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Analysis of A Next Generation Energy System Based on the Integration of Transportation Subsystem Details

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ANALYSIS OF A NEXT GENERATION ENERGY SYSTEM BASED ON THE INTEGRATION OF TRANSPORTATION SUBSYSTEM DETAILS

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To my beloved parents and sister for always supporting my choices

And my wonderful husband for always being there for me

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ABSTRACT

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As the economy continues to grow, the current energy system will need to meet the increasing demand, especially in the developing countries. The depletion of fossil fuels, the surge in energy use, and the growing threat of climate change require rapid development of next-generation energy system. Renewable energy, such as wind, solar, and biomass, will undoubtedly play an important role, as a result of improved technology and enhanced capability in energy storage. For example, the closer integration of transportation to the energy system through vehicle electrification will have an increasing effect on the trajectory of the energy system. In order to gain a deeper understanding of the future energy system, anticipate potential problems during the evolution, and provide constructive suggestions for policy makers, a systematic analysis of the next generation energy system is highly desirable.

In general, the energy system consists of an energy demand sector and an energy supply sector. In this study, both supply and demand sectors are analyzed. For the energy demand sector, Electric Vehicle (EV) battery lifespan is quantified through an integrated battery aging model and a microscopic traffic network simulation model. Beyond EV battery lifespan, solar photovoltaic (PV) systems have also been studied in this research.

A distributed solar PV system model has been built for both research and educational purposes. Using this model, a benefit-cost analysis is applied to evaluate the impacts of combined tax breaks from depreciation and interest paid on home-equity loans on competitiveness under different purchase options for a 4 kW solar PV system in California. For the energy supply sector, this study sets out to investigate the effects of high penetration of renewable generators (wind and solar) on the supply-side of electricity market, particularly on electricity prices and carbon emissions.

CHAPTER 1. INTRODUCTION

With the depletion of fossil fuels, the surge in energy use, associated unpredictable market effects, and the increasing threat of climate change, developing a next generation energy system becomes much more significant than ever. Renewable energy, undoubtedly, will play a significant role in the next generation energy system, since it involves far less pollution compared with fossil fuels, and it is unexhausted with diverse sources. Many governments have made policies to promote the development of renewable energy. For example, California is committed to provide 33% of its electricity by 2020 from qualifying resource such as wind, solar, geothermal, biomass, and small hydroelectric facilities[1]. Germany sets its targets for renewable energy by 27% of electricity by 2020 and at least 45% by 2030[2]. Japan has set renewable targets of between 25%-35% of total power generation by 2030[3].

The transportation sector is an important part of energy system which demands the majority of fossil fuels. It counts for about 70% of the total oil consumption in the US[4][5]. With petroleum prices fluctuated, oil dependency, and large CO2 contribution of conventional vehicles, Electrical Vehicles (EVs) have been introduced to the commercial marketplace to provide alternative [6][7]. Electric drive vehicle technology has been available for several decades [8]. With the advances of material science and continued engineering of rechargeable batteries, and the commercialization of combined hybrid electric-combustion drive vehicles, electric drive vehicle technology will play an important role in powering the light vehicle transportation system. Currently, the electric drive vehicle is in two main configurations, pure electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs). The main difference is that PHEVs contain a backup power source, typically gasoline that can help provide propulsion, while EVs only use electricity as power source [9]. The market share of EVs/PHEVs is increasing in recent years. According to ORNL's (Oak Ridge National Laboratory) study, PHEVs would account for 2.5% of all new vehicles sales in 2015 in the US[10].

However, there are still many challenges for the adoption of both renewable energy and EVs. Take renewable energy as an example, the electricity generated from solar and wind is highly variable related to weather changes. This variability will affect the stability of the existing power grid if integrating solar and wind directly. Large scale energy storage device is one possible solution to the variability of renewable electricity [11]–[13], but the high cost of battery is still one main obstacle for this solution. As for EVs, driving distance per charge, charging time, battery life, and charging infrastructures are all big concerns that affect EV adoption. These challenges are interdisciplinary problems, which involve the area of chemical engineering, civil engineering, mechanical engineering, industrial engineering, and even computer science. The analysis of these problems should not only focus on one area, but integrate all these areas and make an interdisciplinary study with different departments' collaboration.

Therefore, the objective of this thesis is to conduct an interdisciplinary study on the potential problems during energy system evolution using model-based method. Model-based investigation enables efficient and economical studies on these solutions. The collaboration with different departments will provide better understanding of the identified problems and the proposed solutions, and also provides constructive suggestions for policy makers to develop proper strategies to apply these solutions.

1.1 Energy Demand Sector

In general, the energy system consists of an energy demand sector and an energy supply sector. In this study, both supply and demand sectors are analyzed. For the energy demand sector, electric vehicles (EVs) are considered as a promising alternative to the conventional vehicles. Several commercialized EVs have already been in the market for a few years now. However, greater adoption of EVs still faces several challenges, among which is the concern about lifetime of EV batteries due to degradation. Lifespan information of populations of EV batteries is still scarce. Understanding the lifespan characteristics of EV batteries is significant for EV adoption, vehicle resale, and battery warranty strategy design. This study quantifies how different EV usage patterns affect EV battery lifespans with the collaboration of research groups from chemical engineering, civil engineering, and mechanical engineering. Real world household vehicle travel information is extracted from the National Household Travel Survey (NHTS) database. A micro-level transportation model based on the Indianapolis network is built to generate realistic drive cycle data. The household vehicle usage pattern information is then obtained by matching the travel information with drive cycles. A semi-empirical battery aging model is used to predict battery lifespan for a large simulated population of vehicle usage patterns. The simulated results show that both temperature and driving behaviors have great impacts on battery life. As temperature increases, battery life decreases, and the variation of battery life also decreases. As travel distance increases, battery life decreases, but eventually approaches a constant after certain distance point. This study can provide a good reference for battery warranty strategies to EV companies.

Beyond EV battery lifespan, solar photovoltaic (PV) system has also been studied in this research. The residential use of small-scale solar generators in the U.S. has been steadily rising in recent years, which will potentially affect the electricity demand profiles. In this study, a distributed solar PV system model has been built for both research and educational purposes. The model can simulate household's electricity demands for solar PV and energy storage device all over the world. To maximize applicability and interest, the simulation tool allows users to customize electricity demand to match household's characteristics, change weather assumptions, select system location, and vary the solar module area and energy storage capacity. The model has been applied to one graduate course and two undergraduate courses to teach students about solar PV systems. In order to expand availability and potential use, a refined user interface has been created and the tool has been published online on NanoHub. The tool is named as "SolarPV" and can be accessed at: https://nanohub.org/tools/solarpv [14]. To date, the tool has already been used in 10 different countries or regions across the world since published. Moreover, by using this model, a benefit-cost analysis is applied to evaluate the impacts of combined tax breaks from depreciation and interest paid on home-equity loans on competitiveness under different purchase options for a 4 kW solar PV system in California. The results indicated that the additional tax breaks from depreciation in conjunction with those from interest paid on home-equity loans can make purchasing much more competitive.

1.2 Energy Supply Sector

For the energy supply sector, many countries have instituted various policies and targets for the adoption of renewable generators. However, these policies, while effective in increasing renewable penetration, may distort market forces or even disrupt the stability of the energy market. In order to systematically evaluate renewable energy effects, a detailed energy system model based on the city of Singapore is developed to investigate the effects of high penetration of renewable generators (wind and solar) on the supply-side of electricity market. Both marginal electricity prices and carbon emissions are quantified for three different penetration scenarios of wind and solar: a scenario of only wind capacity, a scenario of only solar, and a balanced mix of wind and solar energy sources. It was assumed that the effect of generators' capacity factor (the ratio of its actual output over a period of time, to its maximum possible output if it were operated at full nameplate capacity) was considered when calculating bid prices. When low capacity factors for generators force units to bid at prices that are above the allowed price caps, the generators are assumed to be retired from the system. The loss of some of these dispatch-able generators could amplify market effects during exceptional events. The simulation results reveal that the wind and solar generation affect the assumed electricity system very differently. In general, wind generation would reduce carbon emissions more than solar energy sources with similar effective capacity. However, wind energy increases marginal electricity prices more than equivalent solar capacities, because wind energy contributes a higher degree of uncertainty. It was interesting to note that from a system perspective, renewable energy resources should be favored differently for different system objectives.

CHAPTER 2. QUANTIFYING EV BATTERY LIFESPAN AND ITS IMPACT ON BATTERY WARRANTY STRATEGY THROUGH AN INTEGRATED BATTERY AGING MODEL AND A MICROSCOPIC TRAFFIC NETWORK SIMULATION MODEL

This chapter is based on a manuscript that has been submitted to the Journal of Power Sources. This paper is done in collaboration with the school of Civil Engineering and the school of Mechanical Engineering at Purdue University. The coauthors on this manuscript are Shubham Agrawal, Xing Jin, Ashish Vora, Gregory Shaver, Srinivas Peeta, James Dietz and Joseph Pekny. This chapter quantifies how different EV usage patterns affect EV battery lifespan. Real world household vehicle travel information is extracted from the National Household Travel Survey (NHTS) database. A microscopic traffic simulation model for the Indianapolis road network is built to generate realistic drive cycle data. Then the household vehicle usage pattern information is obtained by matching the travel information with drive cycles. A semi-empirical battery aging model is used to predict battery lifespan for a simulated population of vehicle usage patterns based upon the NHTS data.

2.1 Introduction

The transportation sector is an important component of energy consumption. It accounts for about 70% of the total oil consumption in the US[15] [16]. Conventional vehicles use liquid fossil fuels as their energy sources, and become the largest contributors to urban air pollution as well as to anthropogenic greenhouse gas emissions [17]. In 2013, greenhouse gas emissions from transportation accounted for about 27% of total U.S. greenhouse gas emissions, making it the second largest contributor of U.S. greenhouse gas emissions after the electricity sector [18]. With the fluctuation of petroleum prices and the large CO_2 contribution of conventional vehicles, Electric Vehicles (EVs) have been introduced to the commercial marketplace to provide an alternative. Because EVs have no tailpipe emissions, they use electricity for propulsion, and electricity can be generated from renewable energy, a population of EVs can become non-CO2 emitting as the generation mix evolve. Significantly EVs provide large scale experience in electric energy storage which drives innovation. However, the greater adoption of EV still faces several substantial challenges. These include range anxiety/short range between charges, availability of charging infrastructure, the potential impact on power grid stability, higher vehicle price, and concerns about useful battery life due to degradation [19][20]. This paper is focused on predicting useful battery life under realistic use conditions.

The majority of EVs in the market use a Li-ion battery pack with an energy capacity of around 20 kWh. For example, the battery pack energy capacity for the Nissan leaf is 24 kWh, Honda Fit EV is 20 kWh, Ford Focus Electric is 23 kWh, and Smart EV is 17.6 kWh. The energy capacity of a battery peak degrades with time and usage [21]–[26]. As the energy capacity decreases, the vehicle range drops. An often stated common criteria is that the battery should be retired from the vehicle application if its capacity has depleted to 70-80% of its original capacity [19][24]–[26]. The replacement of a battery pack poses significant cost to vehicle owners, though batteries can be resold and utilized for other applications such as renewable energy storage[27]–[29]. Under this common replacement criterion, a well-designed battery warranty strategy is very important for EV adoption. However, for the current commercialized EVs in the market, only the Nissan Leaf has a battery capacity warranty. Under this warranty, Nissan will repair or replace a Leaf's battery within five years or 60,000 miles if it loses more than 30 percent of its energy capacity [30]. Other EV battery warranties do not include regular capacity degradation. Therefore, quantifying EV battery lifespan for a large population of EVs is very important for vehicle manufacturers, car owners, and battery researchers seeking to support practical applications.

Battery degradation mechanisms are an important consideration to explore EV battery lifespan. Two types of degradation/aging mechanisms are significant: during storage (calendar aging) and during use (cycle aging). Calendar aging is due to side reactions resulting from thermodynamic instability of active materials, while cycle aging results from kinetic effects, such as structural disordering, or concentration gradients [25]. In past work, the total aging effect is considered as the summation of calendar aging and cycle aging, but interactions may occur [25], [31], [32]. Battery aging mainly happens at the two electrodes: anode (e.g. graphite) and cathode (e.g. lithium metal oxide). Aging mechanisms occurring at anodes and cathodes are significantly different. Most researchers believe that changes to the Solid Electrolyte Interphase (SEI) due to reactions of the anode with the electrolyte are the major source for aging at the anode [24], [33]. Unlike the anode, the cathode can be made using different types of metal oxide materials. Different materials have quite different effects on battery life, and the mechanisms of capacity fade at the cathode are not completely understood. Moreover, battery aging is induced by various processes and their interactions, and most of them cannot be studied independently [24]. Due to the complexity of the Lithium-ion battery system, some researchers have created semi-empirical battery life models for specific Li-ion battery chemistries based on experimental data. For example, Wang et al. developed a cycle-life model for graphite-$LiFePO_4$ cells based on a cell test experimental matrix [23]. Using similar method, Wang et al. created another refined battery life estimation model for graphite-$LiMn_{1/3}Ni_{1/3}Co_{1/3}$+$LiMn_2O_4$ (graphite-NCM+LMO) battery cell [22]. This model successfully represents both calendar life and cycle life. They also developed a chemical-mechanical degradation model at the micro-level [21]. Lee et al. did similar work for graphite-$LiNi_{0.6}Co_{0.2}Mn_{0.2}O_2$ cell and created a semi-empirical model [34]. Thomas et al. built a degradation model and an error model using a statistical method based on experimental data [35].

Using the aforementioned battery life estimation models, some researchers have studied the battery lifespan for EVs/PHEVs (Plug-in Hybrid Electric Vehicle). For example, Guenther et al. studied the EV battery lifespan for different charging behaviors and drive cycles scenarios [36]. Marano et al. explored the battery life for PHEV under different drive cycles [37]. However none of these studies use realistic drive cycles for a population of vehicles for a given metropolitan region. Guenther et al. use three fixed drive cycles. Marano et al. combines three standard drive cycles (UDDS, US06, and HWFET) in four scenarios. Other researchers applied standard drive cycles by either repetition or combination. As shown in our study results, driving behavior has a significant impact on battery life. Using standard drive cycles is useful under a variety of considerations, but does not represent the variation in driving behavior and traffic conditions. Hence realistic drive cycles are required for studying EV battery lifespan, insight on the economics of batteries, and to provide targets for researchers seeking to improve battery technology.

This study quantifies EV battery lifespan for a significant population of EVs through a semi-empirical battery aging model [22] and a microscopic traffic simulation model. Realistic drive cycles are generated from the Indianapolis road transportation network because there is good data for Indianapolis. Five different temperature scenarios are examined. The results provide a foundation for EV battery warranty design.

2.2 Methodology

A multi-paradigm modeling approach provides the flexibility to study the lifespan characteristics of a population of EVs. It enables different systems to be simulated with the most suitable modeling methods. Population behavior for a transportation network is addressed using building blocks, each of which represents a relevant set of phenomena. By building up theses blocks together, the whole system can be simulated and investigated in a holistic manner. This paper considers four different building blocks: a microscopic traffic network simulation model which provides realistic drive cycles for thousands of vehicles, an EV energy consumption model which provides power demand results under different drive cycle conditions, a battery circuit model which converts power demands to current flows, and a semi-empirical battery degradation model which simulates battery lifespan based on current flows and temperature.

In the microscopic traffic network simulation model, vehicle trips from the National Household Transportation Survey 2009 (NHTS) database are combined to provide drive cycles that reflect traffic conditions. The drive cycle data is then fed into the EV energy consumption model to simulate power profiles. The simulated power profiles are then fed as inputs to the battery circuit model to obtain current data. In the end, the current data is fed into the battery aging model to simulate EV battery life. Figure 2.1 shows a simplified flowchart of the methodology framework.

2.2.1 Household Vehicle Usage Patterns

Usage patterns affect vehicle health. For EVs, travel distance, travel speed, and vehicle acceleration and deceleration all impact battery health. In this study, real household vehicle daily travel information is extracted from the NHTS database to represent household vehicle usage patterns. This information records trip start time, end time, trip distance, etc., however there is no detailed drive cycle information (i.e. speed vs. time data) for each trip. In order to get speed vs. time data, a microscopic traffic network simulation model has been built based on the city of Indianapolis. This model can generate realistic drive cycles for all the vehicles traveling in the network. Specifically, the drive cycles are matched with each vehicle trip from the NHTS database to obtain the whole household vehicle daily usage patterns.

