p B^p$$

ψ_l is the coefficient of the load forecast L_t.

d_1, d_2, d_3 are three coefficients of the three binary variables $D_{Mon}, D_{Sat}, D_{Sun}$

D_{Mon} is the binary variable indicates whether the observation falls on weekday the model uses Monday as indicator

D_{Sat}, D_{Sun} is the binary variable indicates whether the observation falls on Saturday or on Sunday

ε_t is the white noise.

According to the forecasting test results in the California Power Exchange (CalPX) market [16], the Mean Daily Errors (MDE) of the ARX model is less than 5%.

4.1.4 Vehicle charging demand

In the fast charging scenario, it is assumed that the drivers will charge the vehicle as the same pattern as they fill gasoline into the conventional inner combustion vehicle. The demand for charging in one station may vary because of the location and price. However, the typical demand can be decided once the location of the station is set.

The following is the assumption for the charging demand for station.

1) There will be no charging demand at night, because most vehicles will charge at home at night.

2) The size of the onboard PHEV battery varies from 8.6 to 15.2 KWh from table 2.1. The average of battery size of 12.5 is assumed by the vehicle type ratio.

3) The assumed fast charging process is to charging the battery from 20% state of charge to 90% in 15 min. So that the charging rate of the outlet is 35kW. The maximum power output for a 10-outlet charging station is 350kW.

The profiles of vehicle charging demand are derived in Table 4.2. The uncertainty of charging demand will be considered in the evaluation of the optimization design.

Table 4.2 Assumed Vehicle Charging Demand Profile

Time	Demand (kW)	Time	Demand (kW)
12:00 AM	0	12:00 PM	875
1:00 AM	0	1:00 PM	875
2:00 AM	0	2:00 PM	875
3:00 AM	0	3:00 PM	175
4:00 AM	0	4:00 PM	350
5:00 AM	87.5	5:00 PM	262.5
6:00 AM	175	6:00 PM	175
7:00 AM	350	7:00 PM	87.5
8:00 AM	262.5	8:00 PM	0
9:00 AM	175	9:00 PM	0
10:00 AM	875	10:00 PM	0
11:00 AM	875	11:00 PM	0

4.2 Optimization

The objective functions of the optimization are:

1) Fully utilize the renewable energy.

2) Minimize the charging electric cost.

The constraints are:

1) Size of storage battery unit

2) Charging rate of storage battery unit

According to the objectives and constraints, the formulation of the optimization problem is:

$$Min \qquad MCP * PT^{T} \tag{1}$$

ST:

$$PT \geq -WP - PV \tag{2}$$

$$PT \leq Unit\_Char\_Rate - WP - PV \tag{3}$$

$$En\_in\_Unit \geq Unit\_\mathrm{Re}s \tag{4}$$

$$En\_in\_Unit \leq Unit\_Size \tag{5}$$

The definition of the variables of the formulas is shown in Table 4.3. PT, power trading option, is also the optimization variable in the problem. The positive value of PT represents “Buy from market” and the negative value of PT represents “Sell to market” in this research.

Table 4.3 Definition of Variables of the Problem

Parameter	Meaning
PT	Power trading (MW)
WP	Wind power output (MW)
PV	PV output (MW)
Unit_Char_Rate	Charging rate of storage battery unit (MW)
En_in_Unit	Energy level of storage battery unit (MWh)
Unit_Res	Minimum energy level of storage battery unit (MWh)
Unit_Size	Size of storage battery unit (MWh)

All of the objective and constraints are linear, so the linear programming can be applied to solve the optimization problem in this research.

The optimization algorithm will be run at the interval of 15 minutes to match the real-time operation of the station since Independent System Operator (ISO) usually post real-time MCP every 15 minutes. The optimization cycle is set as 168 hours (one week) considering the higher forecasting uncertainness for longer time. The optimization algorithm is implemented in MATLAB.

The simulation time is set as one-month (31 days) to evaluate the benefits of the optimization approach. Therefore, the proposed optimization approach will be run 2976 (31 days * 24 hours * 4 quarters) times in the entire operation. The optimization problem is solved based on the 168 hours (one week) historical data of wind power and MCP. The following three cases are calculated in this research to evaluate the optimization:

Case1: Power trading when needed (no optimization).

Case2: Optimization based on perfect wind power and MCP data, typical PV output and charging demand.

Case3: Optimization based on inaccurate wind power and MCP data, uncertain PV output and charging demand with 20% of uncertain level.

In the end, the different uncertainty levels of the four uncertain factors are also considered in this research.

