A Linear Program for Control of a System of PHEV Charging Stations

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***Abstract*—This research studies dynamic control of a system of plug-in hybrid electric vehicle (PHEV) charging stations. A finite horizon dynamic problem is presented. Based upon the 15-minute updated period of the electricity market price, the objective function is to maximize profit, which is the revenue benefit from selling back to the grid and the charging of the vehicles minus the cost of buying electricity from the grid. The state variables in each 15-minute time period consist of the total wind purchased by the system, solar power generation at each charging station, total demand at each station, and nodal market price at station locations. As an initial solution analysis, the mean value problem is formulated as a deterministic linear program and solved. Potential policies are presented to provide insight into the behavior of the system.**

***Index Terms*— PHEV Charging Station, Mean value problem, Dynamic control**

I. Introduction

Global demand for energy has been increasing steadily as a result of industrial development and population growth. According to a report from the Energy Information Administration, oil provides 93% of the energy used in transportation. The report also notes that the transportation sector is responsible for up to 34% of total energy-related carbon dioxide emissions in 2012 **Error! Reference source not found.**-[22]. Today, oil production and the price of gasoline influence energy security, politics, and economic concerns. The availability of petroleum in the future is expected to decline as production begins to peak globally. Reserves shall appreciate in value, making further utilization of alternative energy production an attractive choice.

Sustainable energy development, or renewable energy, such as wind, solar, and biomass, has been increasing in an effort to offset both greenhouse gas emissions and the declining production of oil. Domestic electric power includes coal, petroleum liquids, petroleum coke, natural and other gas, nuclear, hydroelectric conventional and renewable sources (such as wind, landfill gas, solar thermal, and biomass) [9]. Compared to oil production, some consider electricity production more predictable. While the sources of alternative energy (e.g. wind, solar) are considered by some as intermittent and uncontrollable, systems utilized in the capture of alternative energy can minimize production of electricity from other connected systems (e.g. natural gas, nuclear) on the power grid and thereby minimize expense. This may result in a relatively stable average price of electricity.

With today's existing technologies, the electric vehicle has great potential to replace the traditional gasoline based vehicle. A Plug-in Hybrid Electric Vehicle is one of the best solutions to reduce the consumption of oil significantly and improve national energy security and fuel economy. The number of consumers who purchase a PHEV has been growing by 80% each year since 2000 [5], and 10% of new vehicle sales in 2015 are expected to be PHEVs. In metropolitans, the overall PHEV charging demand could reach up to hundreds of MW in extreme situations [10]. However, there still exist some obstacles to the proliferation of PHEV use [16]. One of the key barriers to achieving the spread of PHEVs is providing enough reliable access to rapid charging infrastructure [15]. They need to satisfy power demand and to offer a reasonable quality of service to customers [4].

This paper mainly focuses on the dynamic system control for the integration of a level 3 PHEV DC fast charging station, renewable energy resources, and an energy trading strategy with a power grid. PHEV charging station configuration and historical data of wind and solar power generation, and electricity market price, as well as the lists of battery storage technologies are discussed in section II. The formulation for the dynamic control problem of plug-in hybrid electric vehicle charging stations is presented in section III. Results from the mean value problem are shown in section IV. Section V is on future work and conclusions.

II. PHEV Charging Station Configuration

The goal of design is to build a set of fast charging stations that uses solar energy, wind energy, and electricity from a power grid to simultaneously serve multiple vehicles in the same way as the current gas stations serve customers. All the electricity produced from various sources together is called direct charge, and the surplus from the direct charge can be stored in the battery or sold back to the utility grid. The battery is able to store the electricity within a pre-defined range. When demand arrives at the station, the system control makes a decision to serve the demands both from direct charge and the battery storage depending on the energy market price. An

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operation diagram of the proposed charging station is shown in Figure 1.

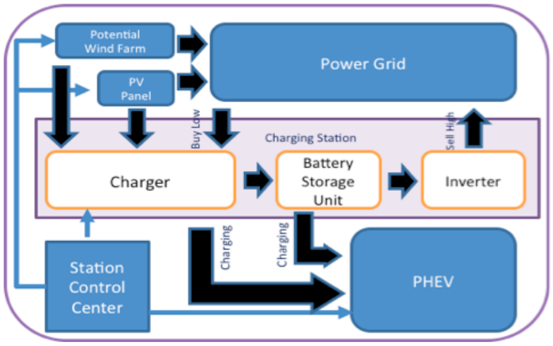

Figure 1. PHEV Charging Station Configuration

A. *Energy Resources in PHEV Charging Station*

Two types of renewable energy resources, wind and solar power energy, are considered in the designed PHEV charging station. Historical weather data and existing forecasting models are used to simulate forecasting and actual realizations of wind and solar power generation every 15 minutes at potential locations of PHEV charging stations.