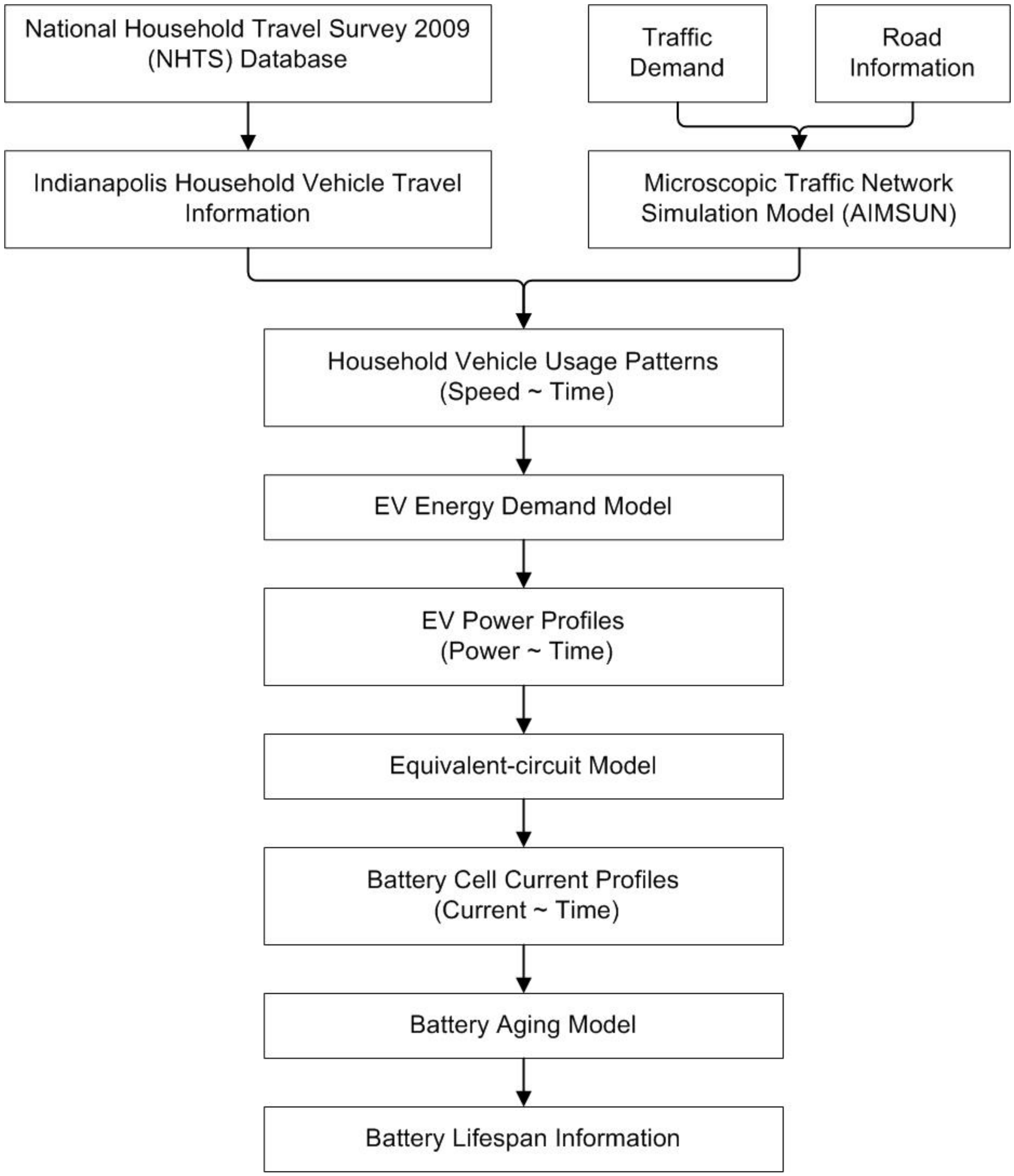

Figure 2.1 Flowchart of framework used in this study

2.2.1.1 Household Vehicle Travel Information

The NHTS 2009 provides a survey of daily trip profiles of 150,147 random households across the United States[38]. The database includes car type, trip start and end time, trip distance, trip origin, trip destination, household location, etc. Among the 150,147 households, 4,350 are from the state of Indiana. This study extracts all of the 2,832 samples which are from Indianapolis urban and suburban areas to represent Indianapolis households. Considering the range of EVs, only samples with daily travel distance less than or equal to 80 miles are selected, resulting in 2,306 (about 81% of 2,832) representative samples of household vehicles. Table 2.1 provides an example of the extracted vehicle travel information from the NHTS database. Each row in Table 2.1 represents a single trip for the example vehicle. The daily travel distance for this vehicle (30 miles) is the summation of all four trips. Figure 2.2 shows the histogram of daily travel distance for the 2,306 selected samples.

Table 2.1 Example of vehicle travel information for a randomly selected vehicle extracted from the NHTS 2009 database.

Vehicle ID	Start time	End time	Distance	Trip from	Trip to	Freeway
26469456_01	16:15	16:35	8	home	buy services	N
26469456_01	16:45	17:00	8	buy services	home	N
26469456_01	17:25	17:42	7	home	religious activity	N
26469456_01	18:42	19:00	7	religious activity	home	N

Since only samples with daily travel distance less than or equal to 80 miles are selected, the maximum daily travel distance is 80 miles. About 70% are below 30 miles and 90% are below 50 miles. By comparison, for the 150,147 household samples in the NHTS, about 90% of the samples' daily travel distance is below 80 miles. For all the samples below 80 miles, 65% are below 30 miles and 86% are below 50 miles. Compared with the total data sample, the selected Indianapolis sample is consistent.

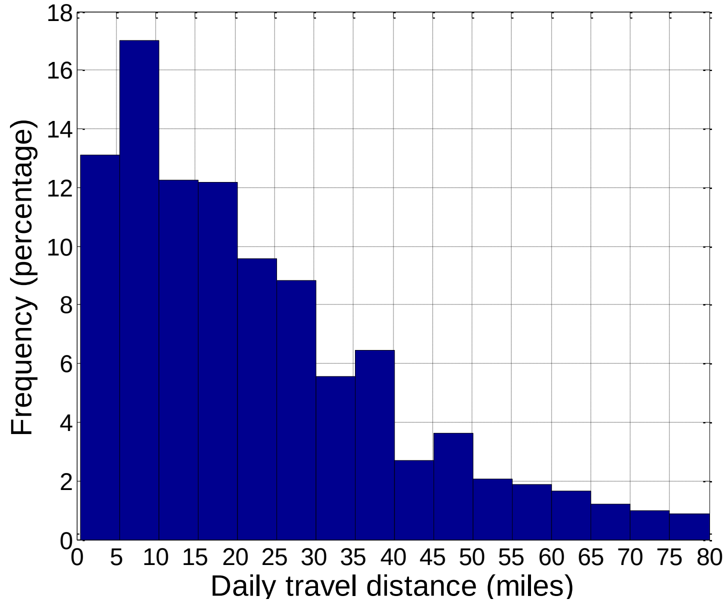

Figure 2.2 Daily travel distance histogram of the selected 2306 vehicle samples

2.2.1.2 Microscopic Traffic Network Simulation Model

Traffic simulation techniques are commonly used to capture the interactions between vehicles as well as between vehicles and infrastructure at a microscopic level. A microscopic simulation model uses various models such as car-following, lane-changing, route choice, etc. to mimic real-world conditions. In this study, detailed drive cycles of vehicles are required to compute the battery life of EVs. The traffic network simulation software AIMSUN is used to generate realistic drive-cycles of the vehicles at the microscopic level. A detailed road network of Indianapolis is developed in AIMSUN. The network contains all the freeways, most of the urban roads and some minor roads as shown in Figure 2.3. The traffic is simulated in AIMSUN for a 24-hour period with a discrete origin-destination (O-D) demand aggregated at 15-minute intervals. The traffic demand level is calibrated based on the NHTS data of the city of Indianapolis in 2009.

In AIMSUN, vehicles are assigned to specific routes based on distance and road-type. The trip data for each vehicle from the 2306 samples is obtained by matching to a specific trip in the network based on the trip departure time, distance, trip purpose, and freeway route indicator. The trip departure time and trip distance are the primary parameters used for matching. From these, the trip end time will be determined automatically as the drive cycle is generated by the network. The trip purpose is used to assign route towards the downtown area or the sub-urban area, and the freeway route indicator is used to check whether the trip uses the freeway. A Python program is developed to gather the drive-cycle data from AIMSUN for specific vehicles that match the 2306 samples of trip profiles based on the above criteria. Therefore, each trip has a unique drive cycle generated from the Indianapolis network. The first plot in Figure 2.4 shows an example of the vehicle drive cycle information.

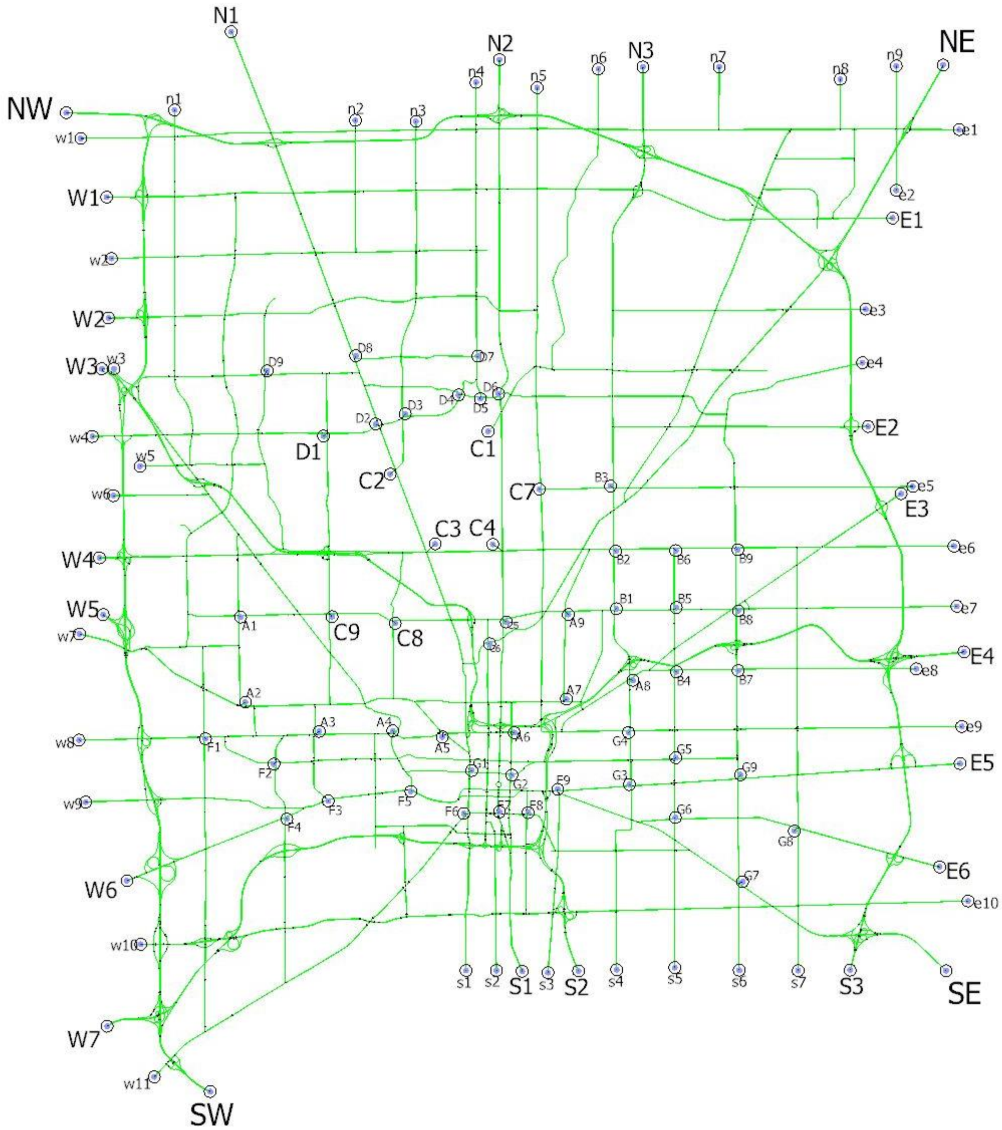

Figure 2.3 Indianapolis road network

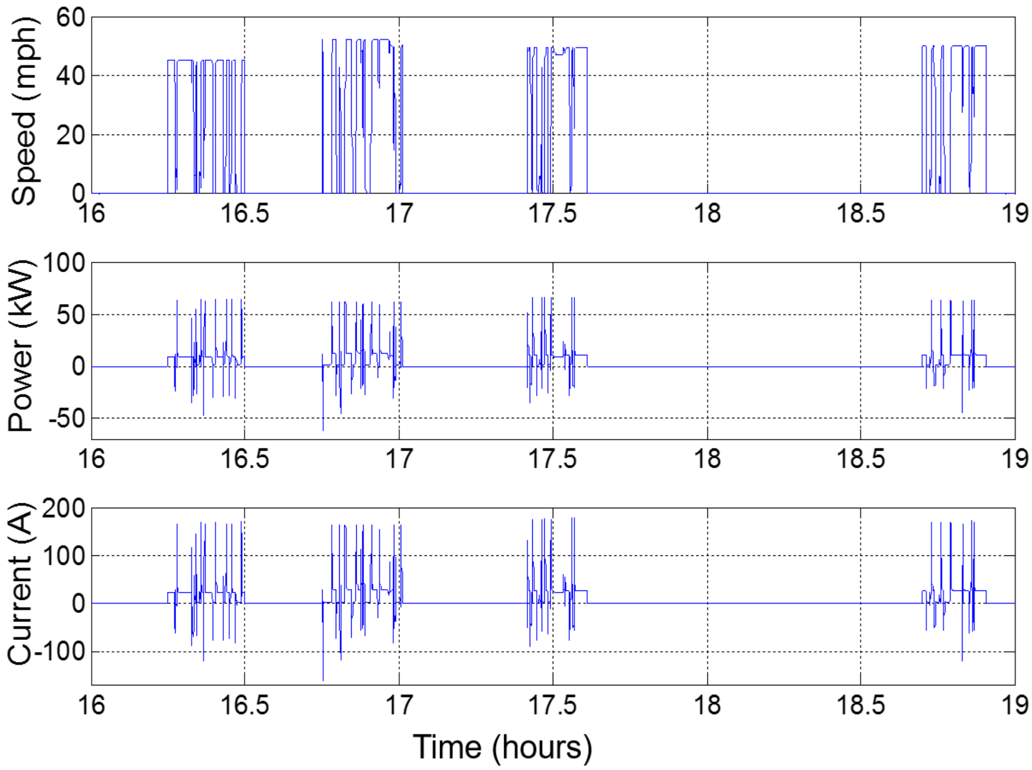

Figure 2.4 Drive cycle profile of the vehicle sample in Table 2.1 and its corresponding power profile and battery pack current profile

2.2.2 EV Energy Consumption Model

Vehicles consume energy differently when following different drive cycles. There are several models or simulation tools that can simulate EV energy consumptions based on the drive cycle data. For example, ADVISOR and Autonomie [39], [40] can simulate an EV's power profile, MPGe (mile per gasoline equivalent), state of charge (SOC) profile, etc. for any given drive cycle. These tools simulate the detailed performance of the power train/propulsion systems, and hence are computationally expensive. A physical model focused on energy demand presented by Tesla Motor's CTO, JB Straubel is used in this study[41][42]. This approach is used because (1) the model illustrates the relationship between EV energy consumption and drive cycle, and (2) the runtime is significantly less compared with using a package like ADVISOR that simulates vehicle behavior details not needed for the objectives of this study.

In the physical model, the total energy consumption is composed of two parts. One is the energy loss that the vehicle needs to overcome to travel at any given constant speed. The other is the kinetic energy loss (or gain) during acceleration or braking. The first part can be further divided into 4 parts: power loss due to aerodynamics, P_{aer}, power loss for drive-train, P_{dr}, power loss for tires, P_{rr}, and power loss for ancillary systems, P_{anc}. These power losses can be expressed as equation (1-4). The definitions and values of the parameters are listed in Table 2.2.

$$P_{aer} = \frac{1}{2}\rho A C_d V^3 \quad (1)$$

$$P_{dr} = \alpha_{dr}V^3 + \beta_{dr}V^2 + \gamma_{dr}V + c_{dr} \quad (2)$$

$$P_{rr} = c_{rr}mgV \quad (3)$$

$$P_{anc} = 0.2\ to\ 2.2\ kW \quad (4)$$

Kinetic energy in the vehicle includes linear kinetic energy E_{lin} and rotational kinetic energyE_{rot}. Typically, rotational kinetic energy is only 5-10% of the total kinetic energy stored in a car. It is assumed that the total kinetic energy E_{kin} is 1.05 times the linear kinetic energy[41][42].

$$E_{kin} = E_{lin} + E_{rot} \approx 1.05 * E_{lin} \quad (5)$$

$$E_{lin} = \frac{1}{2}mV^2 \quad (6)$$

The energy loss during acceleration E_{acc} and energy recuperation E_{dec} during braking are:

$$E_{acc} = \frac{\Delta E_{kin}}{\beta_{eff}} \quad (7)$$

$$E_{dec} = \beta_{rbs} * \Delta E_{kin} \quad (8)$$

β_{eff} is the motor efficiency and β_{rbs} is the efficiency of power transfer from regeneration system to battery. Therefore, the total energy consumption for a drive cycle is:

$$E_{tot} = \sum E_{acc} + \sum E_{dec} + \int P_{aer} dt + \int P_{dr} dt + \int P_{rr} dt + \int P_{anc} dt \qquad (9)$$

The definition and the value used for each parameter are listed in Table 2.2. Using this model, the power versus time profiles for the 2306 vehicles are computationally cheaper to simulate because only what is needed is computed for the next step of the framework in Figure 2.1. The second plot in Figure 2.4 shows an example of the power profile generated using this model.