Main parameters of the station are initially assumed in Table 4.4. Only electricity from virtual wind farm and trading in the market are calculated into the electricity cost. The electricity from PV is not included since PV is owned by the station.

Table 4.4 Main Parameters of the Station

Definition	Value
Charging rate of storage battery unit	0.5MW
Size of storage battery unit	18MWh
Minimum state of charge for battery unit	3.6MWh
PV	12m*15m

Table 4.4 – *Continued*

Capacity of virtual wind generators	1.5MW
Purchase capacity of wind power	0.5MW
Price of wind power	40 $/MWh
Efficiency of charging	0.87*0.9=0.798

4.2.1 Case 1

The typical PV output and vehicle charging demand are assumed in case 1. No forecasting is performed since no optimization algorithm is applied in this case. The rules for power trade in the no optimization are as following:

1) No selling to grid when the storage battery unit is in less than 20% state of charge (SOC)

2) No purchasing from grid when the storage battery unit is fully charged.

3) Sell all the excessive wind and PV power out put when the maximum wind power and PV output is higher than the storage unit charging rate.

The simulation results are shown in Table 4.5, Figure 4.4, and Figure 4.5. The electricity cost is $ 42.51/MWh

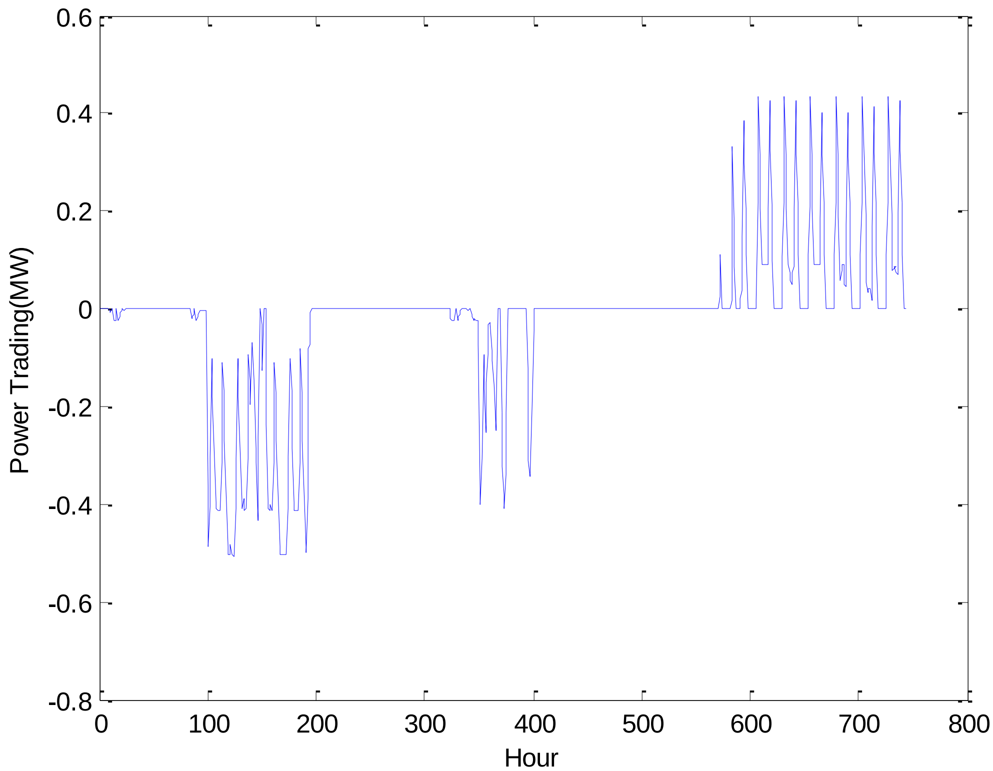


Figure 4.4 Power exchange in power market in case 1

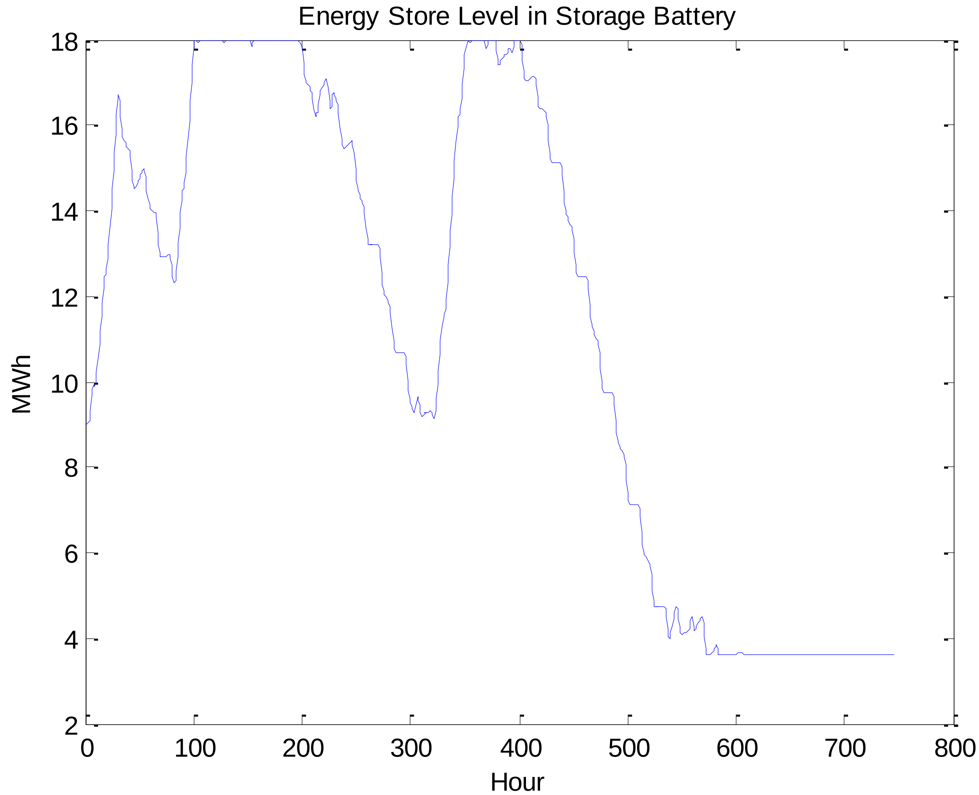


Figure 4.5 Energy level in Storage Battery Unit in Case 1

4.2.2 Case 2

In case it is presumed that the forecasting is accurate i.e., the wind power output and MCPE for next 168 hours are precisely correct and identical to forecasting result. The typical PV output and charging demand are assumed in this case.

The proposed optimization method is applied in case 2. The simulation results are shown in Table 4.5, Figure 4.6, and Figure 4.7 respectively. As shown in Figure 4.5, the station will sell power to the market when MCPE is higher and purchase power from the market when MCPE is lower.