1) Wind Farms in Texas

With more than 10,000 MW in 46 wind farms by 2012, Texas has the highest installed capacity of wind farms in the United States. It is assumed that the PHEV charging station can establish a contract with one of the wind farms. The 15-minute Texas wind output power data are obtained from the Electric Reliability Council of Texas (ERCOT). Figure 2 depicts the profile of a wind farm generation during January 2012.

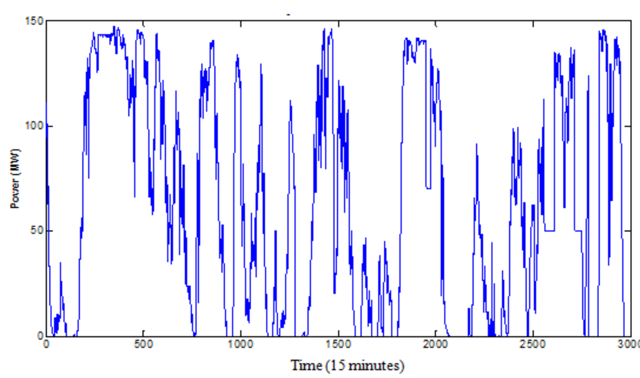

Figure 2. January 2012 wind generation

2) PV Technology and PV generation profile

30 years of historical solar radiation data and supplementary US meteorology data are provided by the National Solar Radiation Data Base (NSRDB) [17]. These data are called Typical Meteorological Year (TMY). A PV generation profile is simulated along with the temperature and solar irradiance by equations (1) and (2). For simplicity, single crystalline is a selected PV technology in this problem, since it provides the highest efficiency compared to other commercially available technologies [3]. The PV generation profiles of 180 m^2 installation areas considered as a roof top PV for PHEV charging station is depicted in Figure 3.

$$\eta = \eta_0 \left[1 - \gamma\left(T_p - T_\gamma\right)\right], \tag{1}$$

$$P = I \cdot A \cdot \eta , \tag{2}$$

where η is an efficiency, η_o is a PV module efficiency from the manufacturer under reference temperature, γ is the temperature coefficient of solar batteries (0.005), T_P is an actual temperature (K), T_γ is the reference temperature (298 K), P is the PV generation (W), I is the solar irradiance (W/m^2) and A is a PV installation area (m^2).

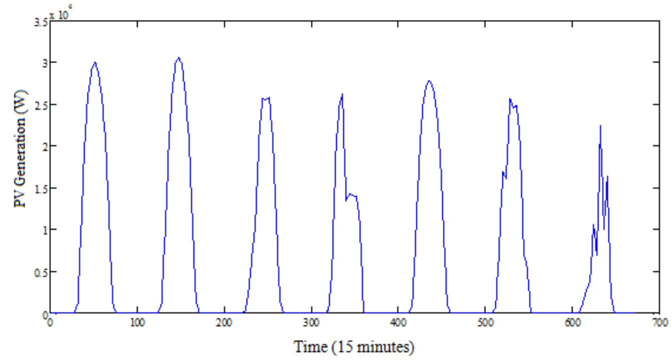

Figure 3. PV generation at Dallas Redbird Executive Airport between January 1st and 7th 2008

B. *Electric Market in the DFW area*

ERCOT was established by Texas Interconnected System (TIS) in 1970 and became a deregulated generation market in 1995 [8]. In this research, Settlement points in ERCOT are represented by supernodes for clustering the market prices location, which ERCOT updates as real-time settlement point prices (SPPs) once every 15 minutes for each supernode within its service territory. These supernodes serve electricity to all demand in the DFW area except co-ops and municipal power systems. As shown in Figure 5, 9 counties in the DFW area with the total of 26 supernodes can be aggregated into 11 clusters of supernodes. January market prices, for instance, for all these 26 supernodes are illustrated in Figure 5.