Table 2.2 Parameter definitions and values for EV energy consumption model [41][42]

Parameter	Definition	Value
C_d	Drag coefficient	0.29
ρ	Air density (kg/m^3)	1.2
A	Vehicle front area (m^2)	2.27
α_{dr}	Drivetrain coefficient 1	$4*10^{-6}$
β_{dr}	Drivetrain coefficient 2	$5*10^{-4}$
γ_{dr}	Drivetrain coefficient 3	0.0293
c_{dr}	Drivetrain coefficient 4	0.375
c_{rr}	Rolling resistance coefficient	0.0075
m	Vehicle mass (kg)	1520
g	Gravity (m/s^2)	9.81
β_{eff}	Battery to motor efficiency	0.85
β_{rbs}	Regeneration efficiency	0.4

2.2.3 Battery Model

Battery degradation rate is different at different C-rates[1], so the current profile is needed to simulate battery life. In this study, an equivalent-circuit model is used to represent the Li-ion battery cell as shown Figure 2.5 . This model enables the

[1] The C-rate is a measure of the rate at which a battery is being discharged. It is defined as the discharge current divided by the theoretical current draw under which the battery would deliver its nominal rated capacity in one hour. A 1C discharge rate would deliver the battery's rated capacity in 1 hour. A 2C discharge rate means it will discharge twice as fast (30 minutes) “A Guide to Understanding Battery Specifications, MIT Electric Vehicle Team, December 2008”

extraction of a cell current profile from each unique power profile. The internal resistance and open-circuit voltage of the cell are implemented as 1-d lookup tables based on instantaneous cell state-of-charge (SOC). The model is implemented as a Simulink block diagram representing equations (10-14). The definition and value used for each parameter are shown in Table 2.3. The third plot in Figure 2.4 shows an example of the battery pack current generated using this model.

$$V_{cell}(t) = V_{OC}(t) - I_{cell}(t) * R_{int}(t) \tag{10}$$

$$P_{cell}(t) = \frac{P_{batt}(t)}{N_{cell}} = V_{cell}(t) * I_{cell}(t) \tag{11}$$

$$V_{OC}(t) = f\big(SOC(t)\big) \tag{12}$$

$$R_{int}(t) = g\big(SOC(t)\big) \tag{13}$$

$$SOC(t) = SOC(0) + \frac{1}{AhCap} * \int_0^t \frac{I_{cell}(t)}{3600} dt \tag{14}$$

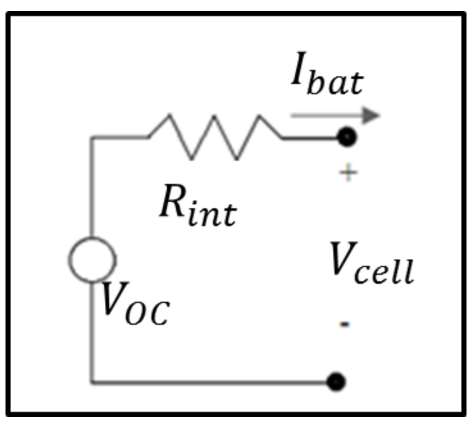

Figure 2.5 Schematic diagram of the equivalent-circuit model used in this study

Table 2.3 Parameter definitions and values for equivalent-circuit battery model

Parameter	Definition
V_{cell}	cell terminal voltage
V_{OC}	cell open-circuit voltage
I_{cell}	cell current
R_{int}	cell internal resistance
P_{cell}	electrical power out of the cell
P_{batt}	electrical power out of the battery pack
N_{cell}	number of cells in the battery pack
$SOC(0)$	initial state-of-charge
f , g	1-d lookup tables
$AhCap$	nominal ampere-hour capacity of the cell

2.2.4 Battery Degradation Model

Battery degradation causes capacity loss and impedance growth during operation and is also a result of storage. Operational degradation is called cycle aging, and storage degradation is called calendar aging. Calendar aging happens regardless of whether the battery is operated or not. It is mainly caused by the Li-ion loss during SEI formation at the graphite anode [22], and is strongly affected by two parameters: time and temperature. Cycle aging only happens when the battery is operating and there is current flow. The total battery energy capacity loss is the summation of these two effects.

Wang et al developed a semi-empirical model which includes three important experimental parameters: time, temperature, and discharge rate [22]. They performed experiments for 1.5 Ah, 18650 cylindrical cells and created a test matrix to measure each cell. The cell has a $LiMn_{1/3}Ni_{1/3}Co_{1/3}$ + $LiMn_2O_4$ (NCM+LMO) cathode and a graphite anode. They modeled both calendar aging and cycle aging using substantial experimental data. According to the results in their published paper in the Journal of

Power Sources, they suggest that under most conditions, the predicted values are within ±5% capacity loss of the measured values [22].

The model developed by Wang et al [22] used in this study is listed in equations (15-17). The coefficient values and units are listed in Table 2.4.

$$Q_{loss,\%} = Q_{loss,cycle} + Q_{loss,calendar} \tag{15}$$

$$Q_{loss,cycle} = (aT^2 + bT + c) \cdot \exp[(dT + e) \cdot I_{rate}] \cdot Ah_{throughput} \tag{16}$$

$$Q_{loss,calendar} = f \cdot t^{0.5} \cdot \exp(\frac{-E_a}{RT}) \tag{17}$$

The cycle aging model is for a given constant C-rate. In reality, it is not possible for an EV to operate at a constant battery C-rate, so the drive cycle is divided into small time windows, and the degradation in each window is calculated independently. The calculation is discussed in section 2.2.5.2.

Table 2.4 Coefficient values and units of the battery degradation model used in this study [22]

Coefficient values and units			
a	8.61E-6,1/Ah-K^2	I_{rate}	C-rate
b	-5.125E-3,1/Ah-K	t	Days
c	0.7629,1/Ah	E_a	24500,J/mole
d	-6.7E-3,1/K-(C-rate)	R	8.314,J/(mole K)
e	2.35,1/(C-rate)	T	K
f	14876,1/$day^{0.5}$		

2.2.5 Assumptions and Simulation

In this study, one type of EV is assumed to be used by all of the households. This EV, closely resembling a Nissan Leaf, has a 24kWh Li-ion battery. The battery is composed of 44 modules in parallel, where each module has 96 cells in serial, and each cell is 1.5Ah and 3.75 V. The cell has a NCM+LMO cathode and a graphite anode. Because a NCM+LMO composite cathode presents a good balance of both energy density and power density [22], [43], [44], it has been considered as a promising candidate for vehicle applications. The EV specifications are listed in Table 2.5.

Table 2.5 Specifications of simulated vehicles

Parameter	Value
Vehicle mass (kg)	1520
Total battery energy capacity (kWh)	24
Drag coefficient	0.29
Front area (m^2)	2.27
Ancillary load (kW)	1
Battery module No.	44
Battery cell No.	96*44
Battery chemistry	Li-ion with NCM+LMO cathode and C anode

2.2.5.1 Assumptions

The simulation of battery life in this study is based on the following assumptions:

First, the battery is considered unusable in vehicle applications when it has depleted to 70% of its original energy storage capacity. This is a common criterion in nearly all studies that EV batteries must be retired once they have reached 70-80% of their original energy storage capacity [19][24]–[26].

Second, the degradation model is applied to the entire temperature range experienced in Indianapolis (monthly average temperature from -2.2 ^{o}C to 24.1 ^{o}C). J. Wang et al performed experiments at 4 temperatures: 10^{o}C, 22 ^{o}C, 34 ^{o}C, 46 ^{o}C. This study assumes the model still applies at lower (but not extreme) temperatures.

Third, this study assumes that EVs are only charged at home with a level 1 (120V) or level 2 (240V) charger.

Fourth, the effects of home charging on battery energy capacity loss can be ignored. Level 1 and level 2 charging are both relatively slow. A 24kWh EV battery takes about 12-13 hours for a full charge on a level 1 charger, and 7-8 hours on a level 2 charger [45], which is equivalent to a 1/13 C-rate or 1/8 C-rate during charging. At such low C-rates, calendar aging is the dominant element that causes energy capacity loss. The energy capacity loss results from cycle aging at 1/8 C-rate at 20 ^{o}C for 8 hours is: 0.00066 %, while the capacity loss results from calendar aging at 20 ^{o}C for 8 hours is 0.37% for a new battery, and 0.0056% for a one-year battery[2]. In reality, a full charge barely happens. Most household vehicle daily trips are within 30 miles, and the energy consumption is less than half of the battery energy capacity. So most home charging events are less than 4 hours. Therefore, it is safe to ignore cycle aging effects on battery energy capacity loss during home charging.

Fifth, when the EV is running, regeneration has the same effects on battery energy capacity loss as discharging at the same C-rate.

2.2.5.2 Simulation

This study simulates 2306 household vehicle samples in Indianapolis. Each vehicle sample follows its unique usage pattern day by day. Five temperature scenarios are analyzed in this study: four constant temperature scenarios (10^{o}C, 15^{o}C, 20^{o}C, 25^{o}C) and one variable temperature scenario. The monthly average temperatures for Indianapolis are used in variable temperature scenario. Figure 2.6 shows the temperature profile of Indianapolis used in this study.

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[2] Since capacity loss due to calendar aging, $Q_{loss,calendar} = f \cdot t^{0.5} \cdot \exp(\frac{-E_a}{RT})$, is a non-linear function of time t, the calendar aging rate decreases as time passed, and becomes almost linear after one year.

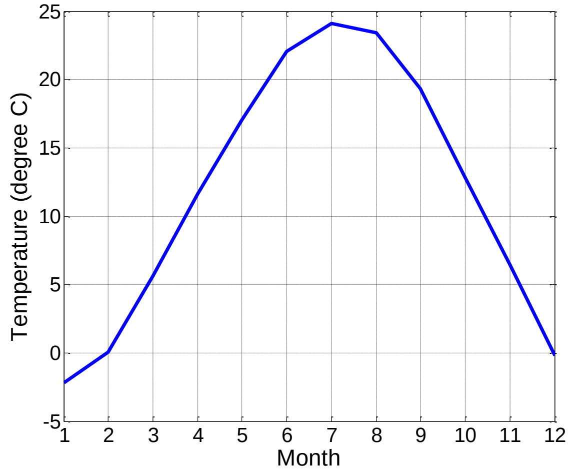

Figure 2.6 Indianapolis monthly average temperature

In simulation, battery energy capacity loss caused by cycle aging is calculated every second. For each second, the current is assumed to be constant, and the energy capacity loss can be expressed as the differential of $Q_{loss,cycle}$ at that time point. The total energy capacity loss of cycle aging is the summation of all the losses in each second.

$$D_{Q_{loss,cycle}} = (aT^2 + bT + c) \cdot \exp[(dT + e) \cdot I_{rate}] D_{Ah_{throughput}} \quad (18)$$

$$Q_{loss,cycle} = \sum D_{Q_{loss,cycle}} \quad (19)$$

Similarly, at variable temperature, capacity loss results from calendar aging can be expressed as:

$$D_{Q_{loss,calendar}} = 0.5f \cdot \exp(-\frac{E_a}{RT}) \cdot t^{-0.5} D_t \quad (20)$$

$$Q_{loss,calendar} = \sum D_{Q_{loss,calendar}} \quad (21)$$

The total battery energy capacity loss is the sum of cycle aging loss and calendar aging loss, which is updated every day until it is greater than 30%. The final time (in days) is the battery life.

2.3 Results and Discussions

The simulation results of EV battery lifespan of the 2306 samples for different temperature scenarios are presented and discussed in the following paragraphs.

2.3.1 Battery Life Distribution

In this study, each EV follows its unique drive cycles every day. Some EVs may have 6 trips every day, and others only have one trip per day. Both travel distance and driving behavior affect battery lifespan. A distribution functions provide a global picture of the battery lifespan.

2.3.1.1 Battery Life Distribution at Four Constant Temperature

Temperature affects both calendar aging and cycle aging. Figure 2.7 shows the simulated battery life histogram at 4 constant temperatures. The results indicate that the EV battery lifespan is (8.58±1.80) years at 10^{o}C, (7.33±0.73) years at 15^{o}C, (5.73±0.19) years at 20^{o}C, and (4.20±0.06) years at 25^{o}C. The EV battery life decreases as temperature increases. At higher temperatures, the battery degrades faster than at lower temperatures. The variation of EV battery life also decreases as temperature increases. The reason is that at higher temperatures, calendar aging is the dominant element that affects battery life, and all EVs are at the same environmental temperature. So at higher temperatures, the variation is smaller.

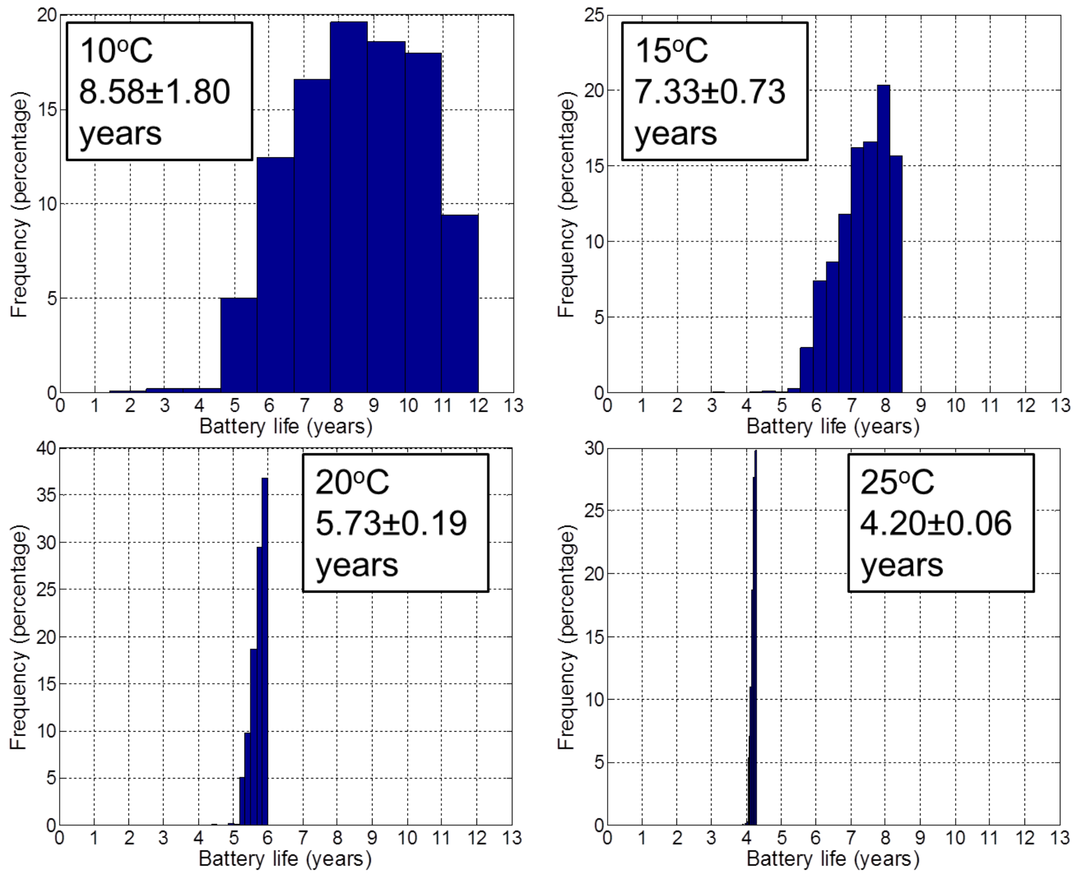

Figure 2.7 Simulated battery lifespan distribution at constant temperatures

Figure 2.8 shows the cumulative distribution function (CDF) of the simulated EV battery lifespan at the four constant temperatures. It is clear that as temperature increases, battery lifespan decreases and the variation of battery lifespan also decreases. Table 2.6 shows detailed percentile of battery lifespan and EV total travel distance for the five temperature scenarios. It shows that at 10°C, 90% of the EV batteries can last for more than 6 years and travel for more than 15,937 miles. 50% of the EV batteries can last for 8.6 years and travel for more than 58,141 miles. Only 10% can last for 10.9 years and travel for 108,763 miles. The percentile at different temperatures can be read from Table 2.6.

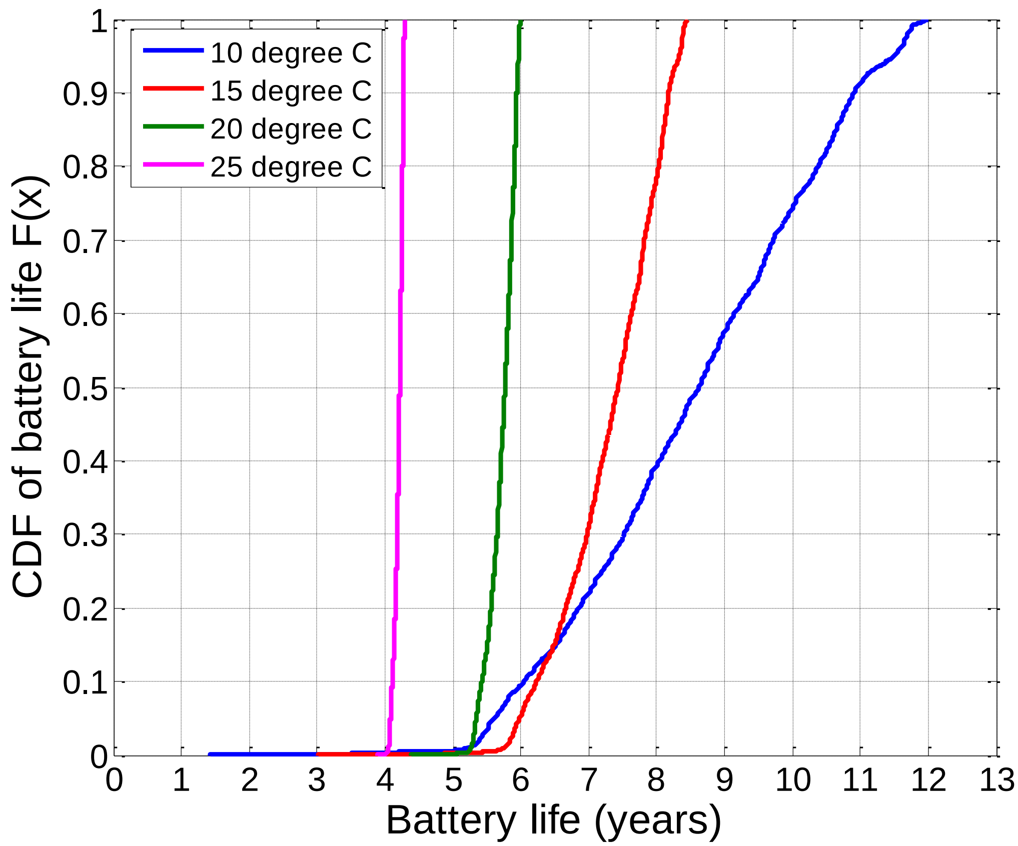

Figure 2.8 Simulated battery life CDF at constant temperature

2.3.1.2 Battery Life Distribution in Indianapolis

In reality, temperature will not be constant all year long. The average monthly temperature profile in Indianapolis is used to simulate the EV battery lifespan in the city of Indianapolis. The annual average temperature in Indianapolis is 11.7^{o}C. The simulated EV battery lifespan is (7.54±1.68) years. Figure 2.9 shows the histogram of battery life in Indianapolis, and Figure 2.10 shows the CDF of battery life in Indianapolis. Although the temperature profile of Indianapolis varies between -2.2^{o}C to 24.1^{o}C, the simulated result is similar to the scenario of 10^{o}C, and lies between the

10 °C and 15 °C scenarios. Therefore, the average annual temperature is reasonable to use as an estimate in computing degradation due to temperature effects.