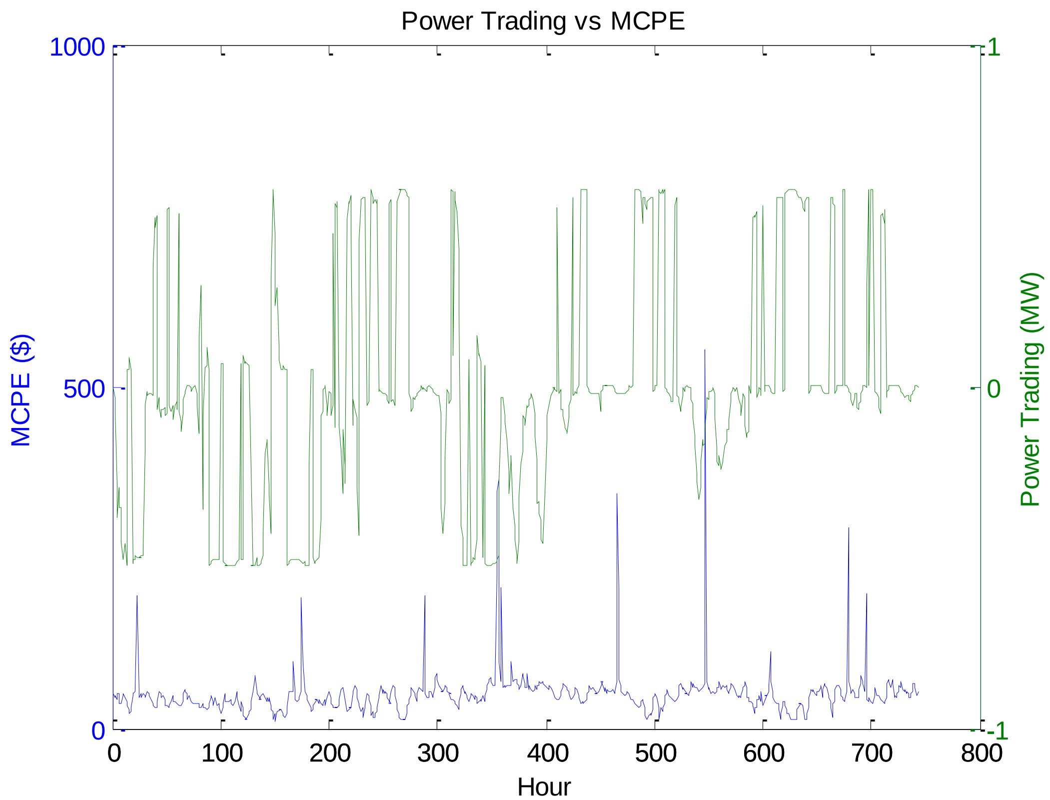


Figure 4.6 Power Exchange in Power Market in Case 2

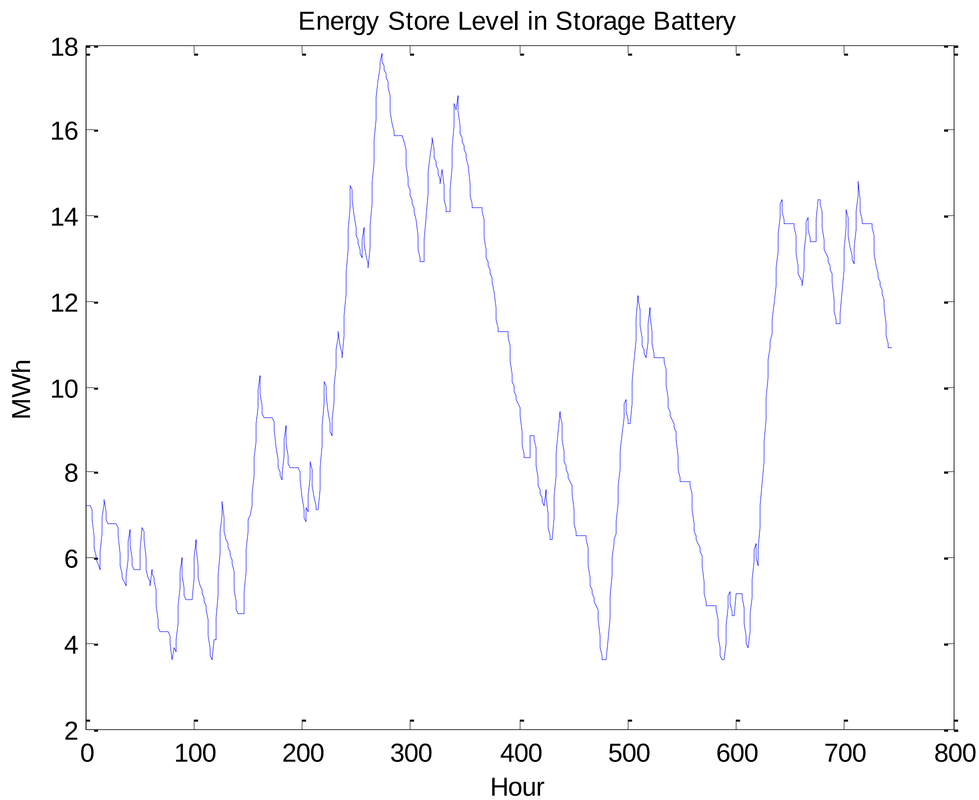


Figure 4.7 Energy level in Storage Battery Unit in Case 2

Based on the accurate forecasting, the optimization approach can dramatically decrease the operating cost of the station. Comparing with no optimization case (case 1), the electricity cost is decreased from $42.51 to $16.70. The economic improvement is about 61%.

4.2.3 Case 3

Accurate forecasting does not always happen in practical situation. Considering the forecasting uncertainties, 20% of noise level is added to the historical data of wind power and MCPE in case 3. Also, 20% of noise level is added to typical PV output and charging demand.

The simulation results are shown in Table 4.5, Figure 4.8, and Figure 4.9. Comparing with perfect forecasting, the electricity price is increased from $16.70 to $22.14. However, the cost of case 3 is still much lower than the cost of case 1.