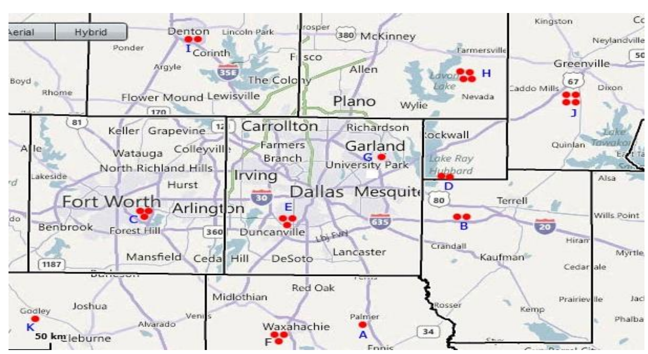

Figure 4. DFW supernodes

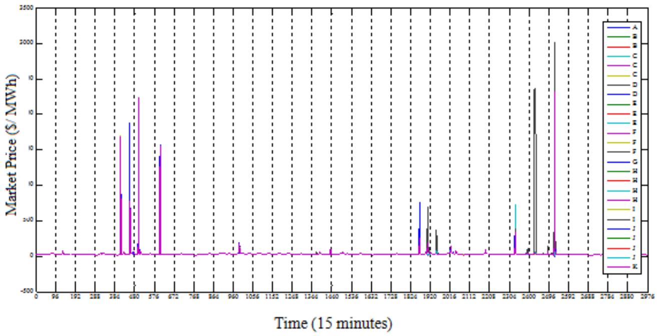

Figure 5. January 2012 supernodes market price **Error! Reference source not found.**

Every 15 minutes, the simulation model will calculate the cost of buying from the power grid and revenue from selling to the power grid and PHEVs. The net cost will be accumulated over a user-specified period of time. The results will be used to evaluate the adequacy of the charging station location and operation strategies.

C. Battery Storage Technology

The potential battery storage technologies that can support DC level 3 fast charging consists of Sodium Sulphur (NaS), Lead Acid (Pbs), Lithium-ion (Li-ion), and Nickel-Metal Hydride (NiMH). The characteristics of batteries are shown below [7], [19] (see Table **I**). For this research, NaS is selected to be the battery for the PHEV charging station because of its high efficiency and cycle life.

Table I
UNITS FOR MAGNETIC PROPERTIES

Technology	Cycle Life at 80% DOD	Efficiency	Advantage	Disadvantage
NaS	4500 cycles	89%	• Good for industrial and commercial sectors • High efficiency	Operates with high temperatures
Li-ion	3000 cycles	70-85%	• High density • Low self discharge rate • No memory effect in positive side	Expensive
NiMH	2000 cycles	50-80 %	• High density • Good abuse tolerance	Damage may occur with complete discharge
Lead Acid • Flooded • VRLA	 1500 cycles 500 cycles	 70-80 % 70-80 %	Inexpensive	Limited cycling capability

III. DYNAMIC CONTROL PROBLEM FORMULATION

The controllability module is a dynamic control problem because decisions are made in several time stages, and the optimization problem becomes dynamic and multi-stage. There is at least one transition equation on the problem, which means that the next state of the process depends entirely on the current state of the process and the current decisions taken [1]..

At each stage, the system is defined by sets of state variables, which include the market price of energy, solar production of each station, the total wind purchased to the system, and the total demand of each station. When a decision is made, a cost is obtained, and the system undergoes a transition to the next stage. The decision variables in this problem are wind allocation fraction among charging stations, electricity sold back to the grid from the battery and direct charge, electricity purchased from the grid, demand satisfied by the battery and direct charge, and battery charging level.

The objective is to maximize profit or, equivalently, to minimize operational cost, which is the cost of buying from the grid minus the revenue from selling back to the grid and charging the PHEV both from the battery and the direct charge across all the stations. Following the timing of the electricity market, the system evolves in 15-minute time intervals. We consider a 24-hour time period. As a mean value problem, we assume that the forecasts are perfect. At each time period, each state variable is equal to its estimated value. The objective is given by equation (3):

$$\max \sum_{t\in T}\sum_{j\in J}\left(\tilde{B}_t(g_{tj}^- + R_{tj}) - \tilde{C}_t g_{tj}^+\right) + r_t\tilde{D}_{tj}\ , \tag{3}$$

where $\tilde{C}_t$ is the market selling price of energy in time period *t*, $\tilde{B}_t$ is the market buying price of energy in time period t, g_{tj}^+ is the electricity bought from the grid of station *j* in time period *t*, g_{tj}^- is the electricity sold back to the grid from the direct charge of station *j* in time period *t*, R_{tj} is the electricity sold back to the grid from the battery of station *j* in time period *t*, r_t is the retail price of energy in time period *t*, and $\tilde{D}_{tj}$ is the total demand in time period *t* at charging station *j*.