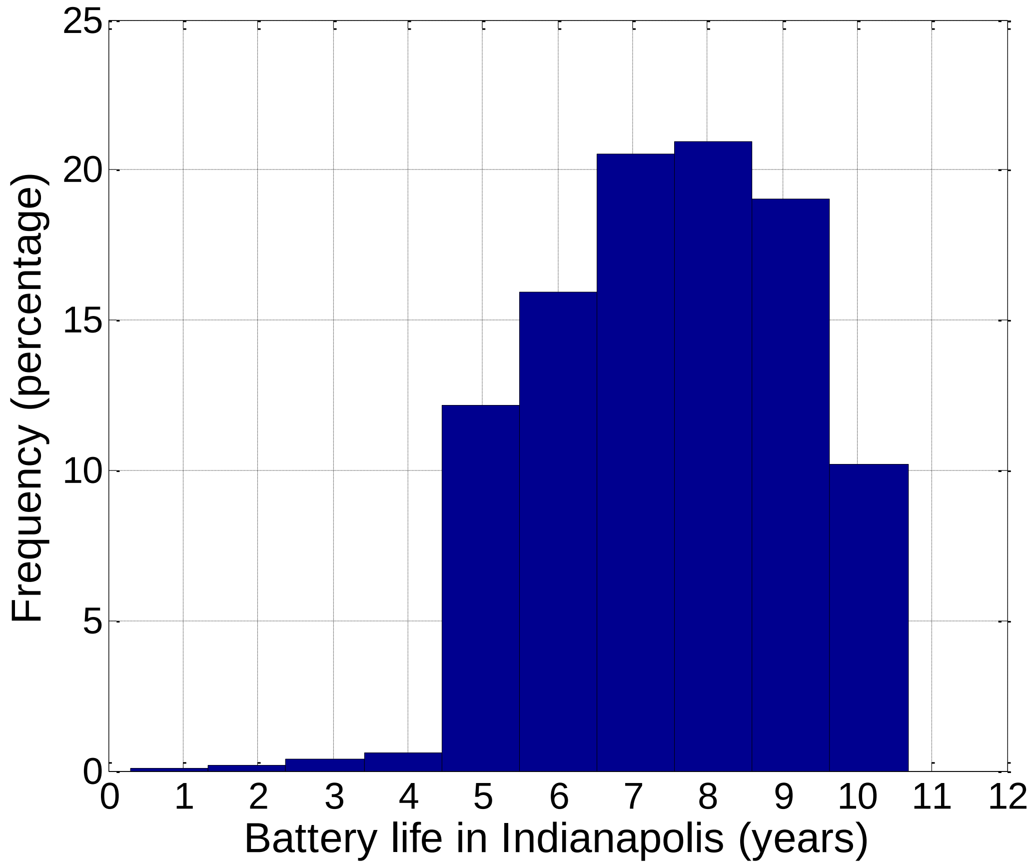

Figure 2.9 Simulated battery life distribution in Indianapolis temperature

According to Table 2.6, in Indianapolis, 90% of the EV batteries have a life more than 5.15 years, and can travel more than 14,080 miles. 50% have a life more than 7.57 years, and can travel more than 50,940 miles. And 10% have a life more than 9.65 years, and can travel more than 94,144 miles. Considering 100,000 miles as a vehicle lifetime milestone, the results indicate that battery replacement is unavoidable for more than 90% of the vehicles in Indianapolis. Thus economic use of EVs seems to depend on secondary use of vehicle batteries whereby owners receive a significant trade-in value for batteries with capacity fading. Over time the population of batteries in societal service will increase and a substantial market will exist for improved battery technologies replacing older ones taken out of service. This used battery market thus has potential to drive battery innovation.

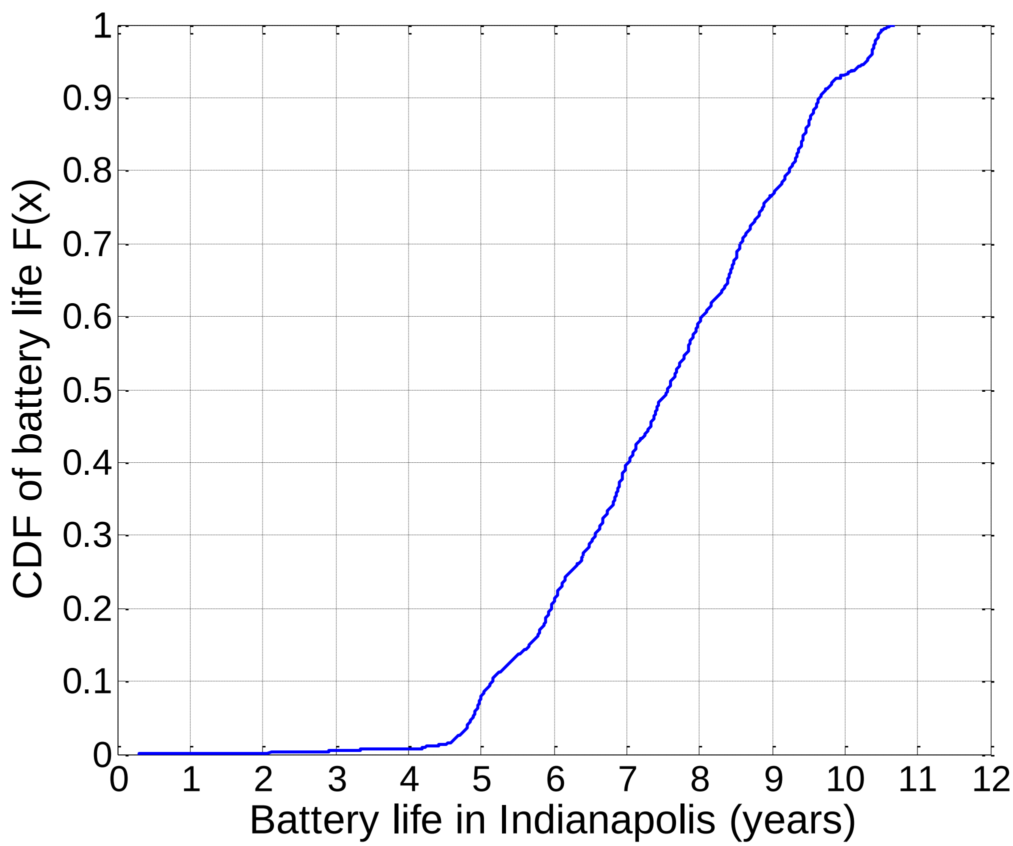

Figure 2.10 Simulated battery lifespan CDF in Indianapolis

Table 2.6 The percentile of battery lifespan and total travel distances for different temperature scenarios

%	**Indianapolis**		**10ºC**		**15 ºC**		**20 ºC**		**25 ºC**	
	Value (yr)	Value (mi)	Value (yr)	Value (mi)	Value (yr)	Value (mi)	Value (yr)	Value (mi)	Value (yr)	Value (mi)
0	0.30	1653	1.42	1845	3.01	1346	4.38	967	3.88	693
5	4.88	7612	5.62	8557	5.98	6128	5.34	4368	4.08	3126
10	**5.15**	**14080**	**6.05**	**15937**	**6.23**	**11960**	**5.42**	**8676**	**4.11**	**6232**
15	5.67	20522	6.52	23167	6.49	17738	5.51	12966	4.13	9336
20	5.96	24057	6.86	27517	6.66	21846	5.56	16210	4.15	11722
25	6.24	28160	7.20	32299	6.83	26037	5.61	19341	4.17	13968
30	6.57	33104	7.52	37529	6.98	29413	5.65	21909	4.18	15884
35	6.84	37303	7.79	42370	7.09	34320	5.68	25692	4.19	18600
40	7.03	41468	8.05	47277	7.21	39438	5.71	29845	4.20	21658
45	7.33	45874	8.34	52302	7.32	44586	5.74	34051	4.21	24739
50	**7.57**	**50940**	**8.62**	**58141**	**7.44**	**49936**	**5.77**	**38548**	**4.22**	**28198**
55	7.83	55766	8.89	63756	7.54	55476	5.79	43793	4.22	32193
60	8.04	59556	9.15	68126	7.63	60685	5.82	48672	4.23	35902
65	8.39	63527	9.51	72704	7.75	66484	5.84	53664	4.24	39676
70	8.57	68782	9.71	78730	7.82	72842	5.86	58531	4.24	43029
75	8.88	74111	10.04	85170	7.93	80160	5.88	65792	4.25	48768
80	9.23	79197	10.37	91204	8.03	88416	5.91	73454	4.26	54756
85	9.44	85882	10.64	98854	8.11	97524	5.92	81784	4.26	60833
90	**9.65**	**94144**	**10.90**	**108763**	**8.18**	**111200**	**5.94**	**96430**	**4.27**	**73250**
95	10.29	107729	11.49	124828	8.34	131553	5.97	116933	4.28	89239
100	10.68	146400	12.00	169360	8.46	177280	6.00	156720	4.28	119280

2.3.2 Travel Distance versus Battery Life

In order to gain insight into the relationship between total travel distance and battery lifespan, the simulated battery life is plotted against the total travel distance. The negative slope indicates that as the EV travels longer, the battery life becomes shorter. The width of the strip shows the variation of battery life resulting from driving behavior such as travel speed and acceleration/deceleration speed.

2.3.2.1 Travel Distance versus Battery Life for Four Constant Temperatures

Figure 2.11 shows total travel distance versus battery life at the four constant temperatures. The figures illustrates that at lower temperatures, the effect of total travel distance is greater than that at higher temperatures. It means that at higher temperatures, battery life is less sensitive to total travel distance. As temperature increases, the strip starts shrinking to almost a line, which indicates that at lower temperature, the effect of driving behavior is greater than that at higher temperature. Another interesting finding is that after a certain point, the strip becomes almost horizontal, parallel to the x-axis. The horizontal part provides intuitive information of minimum battery life at regular conditions, which is consistent with Table 2.6. For example, at 10^{o}C, the horizontal part intersects the y-axis at about 5.6 years. According to Table 2.6, 95% of the EV batteries can last for more than 5.62 years.

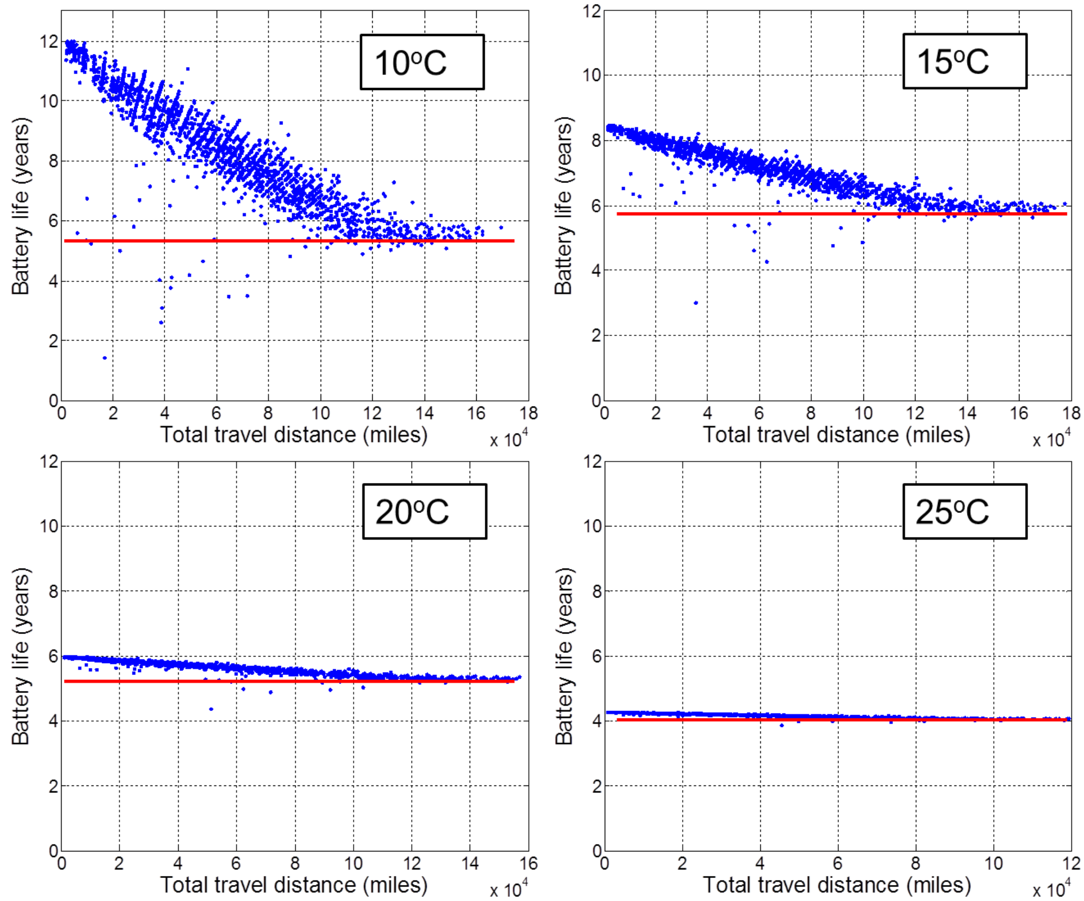

Figure 2.11 Simulated battery lifespan vs total travel distance at constant temperatures

2.3.2.2 Travel Distance versus Battery life in Indianapolis

Figure 2.12 shows the battery life versus total travel distance in Indianapolis. The shape is similar to the constant temperature ones. The horizontal line intersects y-axis at about 4.8 years. The outlier data points which are not inside the strip show more variation than the constant temperature cases. Those outlier points will cause warranty cost for vehicle companies.

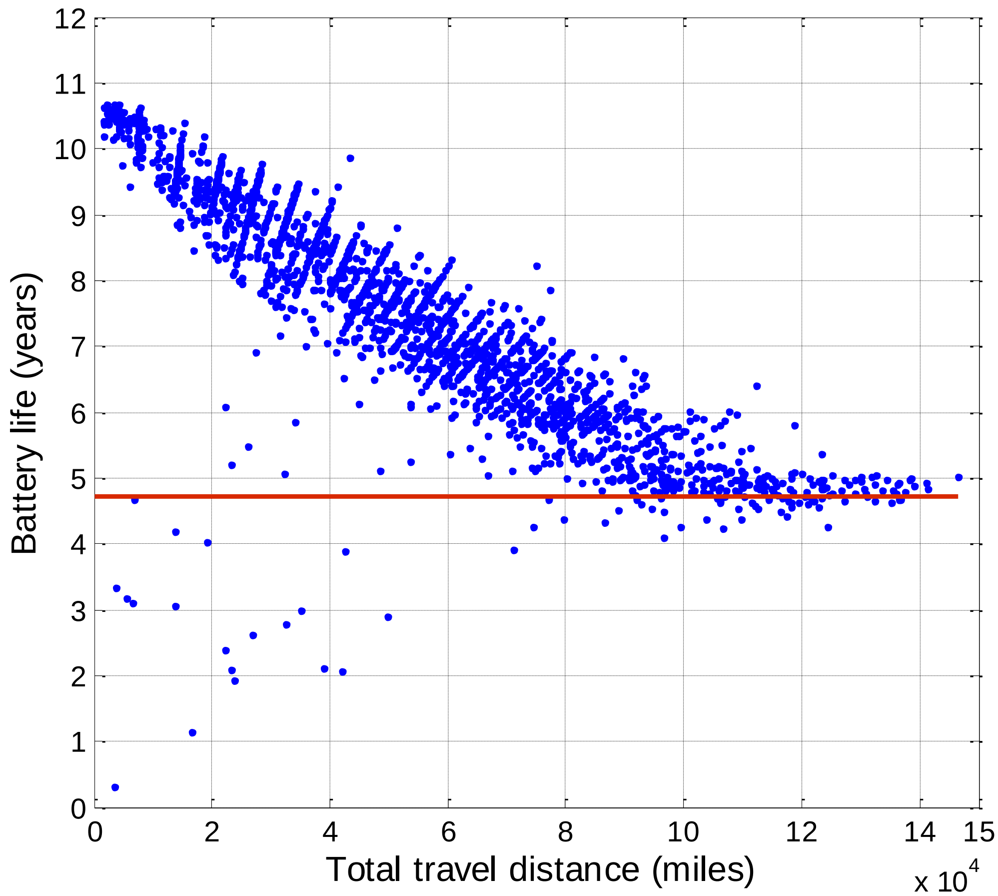

Figure 2.12 Battery life VS total travel distance in Indianapolis

2.4 Conclusion

This study explored battery life characteristics of a large population of EVs through microscopic traffic network simulation model and a semi-empirical battery degradation model. Interpretation of the results leads to the following conclusions:

1. Battery life has a large variation due to vehicle usage patterns and driving behaviors. Generally speaking, the longer an EV travels, the shorter the battery life.
2. Temperature has a substantial impact on battery life. As temperature increases, battery life decreases, and the variation of battery life also decreases. EV companies may need to design different warranty plans for different geographical areas. Future research should be targeted at improving battery life at a given temperature.

3. As travel distance increases, EV battery lifetime decreases and eventually approaches a constant.
4. Battery life percentile data provides detailed information for EV companies to design warranty strategies.

As the results show warranty strategy design is a complex economic problem. The data presented in this paper provides a realistic foundation for future work aimed at warranty strategy design and provides insight into the types of battery research that will impact real world battery lifespan.

CHAPTER 3. A LABORATORY TOOL FOR DISTRIBUTED SOLAR PV SYSTEMS EDUCATION

This paper is based on a manuscript that will be submitted to the Journal of Engineering Education. This paper is done in collaboration with the department of Computer and Information Technology from Purdue University, Information Technology at Purdue (ITaP), and the department of Chemistry and Life Science from United Sates Military Academy. The coauthors on this manuscript are James Dietz, Russell Lachance, Andrew Biaglow, Derrick Kearney, Sudheera Fernando, Ann Catlin, and Joseph Pekny. This chapter presents a developed laboratory simulation tool for distributed solar PV systems, and how this tool is applied to educate university students about solar energy.