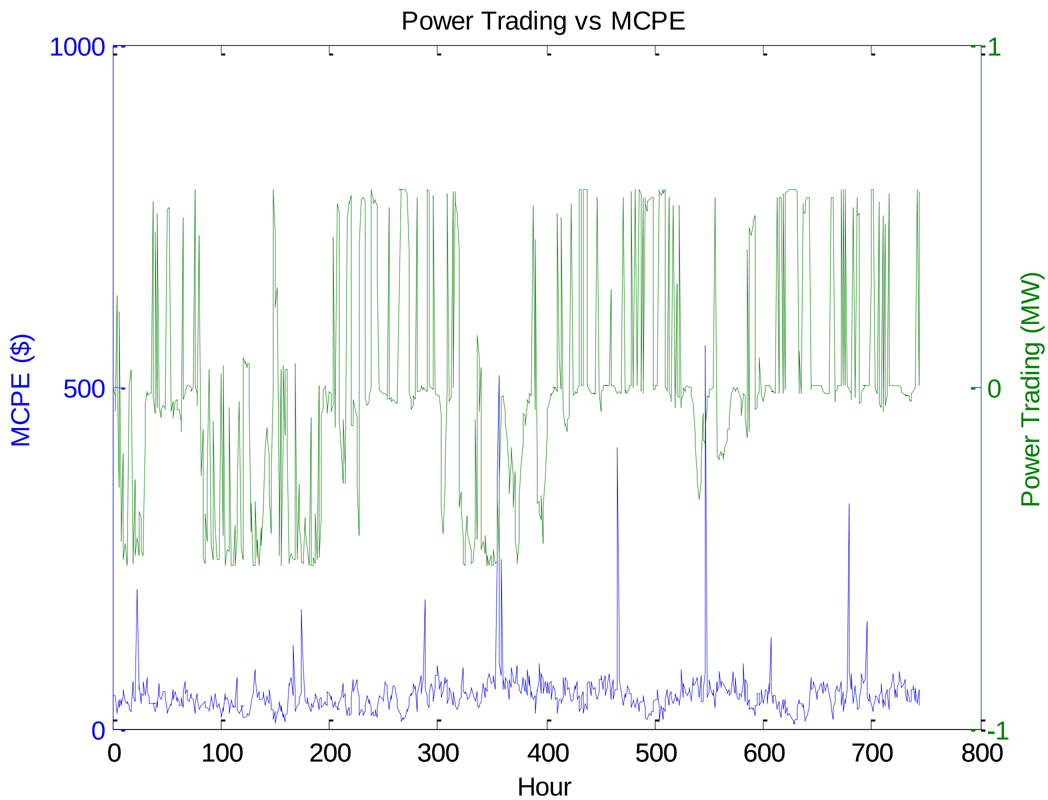


Figure 4.8 Power Exchange in Power Market in case 3

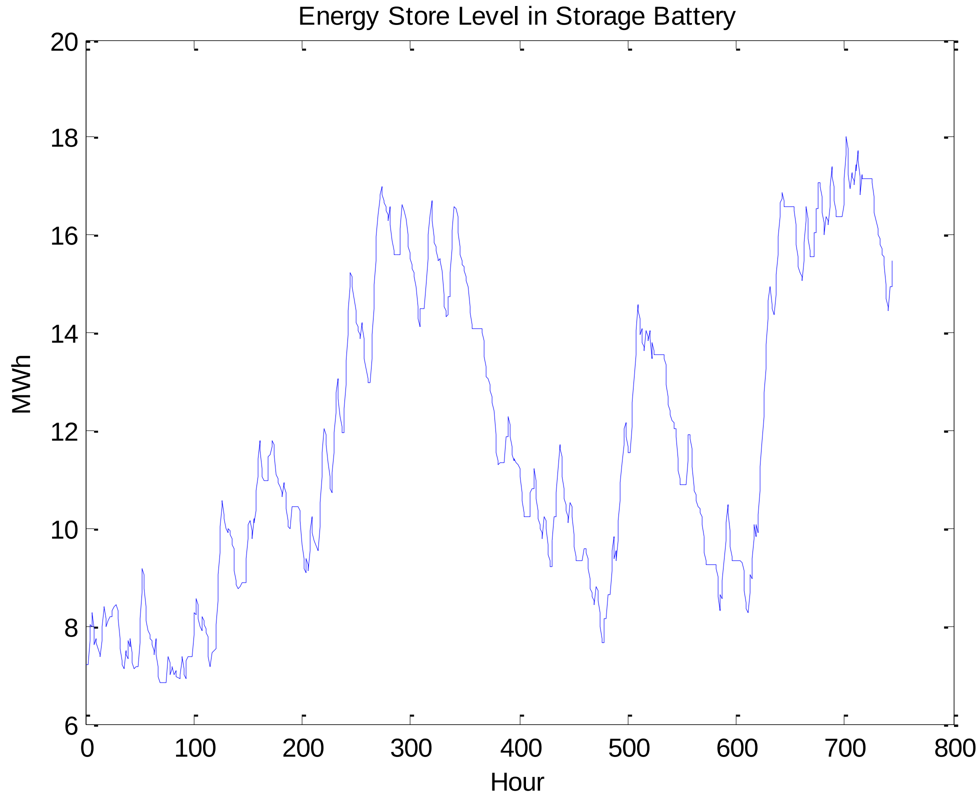


Figure 4.9 Energy level in Storage Battery Unit in Case 3

4.2.4 Comparison of Three Cases

Table 4.5 lists the simulation result of three cases.