The first constraint set (4) includes the battery level transition from period *t*-1 to period *t* for each station *j*:

$$I_{t,j} = I_{(t-1),j} + BC_{tj} - \frac{R_{tj}}{e_j} - \frac{D_{tj}^{\ 2}}{e_j} \qquad \forall j\in J, \forall t\in T\ , \tag{4}$$

where I_{tj} is the battery level of station *j* at the beginning of time period *t*, BC_{tj} is the battery Charge of station *j* in time period *t*, $D_{tj}^{\ 2}$ is the demand satisfied by the battery of station *j* in time period *t*, and e_j is the storage efficiency of station *j*. In our computational results, we assume that the storage efficiency e_j is 79.8% [11].

The second constraint set (5) includes the energy balance for the battery charge at each station.

$$BC_{tj} = \tilde{W}_t W_{tj} + \tilde{S}_{tj} + g_{tj}^+ - g_{tj}^- - D_{tj}^{\ 1} \quad \forall j\in J, \forall t\in T\ , \tag{5}$$

where W_{tj} is the fraction of wind allocated to station *j* in time period *t*, $\tilde{W}_t$ is the total wind purchased in time period *t*, $\tilde{S}_{tj}$ is the solar production of station *j* in time period *t*, $D_{tj}^{\ 1}$ is the demand satisfied by the direct charge of station *j* in time period *t*.

The total demand consists of the demand satisfied by direct charge and demand satisfied by the battery as shown in constraint set (6).

$$\tilde{D}_{tj} = D^1_{tj} + D^2_{tj} \qquad \forall j \in J, \forall t \in T \tag{6}$$

The combination of electricity sold back to the grid from the battery and demand satisfied by the battery together is less than or equal to the discharge rate (*dc*) multiplied by the storage efficiency, as shown in constraint set (7).

$$R_{tj} + D^2_{tj} \le dc * e_j \qquad \forall j \in J, \forall t \in T \tag{7}$$

The battery charge must not be greater than the charge rate (*cr*), and the battery level must be constrained in between the minimum battery level and the battery capacity for each station, as in constraints (8) and (9), respectively.

$$BC_{tj} \le cr \qquad \forall j \in J, \forall t \in T \tag{8}$$

$$Unit\_Min_j \le \mathrm{I}_{tj} \le \ Unit\_size_j \quad \forall j \in J, \forall t \in T \tag{9}$$

The battery level at the last stage is assumed to be equal to the first stage.

$$I_{T,j} = I_{1,j} \ \forall j \in J \tag{10}$$

The fraction of wind allocation, constraint in equation (11), is constructed to allocate the total wind production to each station. Lastly, the set of nonnegative constraints is given in (12).

$$\sum_{j \in J} W_{tj} = 1 \qquad \forall t = 0,1,... \tag{11}$$

$$I_{tj}, W_{tj}, g^+_{tj}, g^-_{tj}, BC_{tj}, R_{tj} \quad \ge \quad 0 \quad \forall j \in J, \forall t \in T \tag{12}$$

As an initial solution analysis, the mean value problem is formulated as a deterministic linear program to provide insight into the behavior of the system.

IV. Mean Value Problem Results

The result from Matlab solving the mean value problem of control for 5 PHEV charging stations over 96 15-minute time periods are described in this section. PHEV charging demand profile in 2012 from [2] is used (including demand in Tarrant, Ellis, Dallas (only Garland area), Collin and Denton). In this model, we assume that we have a contact with wind farm (e.g. 30% of wind energy production) and we do not include this cost in the objective function. This simulation is based on January 2012, and the average retail sale price of electricity in the transportation sector in Texas is 10.17 cents per kilowatt-hour [20]. The maximum and minimum battery capacities are 3.6 and 0.72 MWh per slot. The charging rate and discharging rates are 0.6 and 0.075 MWh per slot. In this simulation, we assume that there is only 1 slot per each station.