3.1 Introduction

With the rapid decrease in solar PV module costs, increasing expense of extracting liquid hydrocarbon fuel stocks, associated unpredictable market effects of fossil fuels, the need to advance billions more people out of poverty, and the desire to reduce CO_2 emissions, there are an array of forces shaping the evolution of the next generation energy system. Renewable energy will play a significant role in the next generation energy system. Solar Photovoltaic (PV) systems, made up of PV panels, inverters, racking, and support elements, use PV cells to convert sunlight directly into electricity. Solar electricity is a promising option for sustainably providing future energy, since it constitutes a renewable energy resource and involves far less pollution, including emission of CO_2, than other power sources (the only pollution arises upstream and downstream, from production and disposal of PV equipment)[46]. With the rapid development of PV technology and the support from governments, solar PV systems are one of the fastest growing applications of solar energy. According to the literature[47]–[49], the global solar PV cells production increased very little from 1975 to 2000, but rose very rapidly from 2000 till present with a dramatic reduction in solar PV module cost. The global solar PV cell production had grown from 277 MW in 2000 to 38.5 GW in 2012. There are also some programs that promote the installation of solar PV systems in the US, such as the California Solar Initiative (CSI) program which provides cash back for solar energy systems for existing homes[50]; The New York State Energy Research and Development Authority (NYSERDA) provides cash incentives for the installation by Eligible Installers of small scale solar PV systems [51]; Southwestern Electric Power Company (SWEPCO) offers rebates to customers that install photovoltaic (PV) systems on homes [52]. As a result, educators have an opportunity to provide a broad based understanding of solar PV systems to promote great awareness of the technology. Some universities are providing master's degree courses in solar energy. However at the undergraduate level, solar energy is mainly the subject of curriculum of engineering and energy courses[53]–[62]. We seek to augment available education material with a practical hands-on experience in the nature and design of solar PV systems. We believe hands-on education is critical to the evolution of energy systems, so that a broad base of people can understand the basics of how energy systems work.

Widespread understanding is important to developing rational policy and the consensus needed for the large capital expenditures required for energy systems. We developed a solar PV laboratory education module to help students and the public understand the fundamental driving phenomena and take advantage of the research findings. The objective of the work underlying this paper is to apply long standing modeling research results to educate university students about solar PV systems and promote public awareness of solar energy. The laboratory simulation tool was developed using AnyLogic. The simulation tool was applied to one graduate course and two undergraduate courses as a lab project. All the undergraduate students were asked to take a survey both before and after the lab project. The comparison of the survey results before and after the lab project demonstrated that the tool helped students learn about solar PV systems. 65% of the students believe that their current knowledge of solar PV systems is equal or above a “medium level” on a self-assessment scale relative to before using the tool. In order to greatly increase availability and potential use, a refined user interface has been created based on the feedbacks from the courses, and the tool has been published online at: https://nanohub.org/tools/solarpv .

3.2 Methodology

A laboratory simulation tool for distributed solar PV systems has been applied on both graduate and undergraduate courses as a lab project. A questionnaire was distributed to undergraduate students at Purdue University and the United States Military Academy at West Point before and after the lab assignment.

3.2.1 The Laboratory Tool

An agent-based model of distributed solar PV systems was developed to help students learn about solar energy. The model is based on Shisheng Huang's Ph. D. work on the dynamic model of household electricity demand [27]. In his study, a discrete event based residential model and an agent-based distributed solar and energy storage model are coupled with historical industrial and commercial demand data. For the laboratory tool, only residential electricity demand is considered, industrial and commercial demands are not taken into account. Therefore, some adjustment and changes were necessary, and the simplified flow diagram of the lab tool model is shown in Figure 3.1. In this model, the residential electricity demand is broken down into its individual households. Each household is then further assumed to be composed of a set of electrical appliances. The appliances form the basic units of electricity demand [27]. The total electricity demand for one household is obtained by summing all the appliances' electricity demand. In this model, the electricity demand is supplied by two sources: one is the solar PV system of households, and the other is power grid. The solar PV system includes a battery or other energy storage device. Solar PV panel generates electricity according to solar radiation and weather conditions. If there is extra solar electricity, it will be stored in battery first and then be utilized when there is no solar electricity generated. Appliances will first use electricity from the solar PV system, and then use electricity from power grid if there is no solar electricity generated and no battery electricity.

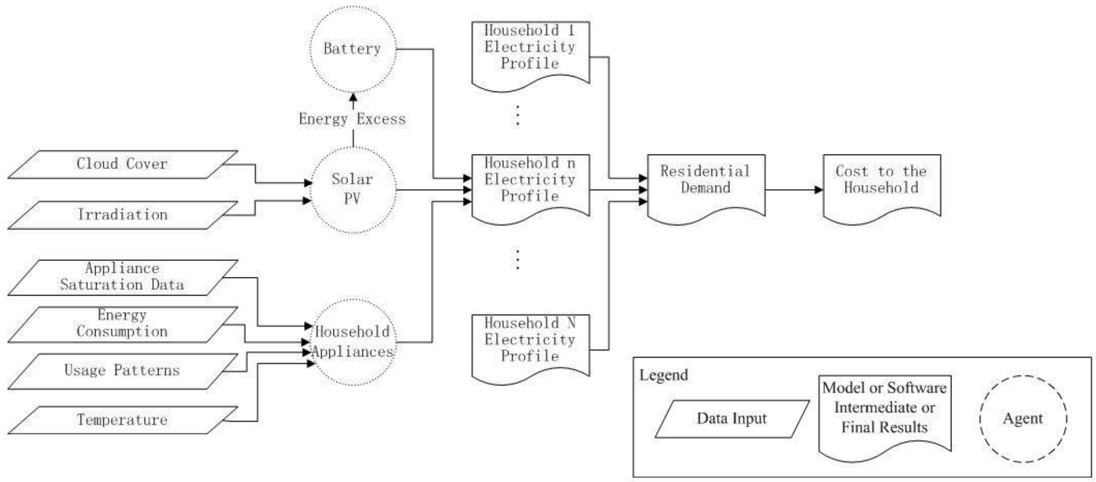

Figure 3.1 Simplified flow diagram of the lab tool model

The model is built using AnyLogic, a software environment which supports multi-method simulation. In order to apply the model to education purposes, it has been compiled and exported as a JAVA application. With the application, students can run the simulation directly, and they do not need to install the AnyLogic environment. The lab assignment is divided into four steps: (1) learning electricity usage patterns; (2) studying the features of solar energy; (3) designing solar PV systems; and (4) comparing different business cases. In the first step, students are asked to obtain the residential electricity demand curve for a specific region. From this step, they will learn that the electricity demand varies at different hours during a day, and weather will also affect the demand of electricity via heating and air conditioning. In the second step, students are able to predict the residential electricity demand on the power grid after installing solar PV systems, so that they can intuitively see the effect of solar PV systems on electricity demand. The third and fourth steps are more difficult as measured by student performance on graded laboratory exercises. Students need to design a solar PV system and compare different business cases based on what they have learned from step one and step two. To conduct the lab assignment, students needs to choose a model set of household appliances or collect data for their own custom appliances, input parameters to control the number of households, capacity of solar systems, weather, and season for the simulation, run simulations, and analyze results. Students develop an intuitive understanding of the variable nature of solar energy, effect of weather on both supply and demand, and the need to complement solar PV systems with energy storage or other forms of electricity generation. After the lab assignment, students self-assess as having a better understanding of electricity usage patterns as well as distributed solar PV systems.

The tool was first introduced to a graduate level course at Purdue University as the final project. The goal of the student project was to provide detailed feedback for both the tool and the design of the assignment. Following the feedback, the tool was updated so that it is more intuitive for undergraduate usage, and a manual book was edited to provide a reference for students.

3.2.2 Questionnaire

The updated tool was applied to two undergraduate level courses from Purdue University and United States Military Academy at West Point. In order to measure students' understanding about solar PV systems, a questionnaire was designed (Appendix A) and distributed to students both before and after the lab assignment. The questionnaire used in this study focused on five main points: 1) the understanding of distributed solar PV systems, 2) the understanding of battery or energy storage device for solar PV system, 3) the willingness to accept solar PV systems, 4) the interest in pursuing further studies or conducting research in an area related to solar PV systems, and 5) other attitudes towards solar PV systems.

3.3 Results and Discussion

There are 7 graduate students, 29 undergraduate students from Purdue University, and 14 undergraduate students from United States Military Academy at West Point undertook the lab assignment. 23 undergraduate students from Purdue University and 3 undergraduate students from West Point finished both the voluntary pre and post questionnaire. The following results are obtained from the questionnaire. The statistical data is calculated from the results of Purdue undergraduate students. The results from West Point are consistent with that from Purdue (Note that question 20-22 are not listed in West Point survey). Since there are only 3 samples in West Point, detailed data analysis is not conducted for it. Only the comparison of pre and post results is shown in Appendix. The detailed survey results from Purdue are also in Appendix A.

3.3.1 The Understanding of Distributed Solar PV Systems

Using this tool, we aimed to facilitate student learning about the characteristics of solar electricity. Questions 1-4, question 8 and 9, and question 23 address the understanding of the characteristics of solar electricity. According to the survey results, most students self-assessed their post-understanding well about solar PV systems after undertaking the lab project. 65% of the students state that their knowledge of solar PV systems is equal or above medium level after the lab project, while only 17% of students claim that their knowledge of solar PV systems is on medium or above level before the lab project (Table 3.1 & Figure 3.2).

Table 3.1 The results of "how would you describe your current knowledge/understanding of solar PV systems"

	High	Medium	Low	NA
Before	0	4	17	2
After	2	13	8	0

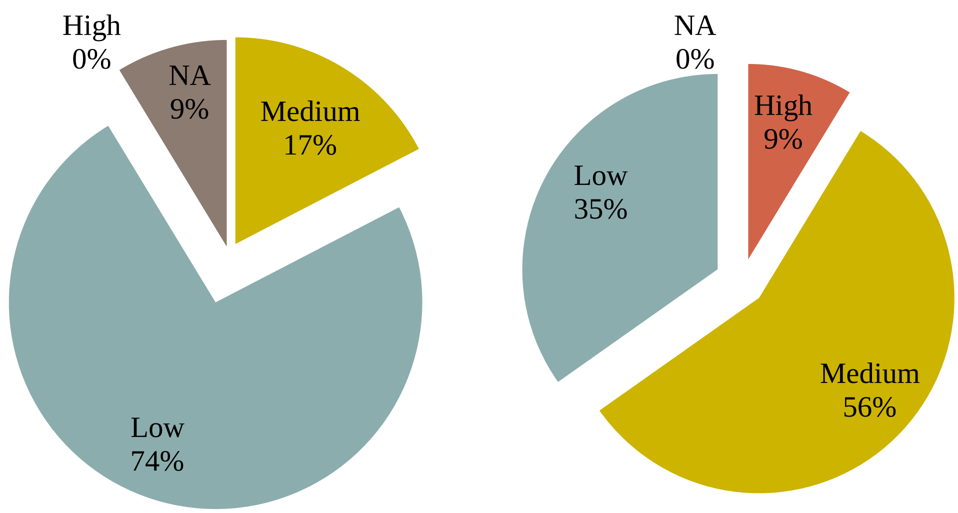

Figure 3.2 The results of "how would you describe your current knowledge/understanding of solar PV systems" before (left) and after (right) the lab project

The results from question 1-4 and question 8 and 9 also demonstrate that from this lab project (Appendix A), students improve their knowledge about solar PV systems. Question 5-7 present the safety of solar PV systems. Almost all the students believe that solar PV system is safe to use no matter before or after the lab project. 70% of the students agree or strongly agree that solar PV systems are reliable to use after the project, while 52% of the students agree or strongly agree with the statement before the project. 48% of the students agree or strongly agree that solar PV systems are easy to maintain after the project, while only 30% of the students agree with this statement before the project. The results also suggest that the coverage of maintenance is currently insufficient with our tool.

3.3.2 The Effect of Battery or Other Energy Storage Devices on Solar PV Systems

The solar PV system studied in this lab tool can be used off-grid since it can be coupled with batteries or other types of energy storage devices. Question 10 and 11 present the understanding of the role of a battery in solar PV systems. According to Table 3.2 and Table 3.3, students with knowledge of batteries confirmed their thoughts after the lab project. 74% of students “strongly agree” with the statement that “Batteries can help to improve the efficiency of solar PV systems” after the lab project, while only 17% of students “strongly agree” with this statement before the project. Similarly, 57% of students “strong agree” with the statement that “Batteries can help to reduce the peak demand of electricity for households” after the lab project, while only 13% of students “strongly agree” with this statement before the project. Most of the students in this study are senior engineering students. As such they may have some knowledge about renewable energy from other courses, and they are also able to analyze the problem based on what they have learned. Based upon the survey results and discussions with the students the laboratory exercise greatly reinforced their intuition about solar PV systems. With the lab project, students learn solar PV systems systematically, and they design a solar PV system for a specific region using the simulation tool. This design and analysis component seem to provide students a clearer and deeper understanding of the behavior and application of solar PV systems.

Table 3.2 The results of “Batteries can help to improve the efficiency of solar PV systems”

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	0	4	15	4	0
After	0	0	6	17	0

Table 3.3 The results of “Batteries can help to reduce the peak demand of electricity for households”

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	1	4	15	3	0
After	1	1	8	13	0

3.3.3 The Acceptance of Solar PV Systems

Question 16-18, and question 24 present students’ willing to accept solar PV systems. The results demonstrate that after the lab project, more students are willing to accept solar PV systems. There are 39% of the students would like to install solar PV system in their houses even if solar electricity is expensive than grid electricity. 91% of the students claimed that they are more likely to accept solar PV systems based on what they have learned in this project. The results illustrate that people are more likely to accept a new technology when they understand it. This supports our conjecture that broad based understanding of the energy system is a strong basis for policy consensus.

3.3.4 The Interested in Learning and Study Solar Energy Related Topics

Question 12-15 poll students' interest in learning and studying solar energy related topics. The results reveal that after the lab project, students' interest in solar PV systems does not increase, but more students are open to pursuing further studies in an area related to solar PV systems. Interestingly the number of students who are interested in conducting research on solar PV systems is the same before and after the lab project.

3.3.5 Other Attitudes toward Solar PV Systems

The survey also covers some other questions about solar PV systems, which include the future of solar PV systems (question 19 and 20), and should government support solar energy (question 21 and 22). The results demonstrate that with this lab project, more students (43% after the project and 22% before the project) firmly believe that solar PV systems will become one of the most popular electricity sources in the future. The results for "should government support solar energy" are overwhelming. More students (70% after compared with 57% before) believe that government should subsidize solar PV systems, and more than 90% students (91% after compared with 96% before) think that governments should support solar energy related research.

3.4 Online Simulation Tool

In order to greatly increase availability and potential use, a refined user interface has been created using Rappture [63] based on the feedbacks from the courses reported above, and the tool has been published online using Purdue University Hub

Technology as part of the NanoHub [64]. The tool is named as "Solar PV" and can be accessed at: https://nanohub.org/tools/solarpv . Up until now, the tool has been used in 10 countries or regions all over the world since it published. The users are from university, industry, national lab and some other undefined.

3.4.1 Online Tool Introduction

The online simulation tool is much easier for users to learn distributed solar PV systems by running simulation. Anyone with internet accessed can use it. The tool's user interface is divided into six graphical user interface screens (shown in Figure 3.3-Figure 3.7, the first screen is an introduction of the solar PV model, which is not shown here). First, users choose the region they would like to simulate, and input the number of households of the region by either selecting from the list of all 50 states' data or inputting manually. Then users need to select a month to simulate from the list. After the region is determined, uses move to the region profile screen where they select profiles for appliances, temperature, cloud cover, and solar irradiation for the region. Users can also create their own profiles and upload them to the tool database. After users' profiles uploaded to the database, they will appear in the profiles lists and be accessible to any users. The last step is to define the percentage of households that have solar PV system, the capacity of solar PV, whether the system includes a battery, and the capacity of battery. After running the simulation, users can automatically view the projected hourly average electricity demand for all the households and the total daily electricity demand over a one month period for the selected region.