Table 4.5 Simulation Results of Case 1, Case 2 and Case 3

Definition	**Case 1 (No Optimization)**	**Case 2 (Optimization with perfect data)**	**Case 3 (Optimization with 20% level of uncertainty data)**
PHEV Demand(MWh)	90.416	90.416	91.705
Electricity from PV (MWh)	7.386	7.396	7.440
Electricity from wind power (MWh)	107.908	107.908	108.497
Electricity net exchange with grid (MWh)	-17.572	-7.124	-5.276
Electricity purchased from grid (MWh)	15.651	81.158	77.59
Electricity sold back to grid (MWh)	37.223	88.282	82.87

Table 4.5 – *Continued*

Total Electricity Cost ($)	3,584.20	1,571.80	2,119.0
Electricity cost per MWh($)	42.51	16.70	22.14

4.3 Uncertainties/inaccuracy Analysis

Through the similar way performed as for 20% of the uncertainty level of the data, the simulation is also performed under 10%, 30% and 40% uncertainty level of forecasting on wind/ PV power production, real time pricing, and charging demand to fully evaluate their impacts on the optimization approach. The simulation results are shown in Table 4.6.

It is easy to see that the electricity price increases when the uncertainty level increases. However, it is still lower than the cost of no optimization case under very inaccurate wind power and MCP forecasting and high uncertain on PV production and charging demand.

Table 4.6 Simulation Results under Different Uncertainty Levels

Uncertainty Level	**10%**	**20%**	**30%**	**40%**
PHEV Demand(MWh)	90.301	91.705	89.532	89.973
Electricity from PV (MWh)	7.348	7.440	7.471	7.430
Electricity from wind power (MWh)	109.195	108.497	107.577	113.929
Electricity net exchange with grid (MWh)	-4.448	-5.276	-5.602	-6.670
Electricity purchased from grid (MWh)	82.833	77.591	76.989	73.697
Electricity sold back to grid (MWh)	87.2825	82.877	82.591	80.367
Total Electricity Cost ($)	1,903.60	2,119.00	2,462.70	2,608.50
Electricity cost per MWh($)	19.74	22.14	25.80	27.60

CHAPTER 5

CONCLUSION

5.1 Conclusion

PHEV is the most feasible approach towards significantly lowering the consumption of oil and improve fuel economy with today's existing technologies. Charging technology is the key factor in the success of full scale PHEV deployment. The research looks into the different charging level for PHEV; a design of fast charging station with storage battery unit is proposed. The station uses on-site solar cell, and off-site “virtual wind farm” to produce the main energy. The power trading in power market is used when the intermittent renewable energy is unavailable. The excessive power will be sell back to market to reduce the cost of electricity.

An optimized schedule of charging station is proposed in the thesis. The ANN model and ARX model are examined for real time wind power and MCP forecasting respectively. The analysis based on the level of uncertain variable is utilized to evaluate the optimization. The solver of linear programming is applied to make optimized storage schedule and power trading decisions.

The electricity price goes down from $42.51 to $16.70 by applying the optimization algorithm under the accurate forecasting and given PV output and vehicle charging demand. The price is as low as $22.41 under 20% inaccuracy of forecasting, uncertain wind and PV output and charging demand. The optimization approach still shows prominent benefits even under poor forecasting and high uncertainties.

By implementing the storage battery unit, the charging station becomes active participant in power market. This can both reduce the system load in peak or congested time and optimize the operation of power system. And eventually helps deploying of clean and green PHEV.

5.2 Future work

PHEV is the transfer type vehicle between conventional vehicle and pure battery electric vehicle (EV). One day in the future, when battery technology is much more advanced, EV will take over the place of what PHEV have now. Thus, the charging static of EV will be needed to study, and take account into charging station design.

Due to the high power/energy feature of the storage battery unit, the charging station can also participate in ancillary service. This will help reduces the operating cost, which should take into the future study. Also, it is important to know the bulk unit is running in the safe, faultless mode. Online fault detection should be added into system.

The optimization is for dispatching single charging station power. There will be multiple stations in the highly populated areas. Thus, the global optimization techniques can be performed among all the charging stations to have better scheduled for both stations and power grid.