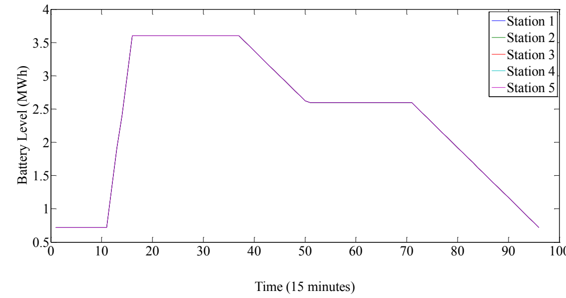

Figure 6. Battery level

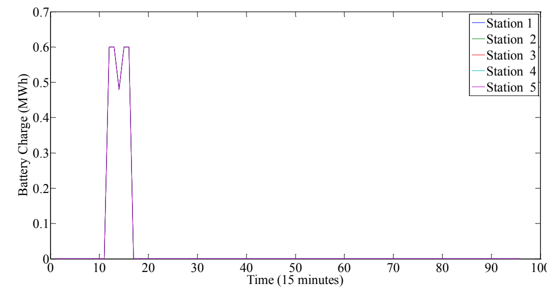

Figure 7. Battery charge

Figure 6 shows that battery level starts to increase at t =12 and reach the maximum level at t = 16. After that, it stays constant until t = 38, and it starts reducing until it t = 71. Then, it reduces again until reaching the minimum at the end of time period. All stations have the same battery level. The battery charge is close to 0 in all time periods, except time periods 11 to 16 as shown in Figure 7. Due to a low market price, shown in Figure 11, the system increases the battery level even if there is a little demand in the system at that time. At t = 14, there is a drop due to a little change in market price. All stations have the same battery charge.

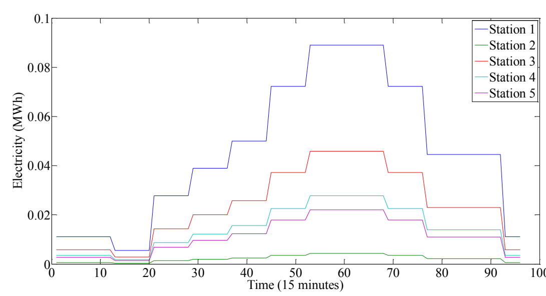

Figure 8. Total demand

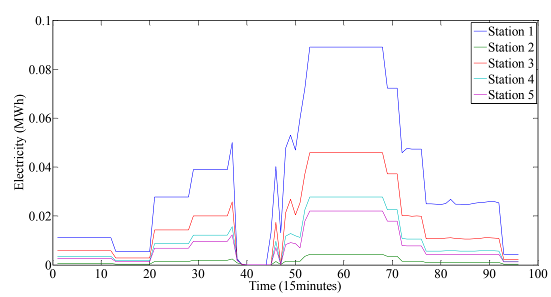

Figure 9. Demand pulled from the direct charge

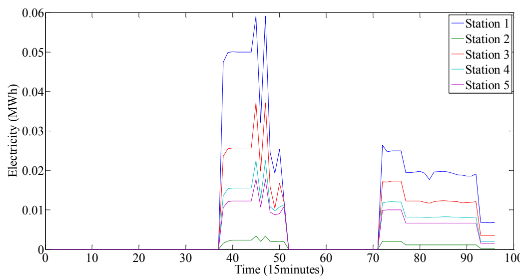

Figure 10. Demand pulled from the battery

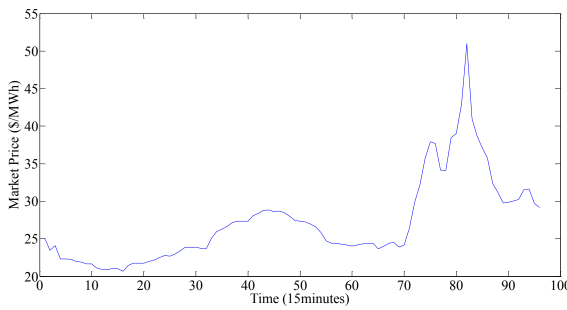

Figure 11. Energy market price

In this system, there are two ways to serve the total demand. The first way is by the direct charge, as shown in Figure 9. The other way is by the battery, which is shown in Figure 10. Since the beginning of time period, the demand is satisfied by direct charge until timer period t = 38. At that time, the market price is increased. Thus, the system takes advantage by serving the demand by some energy stored in the battery. At time period t = 52, the market price is reduced and the demand is supplied by the direct charge again. At time period t = 71, the peak market price occurs. Thus, the system decides to serve the demand by energy stored in the battery as much as it can. However, due to the limit on charging rate and the amount of electricity in the battery, the system still needs to serve some demand through direct charge. The total demands at each station are 17.8, 0.871, 9.166, 5.566 and 4.398 MWh, respectively.