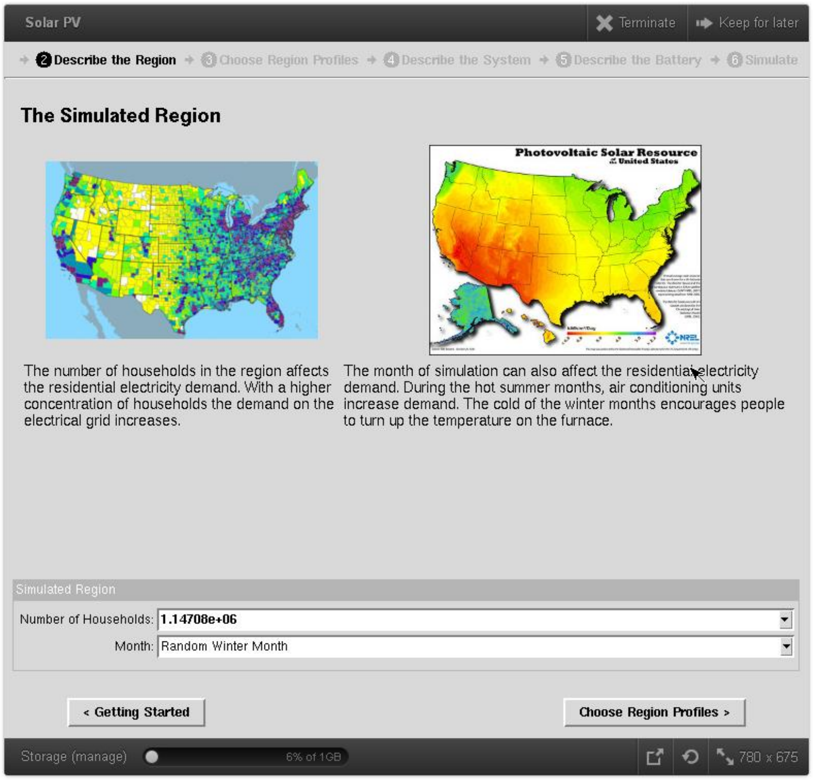

Figure 3.3 Describe the region screen

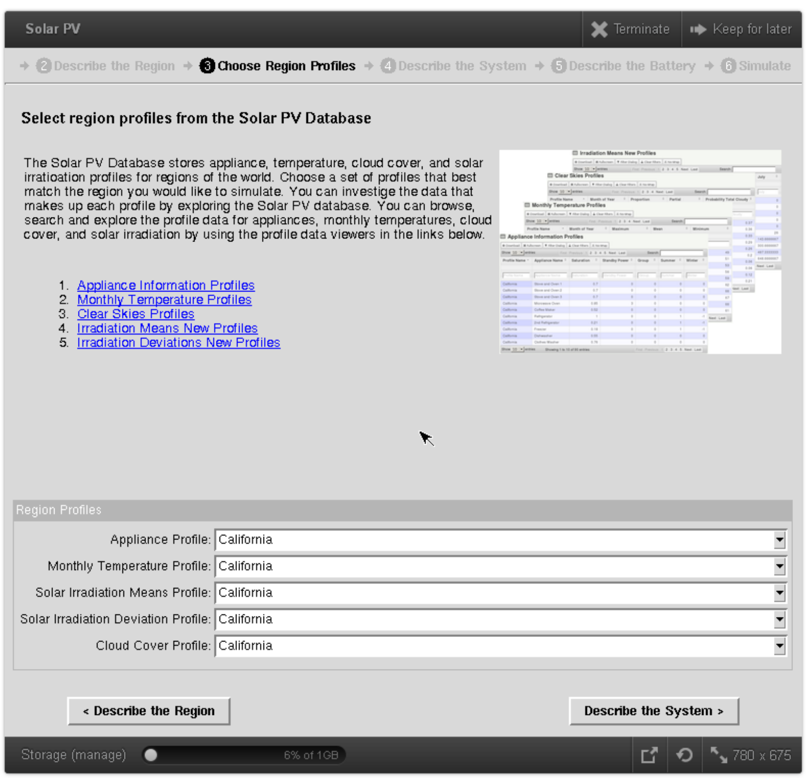

Figure 3.4 Choose region profile screen

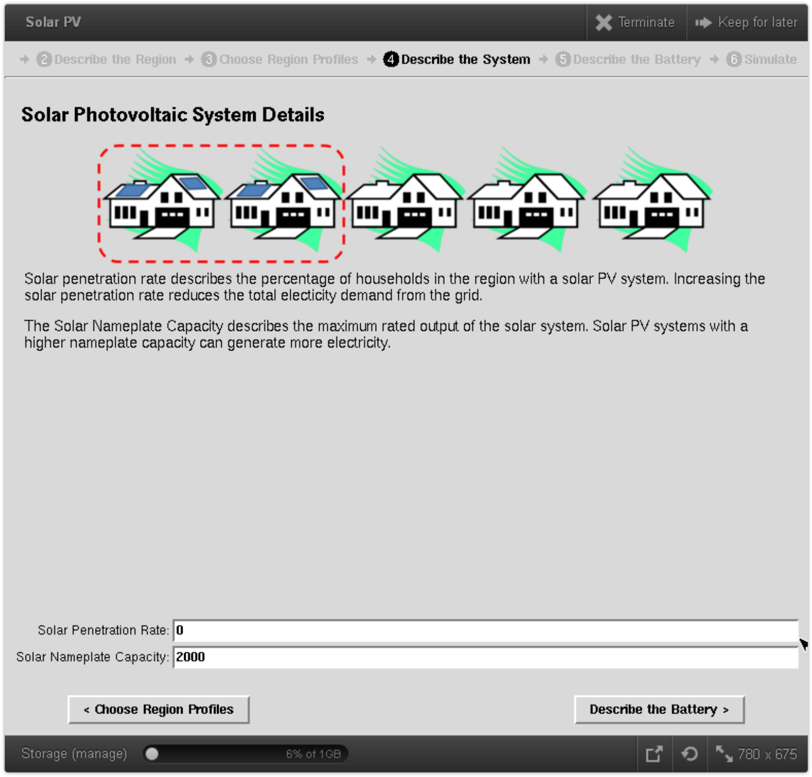

Figure 3.5 Describe the system screen

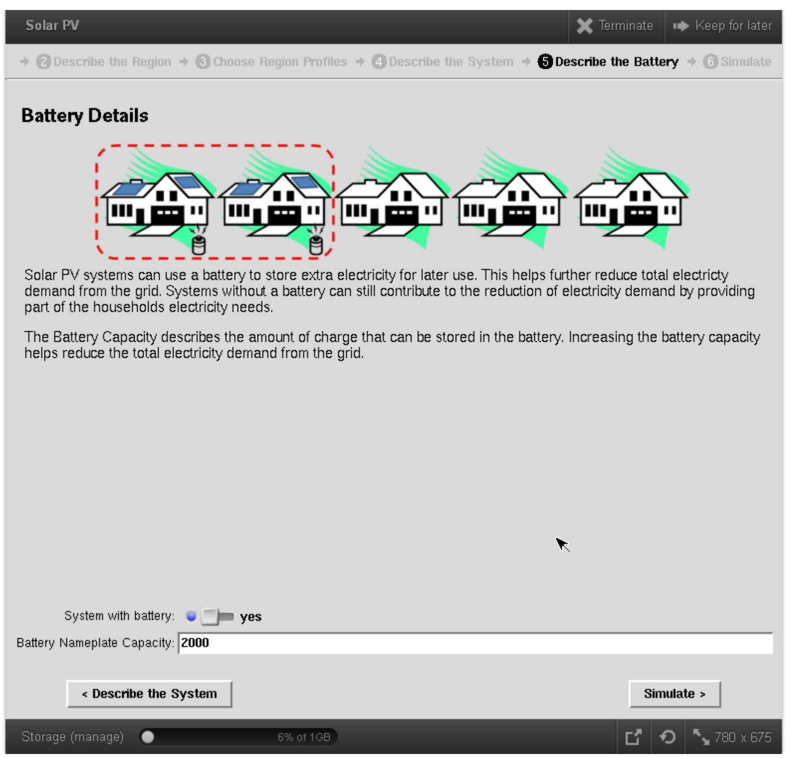

Figure 3.6 Describe the battery screen

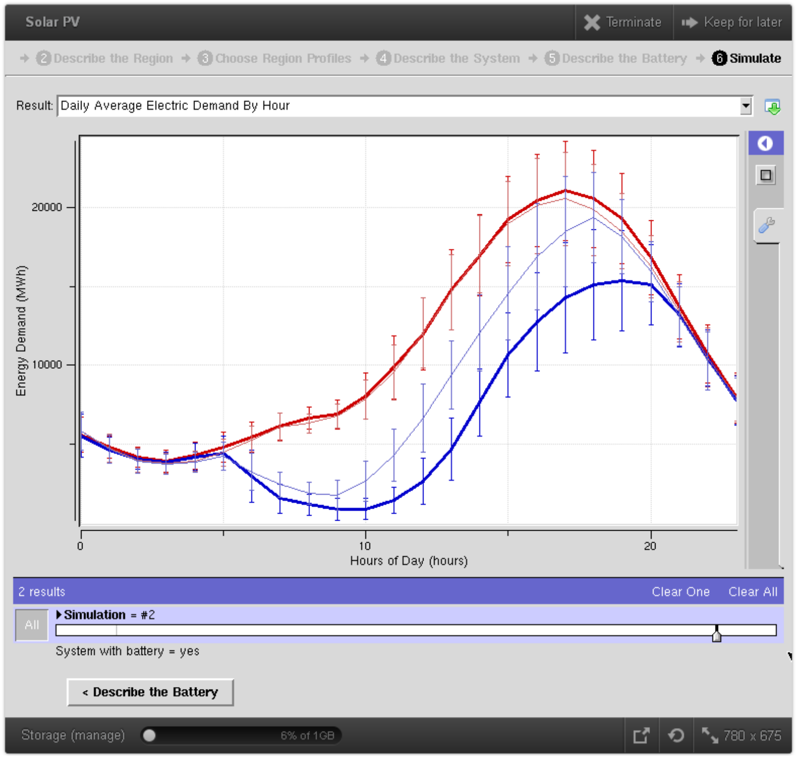

Figure 3.7 Simulation result screen

The online simulation tool has several characteristics including:

1) It is easy to use. Users do not need to install any software. As long as users have a nanoHUB account/google account/facebook account, they can use it.
2) It can be applied to any regions. Users can either select the profiles for a specific region from the existing list, or create their own profiles and upload them to the tool database. After users' profiles uploaded to the tool database, they will be shown in the profiles lists and accessible to any users.
3) The result is shown intuitively. After simulation, the tool will automatically conduct data processing and show the projected hourly average electricity demand for all the households in the selected region. Users can change parameters for solar PV system and run different simulations to compare

results. The tool will maintain all the results for different runs and can show them in one figure. Users can also download the results data to do their own analysis.

4) It is flexible for different purposes. As discussed in section 3.2.1, the tool can simulate households' electricity demand in different regions, under different weather conditions, and with/without solar PV systems. The assignment discussed above is just one possible application of this tool. Users can also use the tool to compare the electricity demand for different regions in different seasons, study the effect of certain appliance on household electricity demand, and etc.

3.4.2 Solar PV Database

Another extended function of the online simulation tool is the solar PV database. There are two databases that users can access to. One is the profile database which includes the profiles of appliances, temperature, clear skies, and solar irradiation for different regions. Users can browse, search and explore the profile data to be familiar with the profiles before they have to make selections to run the simulation as shown in Figure 3.4.

The other one is the "National Solar Radiation Hourly Statistics Viewer". The viewer displays solar irradiation data for all 50 states in 2010. All the data is from National Solar Radiation Database (NSRDB) [65]. Users can use this viewer to: 1) get the solar irradiation data for their own profiles, 2) view the positions of solar irradiation data collection stations on map, and 3) compare the solar irradiation data in different months for one station. The screens of the viewer are shown in Figure 3.8-Figure 3.10.

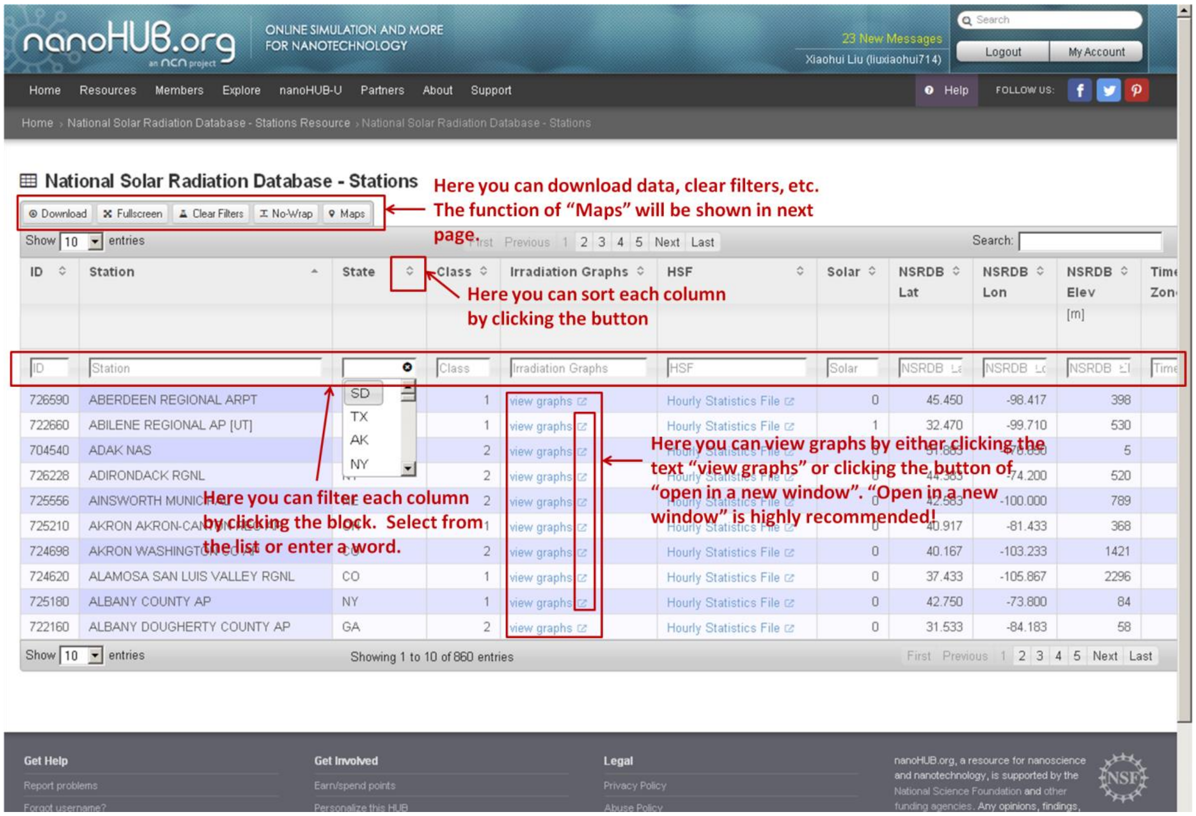

Figure 3.8 Basic functions of the national solar radiation hourly statistics viewer

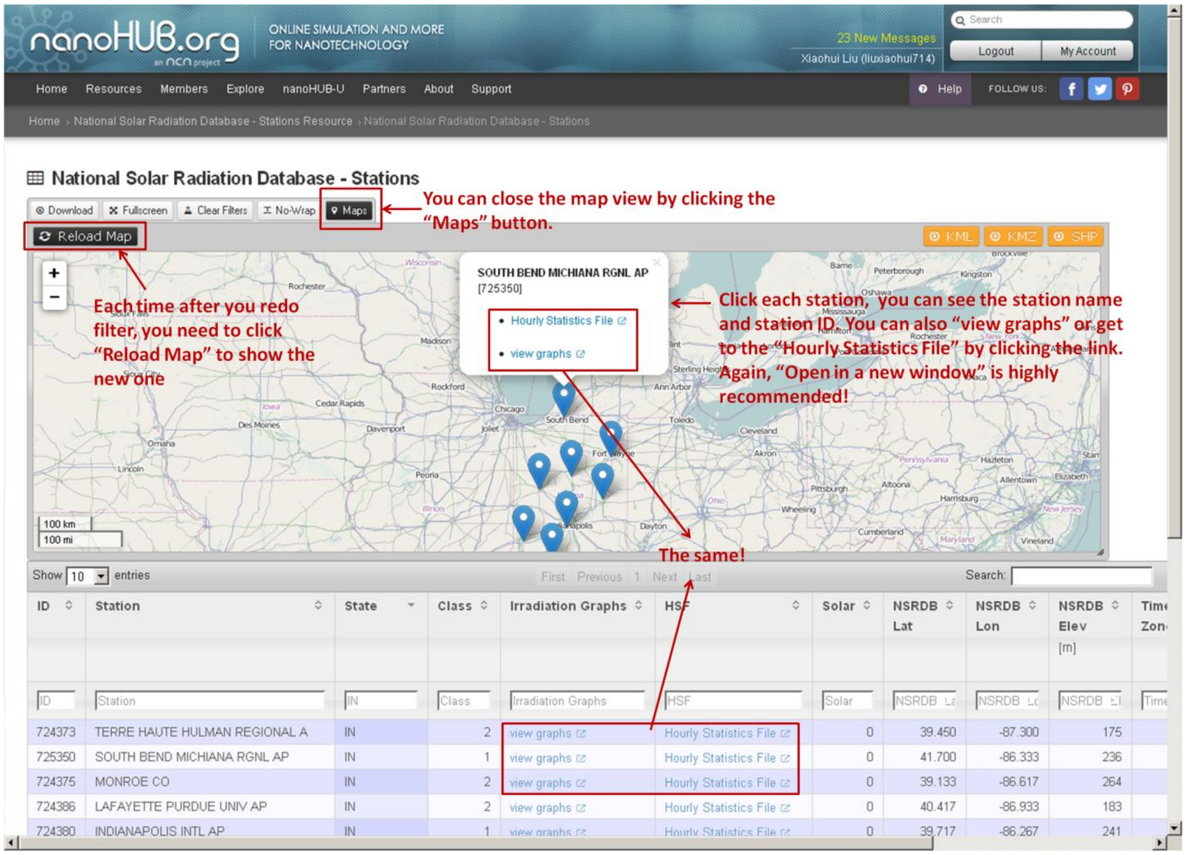

Figure 3.9 Maps in the national solar radiation hourly statistics viewer

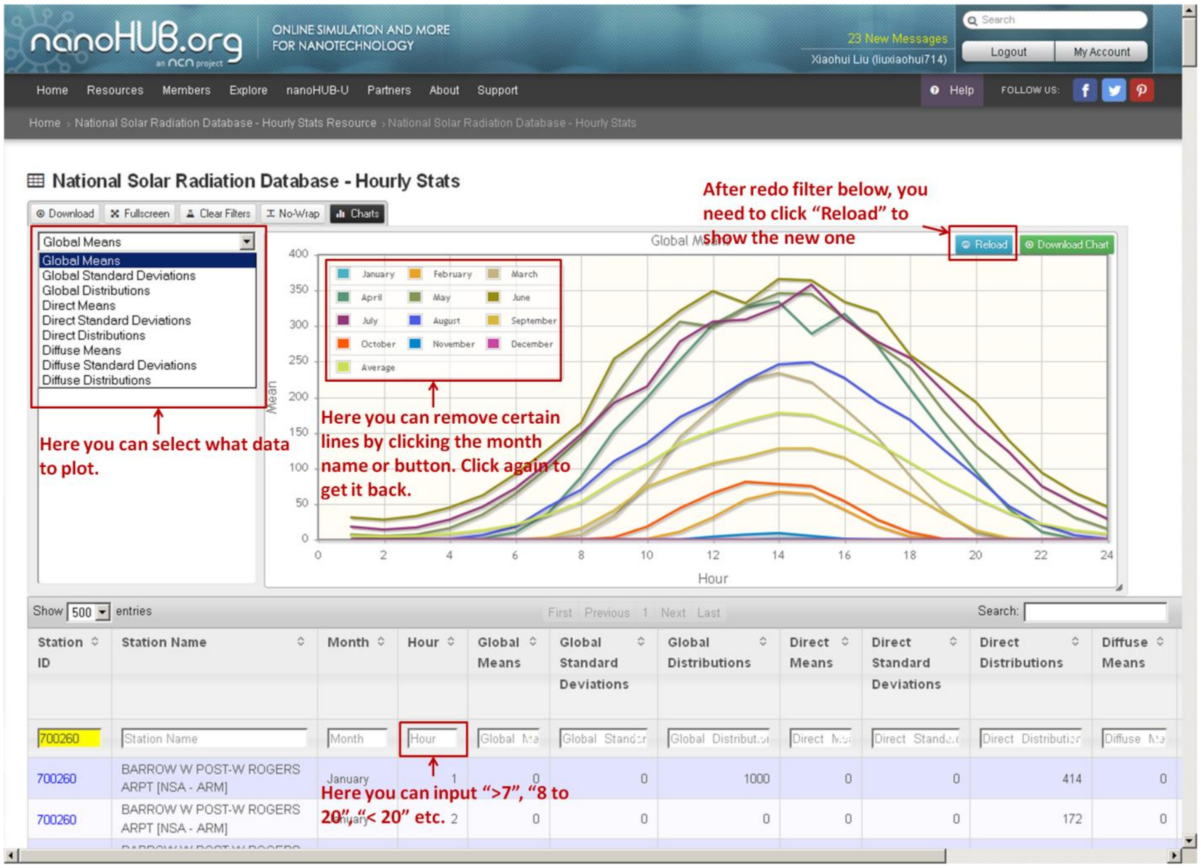

Figure 3.10 Graphs view in the national solar radiation hourly statistics viewer

3.5 Conclusion

Advances in energy system evolution depend greatly on building a sophisticated consensus among the public and leaders. Education plays an important role in promoting public awareness. The simulation lab tool developed for this effort successfully helped students learn solar PV systems systematically. The survey results reveal that students are more likely to accept solar PV system when they are familiar with it. Therefore, we believe that hands on education tools are necessary to provide a broad based understanding of the implications of energy system advances are essential to developing a policy consensus.