APPENDIX A

MATLAB PROGRAMMING CODE

```
clear all

clc


tic

%%%%read the annual electricity price

MCPE_North = xlsread('MCPE_2007(North)');

Nan_ind = isnan(MCPE_North);

% %delete the Nan or insert apre-set price ($30)

MCPE_North(find(Nan_ind)) = 30*ones(length(find(Nan_ind)),1);

MCPE_North_vec = reshape(MCPE_North',prod(size(MCPE_North)),1);

length(MCPE_North_vec);

mean_price = mean(MCPE_North_vec);

max_price = max(MCPE_North_vec);

min_price = min(MCPE_North_vec);

hrs = length(MCPE_North_vec)/4;

El_Price = zeros(hrs,1);

for i=1:hrs

    El_Price(i) = sum(MCPE_North_vec(i*4-3:i*4))/4;

end


windpower_output = xlsread('windpower_output');%1.5MW

windpower_output_vec = reshape(windpower_output',prod(size(windpower_output)),1);

if hrs~=length(windpower_output_vec)/6

    err = 1

else

    WP_output = zeros(hrs,1);

    for i=1:hrs

        WP_output(i)=sum(windpower_output_vec(i*6-5:i*6))/6;
```

```
    end
end

PV_output                                                                    =
[0,0,0,0,0,0,94,188,284,284,284,284,284,284,284,284,284,284,188,94,0,0,0,0]'*.001*.07;
Conv_matrix = zeros(365*24,24);
for i=1:365
    Conv_matrix(i*24-23:i*24,:)=eye(24);
end
PV_output = Conv_matrix* PV_output;

Cap_Windpower = .5;%MW
WP_output = WP_output*Cap_Windpower/1.5;

Char_Effi_Rate = .87;
Stor_Char_Rate = .5;%MW
vehi_Char = [0,0,0,0,0,.35,.7,1.4,1.05,.7,.35,.35,.35,.35,.35,.35,.7,1.4,1.05,.7,.35,0,0,0]'/4/.9;



WP_price = 40;

Stor_Size =18;
Stor_Ini = Stor_Size*.4;
Stor_Res = Stor_Size*.2;
Stor =[Stor_Size, Stor_Ini, Stor_Res];

Operation_days = 31;
Opt_days = 7;
```

```
Opt_Time = Opt_days*24;


D2M = zeros(Opt_Time+Operation_days*24,24);
for n_i=1:Opt_Time/24+Operation_days
    D2M(n_i*24-23:n_i*24,:) = eye(24);
end
vehi_Char = D2M*vehi_Char;


%%%%add noise
sd=0.2;
sd_vc=sd;
vehi_Char_fc = vehi_Char +vehi_Char.*randn(size(vehi_Char))*sd_vc;
sd_WP =sd_vc;
WP_output_fc = WP_output +WP_output.*randn(size(WP_output))*sd_WP;
sd_PV=sd_vc;
PV_output_fc = PV_output +PV_output.*randn(size(PV_output))*sd_PV;
sd_El_price =sd_vc;
El_Price_fc = El_Price +El_Price.*randn(size(El_Price))*sd_El_price;


%%%%Decrease Stor_Size & Increase Stor_Res to meet the constraint of tank
%%%%when the forecasting is not perfect
if sd_vc~=0
    Stor_Size = Stor_Size*(1 - .1);
    Stor_Res = Stor_Res*(1 + .8);
end


%%%% Opt day by day
net_Grid = zeros(Operation_days*24,1);
```

```
Tank_Ini_Eachday = Stor_Ini;

Tank_Ini_day_vec = zeros(Operation_days+1,1);

Tank_Ini_day_vec(1) = Tank_Ini_Eachday;

for n_i = 0:Operation_days-1

    Start_time = n_i*24+1;

    End_time = Start_time+Opt_Time-1;

    lb = -WP_output_fc(Start_time:End_time)-PV_output_fc(Start_time:End_time);

    ub = (Stor_Char_Rate*ones(End_time-Start_time+1,1) + lb*Char_Effi_Rate)/Char_Effi_Rate;

    Cul_Mat = triu(ones(End_time-Start_time+1,End_time-Start_time+1))';

    A = [Cul_Mat*Char_Effi_Rate; -Cul_Mat];


b_1=((Stor_Size-Tank_Ini_Eachday)*ones(End_time-Start_time+1,1)+Cul_Mat*vehi_Char_fc(Star
t_time:End_time))...


-Cul_Mat*(WP_output_fc(Start_time:End_time)+PV_output_fc(Start_time:End_time))*Char_Effi_R
ate;


b_2=-((Stor_Res-Tank_Ini_Eachday)*ones(End_time-Start_time+1,1)+Cul_Mat*vehi_Char_fc(Star
t_time:End_time))/Char_Effi_Rate...

        +Cul_Mat*(WP_output_fc(Start_time:End_time)+PV_output_fc(Start_time:End_time));

    b=[b_1;b_2];