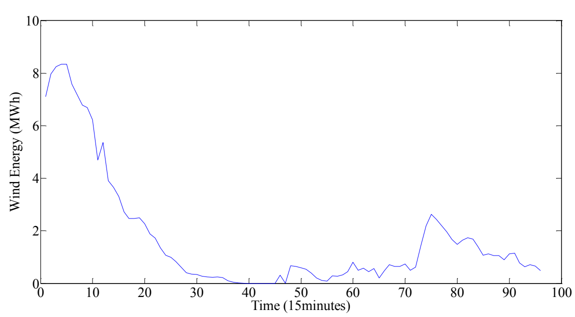

Figure 12. Total wind purchase to the system

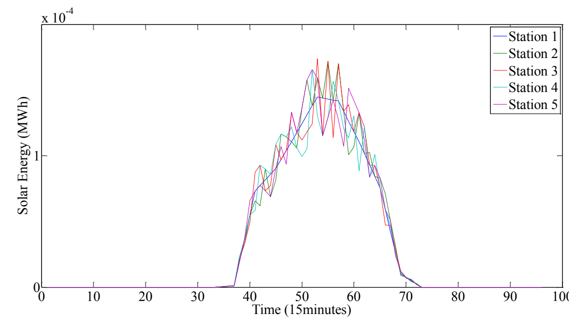

Figure 13. Solar generation

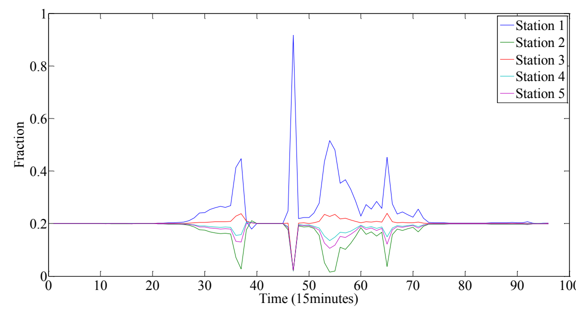

Figure 14. Wind fractional allocation

From Figure 13, solar generation has little impact on the system. The electricity sold is mainly generated by wind power, see Figure 12. Figure 14 shows the allocation of wind generation to each station. The system mainly allocated wind energy to station 1 where the highest demand occurs.