CHAPTER 4. PURCHASING VS. LEASING: A BENEFIT-COST ANALYSIS OF RESIDENTIAL SOLAR PV PANEL USE IN CALIFORNIA

This chapter is based on a paper that is published in volume 66, 2014 of Renewable Energy with Eric O'Rear, Wallace Tyner and Joseph Pekny. This work uses a benefit-cost analysis to evaluate the impacts of combined tax breaks from depreciation and interest paid on home-equity loans on competitiveness under different purchase options for a 4kW solar PV system in California. The results suggest that the additional tax breaks from depreciation in conjunction with those from interest paid on home-equity loans can make purchasing much more competitive. Sensitivity analysis is conducted for key parameters, and all sensitivity tests yielded the expected results.

4.1 Introduction

Small-scale solar electric generation in the U.S. has been on a steady increase in recent years. Solar photovoltaic (PV) cell micro-generation has been used extensively in residential applications [66]. The primary benefit of such a system is that it allows some of the residential electricity usage to be derived from the system – offsetting portions of the demand from grid-based sources. Often times, surplus electricity created by the system can be sold back to the grid to the owners' benefit.

From the perspective of the electricity generation and distribution system, one obstacle is the variability in production related to changes in weather patterns. This can be problematic because scheduled generation may fail to meet anticipated residential demands. Another major obstacle is the incongruity that exists between the timing of electricity generated from the PV system and peak demand hours. Greatest solar PV generation occurs close to the middle of the day when solar irradiance is at its highest. Peak electricity demand for households, however, occurs usually in the evening. This creates incongruity between PV supply and household demands and inefficient use of the overall system.

Residential solar PV systems can be installed in one of two ways: (1) electricity production with distributed storage systems; and (2) connection to a major grid where excess electricity is exported back to the grid through net-metering. In this study, the household participates in net-metering. Residential systems can be purchased by the homeowner or leased through a licensed distributor. With leasing the homeowner enters into an agreement in which they are obligated by a lessor to make monthly payments over a period of time. While under contract they are able to consume an unlimited amount of electricity from the PV system. Most leased systems are connected to the power grid and do not have an energy storage system in place. Because leasing does not require substantial upfront costs and scheduled maintenance is typically handled by the lessor, it has become the more popular option. Deployment of leased PV systems has increased in the U.S. relative to system purchases. Homeowners currently are unable to depreciate solar capital under existing U.S. tax law. But a lessor can depreciate the equipment it leases. Inability to depreciate continues to give lessors the competitive edge in the PV market. Homeowners can benefit from tax deductions based on interest paid on a home-equity loan if the loan were used to finance the system, but they cannot deduct interest on any other form of loan used to finance the system. Our study evaluates the effects of tax breaks related to depreciation and interest payments on the competitiveness of different purchase options within the residential solar PV market in California.

4.2 Leasing versus purchasing

Leasing allows residents to finance capital equipment for the solar PV system over a set contractual period. The lessee enters into a contract with a lessor that establishes monthly payments for the PV system. During this period the lessee consumes electricity from both the PV system and the grid. Leasing is economical for the lessees as long as the combination of monthly leasing fees and the costs of grid electricity consumption are lower than the costs if all electricity demands were being completely met by the grid. Different companies offer different forms of leasing agreements. Lessors usually provide an option to the lessee to extend contracts beyond initial agreement periods. The option to purchase the system at the end of the contracted period at a reduced value is also offered. Leasing payments often include any operation and maintenance (O&M) costs associated with the upkeep of the solar PV system. These O&M costs include cleaning costs, repair costs, and inverter replacement every ten years. With improving inverter technologies, O&M costs along with regular replacement is sure to change [67]. Households that choose to purchase the systems are responsible for covering this burden – making the purchase of a system less appealing.

There are tax credits and incentive-based programs that help to make residential solar PV generation more economical. By selecting the leasing option, homeowners forgo all of these benefits, and the lessor becomes the recipient of these incentives instead. The Energy Policy Act of 2005 (EPAct), for example, established a 30% tax credit for the purchase and installation of home solar electricity and solar water heating systems. It was initially capped at $2,000 until the Emergency Economic Stabilization Act of 2008 removed the cap. The California Solar Initiative (CSI) Program offers rebates for solar PV electricity generation, which varies according to system size and capacity, performance, utility territory, etc. Incentives are based on system performance. Consumers can benefit from two major incentive programs through CSI. The Expected Performance-Based Buydown (EPBB) option provides an upfront lump-sum rebate based on performance expectations. The other, the Performance Based Incentive (PBI), is a monthly payment for which payment size is based on actual system performance over the course of five years. EPBB is available for small systems only and is an up-front incentive. The program uses an EPBB calculator to determine the size of the rebate based on a number of system characteristics [68]. Our analysis considers only the EPBB rebate in our assessment of the benefits tied to purchasing and leasing a solar system.

4.3 Materials and Methods

Each of the following sections breaks down the different data components that go into completing our benefit-cost analysis. We first summarize the costs of owning/leasing a residential PV system, followed by a summary of financing methods. We then explain our approach to depreciating capital equipment, simulating electricity demands, and our assessment using benefit-cost analysis.

4.3.1 Solar PV System Cost

A solar PV system is made up of one or more solar PV panels, an inverter, energy storage system/batteries (optional), and other components. Our study considers a system that does not use batteries for storage since customers in California can sell additional electricity back to the power grid at full retail price under net-metering [69]. The most popular installation size in California is 4 kilowatts (kW) [70] – therefore, we assume that the capacity of our reference solar PV panel will be 4kW. The lifetime for a solar PV panel on average is 25 years, with an inverter that should be replaced in years 11 and 21 (every ten years) [67], [71], [72]. Inverter replacement costs including labor are estimated to be approximately $3600 [73]. Purchase and leasing options will be analyzed over a 25 year policy horizon. It is assumed at the end of the 25 year contract period residential systems will be retired.

The costs for purchasing a home PV system include capital costs, installation costs, O&M costs, and the costs for the replacement of parts. The residential solar PV system in general needs little maintenance. Maintenance requires basic panel cleanings which residents can often do on their own to save on costs. According to Go Solar California (2013), the average cost of a small scale solar PV system (less than 10 kW) in California is $6.73/W in 2012, which includes both the equipment and installation costs [74]. Average installation prices have declined annually by 5-7% from 1998-2011 – indicating a growing affordability for residential systems [75].

This analysis assumes system purchase costs of \$6.73/W. Operation and maintenance costs used in the analysis (\$32.80/kW-year) are based on the Department of Energy's Energy Efficiency and Renewable Energy (EERE) SunShot study [73].

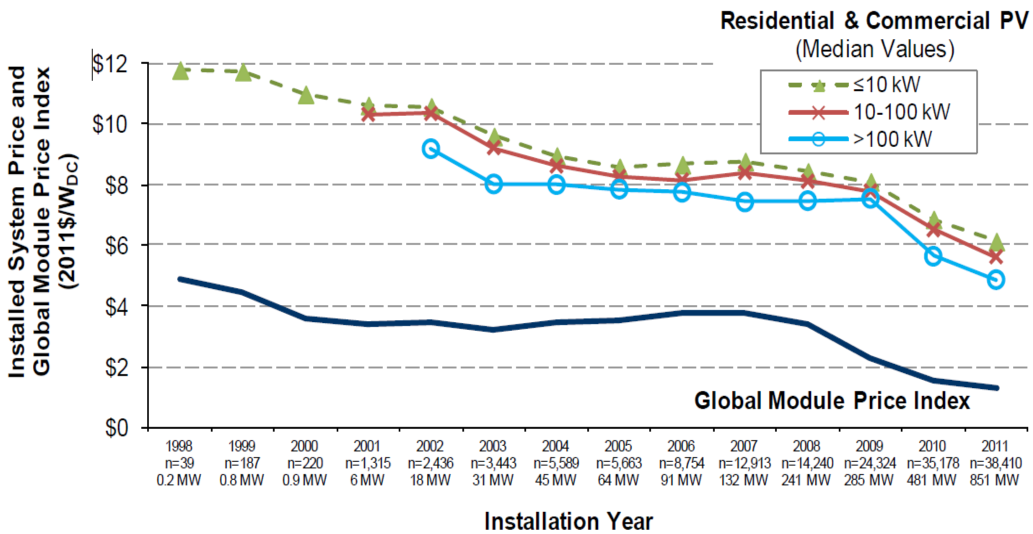

Figure 4.1 Installed price of residential and commercial PV systems over time [75]

4.3.2 Financing and Incentives

Financing solar PV systems can be done through a home equity loan, leasing, or a cash purchase. This analysis assumes that the household has the option to either finance the system using a home equity loan with a 10-year financing period or a lease with a contract period spanning over the lifetime of the solar panel (25 years). Regarding the loan option we assume that the bank will finance at most 80% of the initial capital costs at an interest rate of 6%. Based on our conversations with an associate of Sungevity – a solar electric company based out of Oakland, California – a 4kW residential PV system in San Diego would on average be leased for \$100 a month. The rental cost in our evaluation will be \$1200 to reflect yearly leasing costs.

Because leasing security deposit amounts are negligible, we will not consider them in the study. Yearly rental costs increase annually by 3% to keep up with the rate of inflation which is typical of many leasing agreements.

Households that choose to purchase solar PV systems as either a cash purchase or with home-equity financing can directly benefit from both federal and state-wide subsidies and tax credits. Residential solar PV users in California benefit from incentive-based programs like the EPBB program as a part of the California Solar Initiative. Lump-sum payments under the EPBB program are payable to households who own smaller systems and are available for systems under 30kW after 2010. According to EPBB system, the current (December 2012) rate for residential systems is $0.20/W for Pacific Gas & Electric (PGE) and California Center for Sustainable Energy (CCSE) and $0.25/W for Southern California Edison (SCE). We selected the $0.20/W subsidy rate given the system size assumed in the study [68]. The EPAct of 2005 establishes a 30% federal tax credit for the purchase and installation of residential solar electricity and water heating. We incorporate this tax credit in our study as well. There are other local incentive programs that exist for residential PV purchasers. Since we are basing our assessment on the entire state of California, we have chosen to ignore local rebate programs.

4.3.3 Depreciation

The inability by households to capture some of the benefits of depreciating solar equipment continues to make the leasing option much more competitive. In this study we test the importance of the depreciation rules. We allow for households to earn tax savings from depreciating using the **Modified Accelerated Cost Recovery System (MACRS)** depreciation system. MACRS is the current tax depreciation system in the U.S. It allows for capital costs to be recovered through annual deductions of depreciation. The IRS classifies solar electric and solar thermal technologies as solar energy related personal property having a five-year class life. This is the period over which the property can recoup any depreciation. Therefore, we will refer to the five-year property general depreciation system (GDS). This method uses declining balance depreciation before switching to straight-line depreciation at the point at which straight line exceeds declining balance. Table 4.1 shows the MACRS applicable percentages used in the study [76].

Table 4.1 Applicable MACRS depreciation percentages

Recovery year	5-year depreciation rates
1	35.00%
2	26.00%
3	15.60%
4	11.01%*
5	11.01%
6	1.38%

Note: The * signals that the depreciation schedule has switched to straight-line.

4.3.4 Electricity Demand

An agent-based residential electricity demand model is applied to obtain the electricity demand from the power grid in conjunction with a residential solar PV system. This equals the difference between electricity demand without the solar PV system and total electricity generated by the solar PV system. The model was constructed by Shisheng Huang, and further details concerning the framework has been described in [27]. In simulating the electricity generation by a 4kW solar PV system, weather information for San Diego, California was used to generalize the overall weather conditions for the state of California. Other parameters such as solar radiation and electricity usage patterns are default data for California in the model. The simulation shows that a 4kW solar PV system in San Diego will generate around 4500 kWh of electricity yearly. This is comparable to a real case in which a 4kW solar PV system generated close to 4405 kWh for the city of Los Angeles, California[77]. Total electricity demanded by the household for this study is approximately 7272 kWh/year [78], [79].

4.3.5 Benefit-cost Analysis

We conduct the study using a benefit-cost approach to assess the net benefits associated with each of the different financing options. Three primary financing options a residential solar PV system are evaluated in this study: (1) a cash purchase; (2) a home-equity loan purchase; and (3) the leasing a 4kW system. In the case of a purchase using a home-equity loan, we consider cases where capital equipment can and cannot be depreciated.

The benefit-cost analysis produces two forms of metric that we use in our evaluation of each of the three financing options. We look at the net price of electricity on a $/kWh basis. A net electricity price exploits the savings in annual utility bills caused by displacement of grid-based electricity due to solar generation. We also look at the total annualized cost incurred by the purchaser. Both metrics consider subsidies, tax credits, and any cost savings stemming from depreciation, tax savings from interest paid on home-equity loans, and the grid-based electricity displaced by solar generation. Utility electricity prices are assumed to increase yearly with inflation. Table 4.2 reveals all of the data assumptions used in the analysis:

Table 4.2 Benefit-cost analysis assumptions

California solar PV analysis assumptions	
Policy horizon/lifetime of solar panel (years)	25
Solar PV panel capacity (W)	4000
Installed PV system cost ($/W)	6.73
Cost of inverter	$3000
Costs of inverter replacement (labor)	$600
EPAct 2005 tax credit	30.00%
EPBB subsidy ($/W)	0.2
Real decline in inverter costs	4.00%
Inflation rate	3.00%
Solar PV panel life (years)	25
Lifetime of system inverter (years)	10
Real electricity price ($/kWh)	$.167
Home-equity loan financing percentage	80.00%
Loan financing period	10
Loan interest rate	6.00%
Real discount rate	10.00%
Leasing charge per year (in real dollars)	$1200
Total household electricity demand (kWh/year)	7272
Solar PV electricity generation (kWh/year)	4500
O&M cost ($/kW-yr)	$32.80

4.4 Results and Conclusion

Table 4.3 and Table 4.4 illustrate the net electricity prices and the annual electricity costs for each of the financing options. Purchasing a system with cash results in a higher net electricity price relative to all other cases. The higher net price underlines the failure to reap the benefits of equipment depreciation and other tax breaks. On the other hand, financing a system through a home equity loan becomes a lot more competitive as long as the homeowner is capable of capturing the combined tax breaks from depreciation and interest paid on the home-equity loan. Tax savings from interest paid are not enough to make purchasing a more economical route as witnessed in current solar PV markets. The inability to capture the tax savings as a result of depreciation is what is creating this gap in net electricity prices between leasing and a home-equity loan purchase. Permitting depreciation allows much of this gap to shrink as shown in Table 4.4. With a net electricity price of $0.24 per kWh, leasing remains only slightly more competitive than loan financing.

Table 4.4 reflects the changes in annual electricity costs over the different business cases – highlighting differences in net electricity costs after accounting for rebates, tax credits, and savings in electricity costs. There is less than a $100 difference in annual costs between the leasing option and the home-equity loan purchase with depreciation. The results in the table once again illustrate the importance of tax breaks from capital depreciation and loan interest payments in making the purchase of a residential system more competitive. Without these savings, leasing will remain substantially more economical as lessors continue to earn the benefits of depreciation and interest deductions.

Table 4.3 Net electricity prices

Financing cases	**Net electricity price ($/kWh) Consider O&M costs**
Cash purchase	$0.37
Home-equity loan purchase w/o depreciation	$0.30
Home-equity loan purchase w/depreciation	$0.24
4kW solar PV leasing	$0.23

Table 4.4 Annualized costs for each case

Financing cases	Annual electricity costs ($/year)
Cash purchase	$2,684
Home-equity loan w/o depreciation	$2,153
Home-equity loan purchase w/depreciation	$1,712
Leasing a 4kW system	$1,663

Regular system maintenance is necessary to keep residential PV systems fully functional. Leasing agreements usually include regularly scheduled maintenance with the costs of upkeep already built into monthly leasing prices. For residential system buyers, regular maintenance may be performed by the owner themselves or an outside company. Because the costs of system upkeep are small, many owners are willing to pay for external services. Our study reveals that electricity prices fall by $0.02 in each of the buyer cases if the homeowner personally maintains the system themselves (not shown). Personal maintenance makes purchasing slightly more competitive.

Our analysis indicates that the option to buy will only prove to be more economical for the homeowner if s/he is able to access tax breaks from depreciating capital equipment and interest paid on the loan used to purchase the system. Residential solar PV lessors and commercial generators currently reap both depreciation and interest deductions. Homeowners can deduct interest only if the PV system is bought with a home equity loan. Unless households have similar tax deductions available to lessors, the option to lease will continue to be the less costly approach to residential electricity generation.