    f = El_Price_fc(Start_time:End_time);

    [x,fval,exitflag,output,lambda] = linprog(f,A,b,[],[],lb,ub);

    net_Grid(Start_time:Start_time+23) = x(1:24);

    exitflag; %% 1 means success


    %%%check net_Grid for upper and lower limit

    lb = -WP_output(Start_time:End_time)-PV_output(Start_time:End_time);
```

```
    ub = (Stor_Char_Rate*ones(End_time-Start_time+1,1) + lb*Char_Effi_Rate)/Char_Effi_Rate;
    for n_j=1:24
        if net_Grid(Start_time+n_j-1)<lb(n_j)
            net_Grid(Start_time+n_j-1) = lb(n_j);
        elseif net_Grid(Start_time+n_j-1)>ub(n_j)
            net_Grid(Start_time+n_j-1) = ub(n_j);
        end
    end

    En_stor_tmp                                                                              =
(PV_output(Start_time:Start_time+23)+WP_output(Start_time:Start_time+23)+net_Grid(Start_time
:Start_time+23))*Char_Effi_Rate;
    Tank_Ini_Eachday                                                                         =
Tank_Ini_Eachday+sum(En_stor_tmp-vehi_Char(Start_time:Start_time+23));
    Tank_Ini_day_vec(n_i+2) = Tank_Ini_Eachday;

end



%%%check net_Grid for upper and lower limit
lb = -WP_output(1:Operation_days*24)-PV_output(1:Operation_days*24);
ub = (Stor_Char_Rate*ones(Operation_days*24,1) + lb*Char_Effi_Rate)/Char_Effi_Rate;
for n_i =1:Operation_days*24
    if net_Grid(n_i)<lb(n_i)
        disp 'err'
    elseif net_Grid(n_i)>ub(n_i)
        disp 'err'
    end
```

```
end

%%%check the tank level
Stor_Char                                                                          =
(PV_output(1:Operation_days*24)+WP_output(1:Operation_days*24)+net_Grid(1:Operation_day
s*24))*Char_Effi_Rate;
Cul_Mat = triu(ones(Operation_days*24,Operation_days*24))';
En_in_Stor = Stor_Ini + Cul_Mat*(Stor_Char(1:Operation_days*24)
-vehi_Char(1:Operation_days*24));
if sd_vc~=0
    if find(En_in_Stor>Stor_Size)
        disp 'En_in_Stor>Stor_Size'
    end
    if find(En_in_Stor<Stor_Res)
        disp 'En_in_Stor<Stor_Res'
    end
end


Stor_Char                                                                          =
(PV_output(1:Operation_days*24)+WP_output(1:Operation_days*24)+net_Grid(1:Operation_day
s*24))*Char_Effi_Rate;
Cul_Mat = triu(ones(Operation_days*24,Operation_days*24))';
En_in_Stor = Stor_Ini + Cul_Mat*(Stor_Char(1:Operation_days*24)
-vehi_Char_fc(1:Operation_days*24));
En_stor_total = sum(Stor_Char)
PV_output_total = sum(PV_output_fc(1:Operation_days*24))
WP_output_total = sum(WP_output_fc(1:Operation_days*24))
```

```
net_Grid_total = sum(net_Grid(1:Operation_days*24))
total_elec = WP_output_total+PV_output_total+net_Grid_total
from_Grid_id = find(net_Grid>0);
from_Grid_total =    sum(net_Grid(from_Grid_id))
to_Grid_id = find(net_Grid<0);
to_Grid_total =    sum(net_Grid(to_Grid_id))

Elec_cost_total =
El_Price(1:Operation_days*24)'*net_Grid+WP_price*sum(WP_output(1:Operation_days*24))
unit_cost= Elec_cost_total/En_stor_total
vehi_char_total = sum(vehi_Char_fc (1:Operation_days*24))


figure(1)
x=[1:Operation_days*24];
[AX,H1,H2] = plotyy(x,El_Price_fc(x),x,net_Grid);
set(get(AX(1),'Ylabel'),'String','MCPE ($)')
set(get(AX(2),'Ylabel'),'String','Power Trading (MW)')
xlabel('Hour')
title('Power Trading vs MCPE')

figure(2)
plot(En_in_Stor)
xlabel('Hour')
ylabel('MWh')
title('Energy Store Level in Storage Battery')
%
toc
```

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