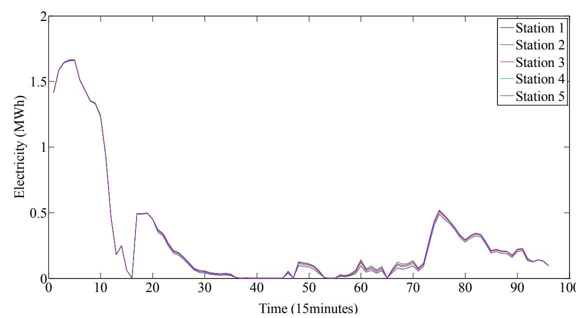

Figure 15. The electricity sold from direct charge

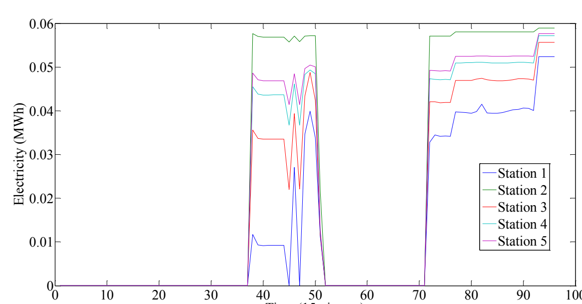

Figure 16. The electricity sold from battery

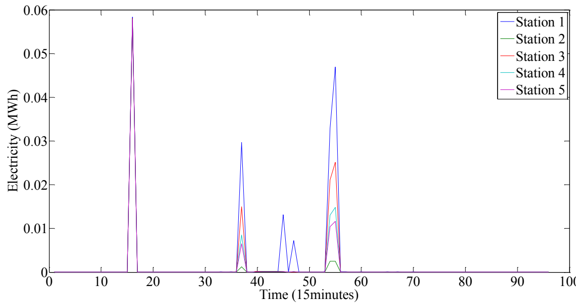

Figure 17. The electricity bought from the power grid

The electricity sold back to the grid from direct charge is similar to the total wind energy purchased to the system, except in time periods between 11 and 16 when the low market price occurs, Figure 15. The system decides to sell some energy from the battery back to the grid when the market price is high. However, the demand must be satisfied first. Thus, sometime when we have some demand in the system but the direct charge energy is not enough, it is necessary to purchase some energy from the grid even if the market price is not low, Figure 17.

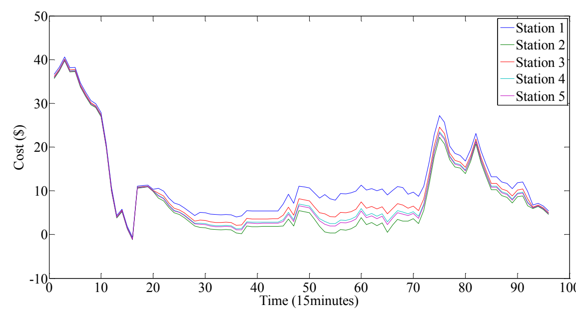

Figure 19. The objective function output

The objective function is calculated by equation (3) with 5 stations and 96 time periods. The maximum profit over the 96 time periods is $4933.7

V. Conclusions and Future Work

The mean value problem is formulated as a deterministic linear program and solved for solution analysis. The potential policies are presented to provide understanding into the behavior of the system. Results suggest that the system takes advantage of the low market price in the morning and uses direct charge from the wind and the grid to store energy in the battery before peak demand occurs. Once the system has satisfied all demand for the day, the remaining stored electricity is sold back to the grid at the peak market price. It is beneficial to use the direct charge from the wind, the utility grid, and solar to supply demand.

In future work, this problem will be formulated as an infinite-horizon stochastic dynamic programming considering many time periods.

Acknowledgment

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VI. BIOGRAPHY

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Wei-Jen Lee (S'85-M'85-SM'97-F'07) received the B.S. and M.S. degrees from National Taiwan University, Taipei, Taiwan, R.O.C., and the Ph.D. degree from the University of Texas, Arlington, in 1978, 1980, and 1985, respectively, all in Electrical Engineering. In 1985, he joined the University of Texas, Arlington, where he is currently a professor of the Electrical Engineering Department and the director of the Energy Systems Research Center. He has been involved in research on power flow, transient and dynamic stability, voltage stability, short circuits, relay coordination, power quality analysis, renewable energy, and deregulation for utility companies. Prof. Lee is a Fellow of IEEE and registered Professional Engineer in the State of Texas.

Victoria C. P. Chen is Professor and Interim Chair of Industrial and Manufacturing Systems Engineering at The University of Texas at Arlington. She holds a B.S. in Mathematical Sciences from The Johns Hopkins University, and M.S. and Ph.D. in Operations Research and Industrial Engineering from Cornell University. Dr. Chen is actively involved with the Institute for Operations Research and Management Science (INFORMS), having co-founded the INFORMS Section on Data Mining, and served as officers for the Section on Data Mining and Forum for Women in OR/MS. She is currently serving on the INFORMS Subdivision Council. Dr. Chen is a guest editor for the Annals of Operations Research and an associate editor for the journal Elementa: Science of the Anthropocene. Dr. Chen's research utilizes statistical perspectives to create new decision-making methodologies that accommodate the uncertainty and complexity of real world problems. She has expertise in the design of experiments, statistical modeling, and data mining, particularly for computer experiments and stochastic optimization.

Piampoom Sarikprueck (S'11) received the B.Eng and M.Eng degrees from King Mongkut's Institute of Technology Ladkrabang (KMITL), Bangkok, Thailand in 2002 and 2005, respectively. Since 2005, he has been a lecturer in the Electrical Engineering Department at KMITL. Currently, he is on sabbatical leave as a Ph.D student in the Energy Systems Research Center at the University of Texas at Arlington in Arlington, Texas USA. His research areas of interest include energy conversion technologies, power systems, renewable energy application, PHEV charging infrastructure and energy forecasting.