In another sense, this is about leveling the playing field. All other forms of electricity generation are entitled to deduction of depreciation and interest on the capital equipment. If homeowners could deduct depreciation and interest on solar equipment, it would have the same tax advantages afforded other means of supplying electricity. The results of this analysis suggest that providing these tax incentives for solar capital equipment should stimulate interest in homeowner purchase of the equipment.

4.5 Sensitivity Analysis

The primary driver behind our results is the underlying parameter assumptions. We conduct a sensitivity analysis to observe how changes in these assumptions can potentially affect the robustness of our results. Three cases are considered: (1) discount rates of 5% and 15% are tested compared to the base case value of 10%; (2) initial PV system costs fall by 15%; and (3) PV system panels are replaced every 10 years assuming a 10% failure rate [3] [80]. All other parameters values remain unchanged. The findings from the sensitivity analysis are shown in Table 4.5 and Table 4.6.

Table 4.5 Net electricity price for sensitivity analysis

	Net electricity price ($/kWh)				
Financing cases	Original Result (10% real discount rate)	5% real discount rate	15% real discount rate	Installed PV system cost decrease 15%	Replace 10% of panels every 10 years
Cash purchase	$0.37	$0.27	$0.48	$0.33	$0.38
Home-equity loan purchase w/o depreciation	$0.30	$0.25	$0.34	$0.26	$0.30
Home-equity loan purchase w/depreciation	$0.24	$0.20	$0.26	$0.21	$0.24
4kW solar PV leasing	$0.23	$0.23	$0.23	$0.23	$0.23

[3] National Renewable Energy Laboratory (NREL) has found that system performance will degrade less than 1%/year. This translates to 10% of panels being replaced every 10 years.

Table 4.6 The resulting annualized electricity costs under sensitivity analysis

Financing cases	Annual electricity costs ($/year)				
	Original Result (10% real discount rate)	5% real discount rate	15% real discount rate	Installed PV system cost decrease 15%	Replace 10% of panels every 10 years
Cash purchase	$2,684	$1,986	$3,473	$2,373	$2,729
Home-equity loan w/o depreciation	$2,153	$1,814	$2,461	$1,925	$2,198
Home-equity loan purchase w/depreciation	$1,712	$1,486	$1,910	$1,549	$1,747
Leasing a 4kW system	$1,663	$1,663	$1,663	$1,663	$1,663

Our original analysis uses a discount rate of 10%. Higher discount rates suggest that consumers become even less willing to invest today for any future cash flows. With a discount rate of 15%, buying a solar PV system (i.e. home-equity loan) is no longer a competitive alternative to leasing. It only becomes more competitive once discount rates are lower (5%). Alternatively, relying on a loan to purchase a system with the ability to depreciate capital equipment becomes an even more viable option if initial start-up costs are reduced by 15%. Evidence of this can be seen by the 9.5% reduction in annualized electricity costs, and a net electricity price that is about $0.02/kWh lower than prices tied to leasing. These sensitivity results are related to the importance of the initial capital cost in the overall cost for a solar system.

Assuming a tenth of the panels are replaced every 10 years, annual costs will only increase slightly whenever cash or a home-loan is used to purchase residential systems. However, we do not witness similar increases with leasing as these agreements generally have the costs of regularly scheduled maintenance and upkeep built into their monthly leasing fees. The increases in annual electricity costs we do see are relatively small (less than $50), so it is safe to say that 10% failure rate will ultimately not harm the competitiveness of purchasing PV systems with depreciation.

CHAPTER 5. HIGH PENETRATION EFFECTS OF SOLAR PHOTOVOLTAIC AND WIND ON ELECTRICITY PRICES AND CARBON EMISSIONS

This chapter is based on a paper that has been submitted to the journal of Renewable Energy. This paper is done in collaboration with Singapore University of Technology and Design. The coauthors on this paper are Shisheng Huang, Lynette Cheah, Joseph Pekny, James Dietz and Kristin Wood. In this chapter, a detailed energy system model based on the city of Singapore is presented to examine the effects of high renewable penetration on the system. Both marginal electricity prices and carbon emissions were quantified for three different penetration scenarios of wind and solar energy: a balanced mix of wind and solar energy sources (WS), a scenario of only wind capacity (W) and just solar (S).

5.1 Introduction

Globally there has been a significant push for renewable energy adoption. Some of the reasons for this drive include the need for carbon reduction in energy sources, energy security in light of increasing political tensions in energy producing regions and increasing cost of fossil fuel reserves. Many countries have instituted various policies and targets for the reduction of carbon in the energy system. These include subsidies like feed-in tariffs or tax incentives for renewable energy sources, priority dispatch in the merit order in the electricity market and even carbon emission caps or taxes on fossil fuel plants.

However, these policies, while effective in increasing renewable penetration, may distort market forces or even disrupt the stability of the energy market. Although it has been shown that the presence of renewables in the electricity system decreases the price of electricity by a certain percentage, known as the merit order effect, there could also be negative effects on the system. Recent articles have highlighted the increased electricity prices in Germany and the increasing opposition to current renewable policies [81]. In the last few years, the number of instances of negative prices, where generators must pay to provide electricity to the grid instead of receiving compensation, in the market has increased significantly with the increased penetration of wind farms[82]. This phenomenon in part results from the fact that renewable energy sources are non-dispatch energy sources and in part because existing energy sources may not be able to adjust production fast enough and would rather pay money to maintain constant energy production. This also highlights effects such as the uncertainty in renewable electricity sources and its inability to be used for on-demand purposes.

This study sets out to investigate the effects of high penetration of renewables in the electricity market, particularly on the stability of the system and price volatility. Concurrently, the temporal effects on carbon emissions are also quantified and analyzed. It is hypothesized that with the increase of renewable generators in the system, traditional fossil fuel generators may be displaced from the electricity market. Low marginal cost of electricity production, coupled with priority dispatch could reduce or eliminate profit avenues for these traditional generators. If the generators do not foresee profitable operations in the electricity market, the generators could reduce their presence in the market and retire certain generators. The resultant loss of some of these dispatch-able generators could amplify market effects during exceptional events. Also, the effects of renewable generation on the diurnal profile and quantity of carbon emissions will also differ with different renewable mix and penetration levels.

5.2 Background

5.2.1 Variable Energy Systems Effects

The effect of variable renewable energy sources on the energy system has been an important topic of research recently. There have been multiple publications analyzing possible scenarios where the level of variable energy sources becomes significant. Earlier research [83], [84] found that increasing levels of wind power will reduce the overall systems operation costs. However, as the operation costs in these studies are assumed as only fuel costs; then the investment costs, fixed costs and all the other costs related to electricity prices are not taken into account.

Some groups have studied the impact of variable renewable energy on the Australian electricity market [85], [86]. Forrest and MacGill applied econometric techniques to quantify the impact of high wind generation on electricity price, and concluded that wind energy will reduce the electricity wholesale market price in the short-term [85]. McConnell et al. modeled the impact of solar energy and showed that solar energy reduces electricity price, especially during summer peaks [86]. However, both of these studies do not consider the effect of large-scale penetration of renewable energy on the reliability of the power system and the effect of reduced generation on the capacity factor of existing generators.

Other groups have shown that the increase in variable energy sources will increase system reliability costs. Woo et al. found that increasing wind capacity tends to reduce electricity spot prices and enlarge the spot price variance. This increase in variance points to a lower system reliability, which would require increased costs to improve reliability [87]. Mount et al. report that the effect of wind farms on the total annual system costs is very sensitive to the installed capacity of wind farms [88].

Increasing levels of renewables will impact other players in the electricity market. Hirth studied the effect of solar and wind on their market value (a relative price: the ratio of the hourly wind-weighted average electricity price and its time-weighted average (base price)), and found that the market value (or benefit) of variable renewables falls with higher penetration [89]. Cutler et al. applied statistical techniques to analyze market data over 2 recent (2008-2010) years and found that wind generation and electricity price have a negative correlation. That is although wind does decrease electricity market spot prices (merit order effect), it also pushes up electricity prices when wind production is low. They also noted the increased occurrence of extreme price events (negative and high electricity prices)[90] .

5.3 Methodology

This study sets out to determine the effects of high levels of penetration of variable renewable energy sources (solar photovoltaic and wind) in the electricity market. We look at the potential effects on electricity prices as a measure of electricity costs. This is done through first establishing a reference electricity market and developing scenarios where increasing levels of renewables are examined. The scenarios are examined first assuming that the electricity mix of the reference electricity market remains unchanged, and then subsequently adjusting the electricity mix by retiring electricity generators that become uncompetitive. As a basic case to study these effects, the Singapore electricity system is used as the reference case for this analysis. An electricity system based on the Singapore system is first modeled and validated and subsequently what-if scenarios with different levels of renewable energy are analyzed. Although Singapore does not possess enough renewable resources to achieve the penetration levels in these scenarios, the analysis still serves as reference cases for systems that have approximate electricity generating profiles similar to the Singapore system.

The approach used is an agent-based modeling approach to represent the electricity market [91], [92]. The basic approach is then to model key players in this market as agents that are capable of interacting and making critical decisions while observing emergent trends and effects. The agents as defined in this model are then the Independent System Operator (ISO), traditional electricity generators, renewable electricity providers and a balancing ancillary market. The ISO is responsible for managing the electricity market, ensuring that electricity supply matches electricity demand. Electricity demand is assumed to be inelastic and in this study modeled through historical data. Electricity supply is assumed to be provided by both traditional and renewable electricity generators. A final balancing ancillary market is modeled as to provide the remaining balance of electricity demand to maintain equilibrium. Figure 5.1 shows a simplified flowchart of the system.

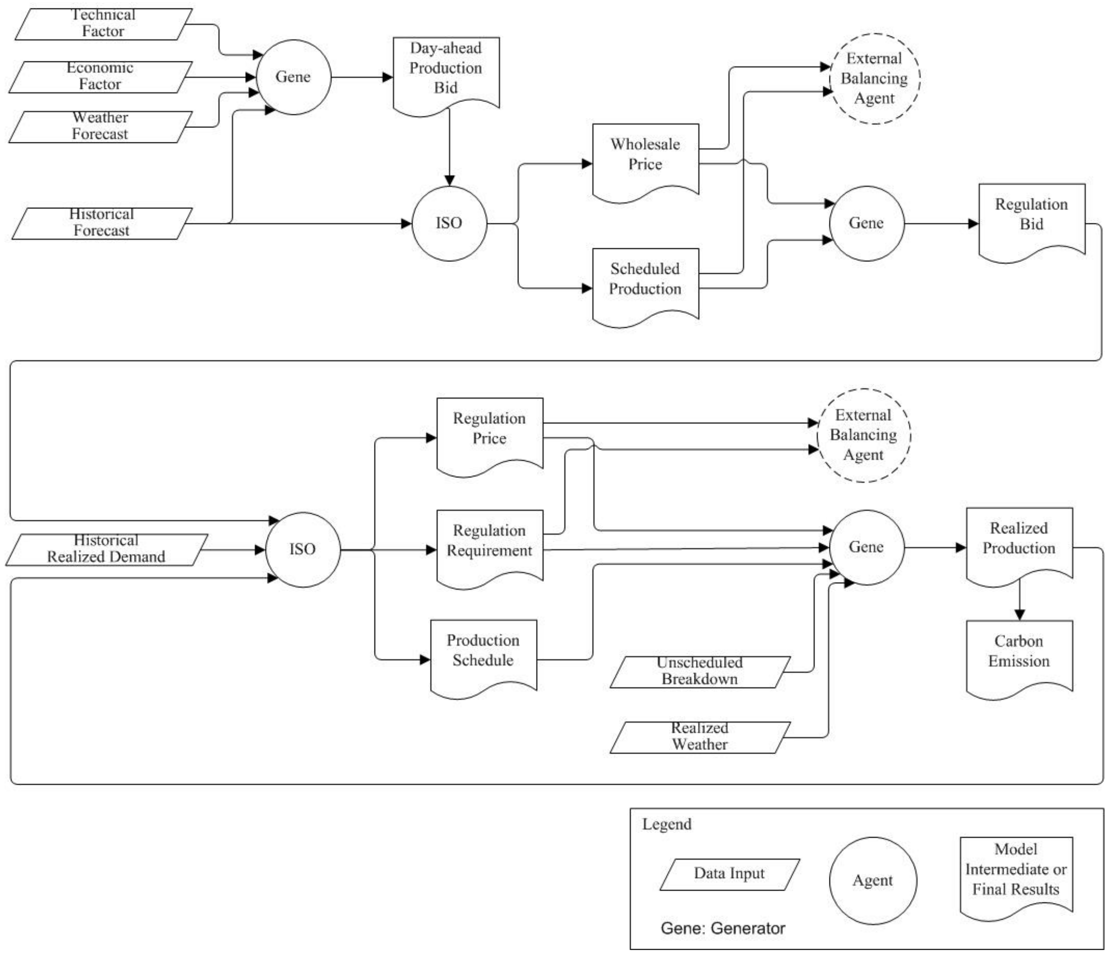

Figure 5.1 Simplified flowchart of model used in study

5.3.1 ISO

The ISO's primary responsibility is to manage the whole power system; making sure that the supply and demand remains in equilibrium. The main process is through the provision and support of electricity markets where electricity users can procure electricity from competitive electricity suppliers in an open market. In the modeled energy system, the demand is assumed to be inelastic, hence the ISO's main role is to procure enough electricity supply to meet this demand. We assume that this procurement is done through two different electricity markets, a day-ahead electricity market and a real time regulation market. A third simplified ancillary market serves as a balancing market for model mismatch.

5.3.2 Generators

Generating units are assumed to be classified as either conventional fossil fuel units or renewable units. Both classes of generators are allowed to participate in the wholesale energy market but only conventional units are assumed to be dispatch-able and allowed to participate in both up and down regulation markets (Renewable units can opt to curtail production to participate in the down regulation market). Individual generators formulate their day-ahead energy bids according to their own characteristics and through the market process receive day-ahead production schedules. These characteristics can be classified into technical and economic parameters. Technical parameters include generation technology such as Combined Cycle Gas Turbines (CCGT), Open Cycle Gas Turbines (OCGT) and Steam Turbines (ST), fuel types (nature gas, coal, fuel oil, etc.), nameplate capacity, generator age, thermodynamic efficiency, load factor, etc. Economic parameters include investment costs and operating and maintenance costs (O&M). O&M costs are further divided into fixed and variable costs. A full list of the parameters can be found in Table 5.1.

Table 5.1 The list of parameters for generators

Technical Parameters	**Economic Parameters**
Generation Technology	Annual Investment cost, C_{in}
Fuel Type	Fuel Unit Cost, C_{fuel}
Nameplate Capacity	Annual Fixed O&M Cost, C_{fOM}
Generator Age	Variable O&M Cost, C_{vOM}
Load Factor, $\boldsymbol{f_{load}}$	
Base Thermal Efficiency, $\boldsymbol{\eta_0}$	
Thermal Efficiency, $\boldsymbol{\eta}$	
Lower Limit of Operational Thermal Efficiency	
Cooling Water Factor Temperature	
Forced Outage Rate	
Planned Outage Rate	
Forced Outage Hour	
Planned Outage Hour	

It is worth noting that the investment costs and fixed O&M costs are incurred no matter if the generators produce electricity or not. That implies that if a generator generates more electricity, the investment costs and fixed O&M costs can be amortized over a larger pool of electricity, resulting in lower per unit electricity costs. In this study, it is assumed that the generators do not receive additional payments from the market and must recover costs through the market process. Therefore, the capacity factor (the ratio of its actual output over a period of time, to its potential output if it were possible for it to operate at full nameplate capacity indefinitely) is a significant factor that affects electricity cost.

5.3.2.1 Conventional Generators

The Singapore electricity system is assumed to be the system on which the study will be based. In the Singapore system, the dominant fossil fuel used is natural gas followed by fuel oil and waste. This system is characterized by 32 units with nameplate capacities ranging from 22 MW to 600 MW [93] . A general summary of this capacity is shown in Table 5.3 with more details in a later section.

5.3.2.2 Renewable Generators

Renewable units are mainly characterized by parameters included in Table 5.1, except that these generators do not consume fuel. The generation data is assumed to be similar to published information available online and from models used in previous studies. Wind generation data is obtained from the NREL wind integration datasets adapted from a previous study [94][95], [96]. Solar generation data has been derived from a variety of databases using the model developed in a previous publication [27], the same data is used in this study.

5.3.3 Electricity Market

In this study, the electricity system is assumed to be a fully deregulated electricity market that is similar to the Singapore electricity market. Singapore operates a deregulated wholesale electricity market through the Energy Market Company. Generators are able to bid into three markets which are cleared either half-hourly. The markets are the Energy Market, Reserve and Regulation Market [97]. The Energy Market provides a wholesale environment where consumers procure electricity to fulfill load demands. The Reserve Market provides for backup generation to support the electricity system in exceptional events. There are three types of reserves in the Singapore market, primary, secondary and contingency reserve which defer in the required response time in exceptional events. The Regulation Market provides regulation services that cover the immediate temporal variations in load from forecasted load so as to ensure supply demand equilibrium. Other ancillary services such as reliability must-run services and black-start capabilities are secured on a procurement basis.

In this paper, only the main energy market and regulation market are modeled while the reserve market is assumed to be part of a simplified ancillary market. A 24 hour day-ahead market is cleared one day in advance together with solicited bids for the regulation market, producing the day-ahead wholesale price. During actual realization of demand, the regulation market clears in real time for determination of regulation price.

5.3.3.1 Day-ahead Energy Market

At the start of the day-ahead market, the ISO generates a forecasted electricity demand for the next day and invites market participants to submit electricity generation bids. This forecast is usually a function of historical electricity demand, predicted weather conditions, and other predictive parameters. In this study, historical data for forecasted demand is used from the Singapore electricity market. This data is available from the online database maintained by the local ISO, the Energy Market Company [98] and represents the day ahead forecasts that the ISO provides to generators.

All the generators then bid for the next day's hourly electricity generation according to their own nameplate capacity, forecasted generation and costs. The generators produce a series of production, marginal price bid pairs for different generating capacities. The generating units would have varying thermal efficiencies at different loading capacities, hence, the marginal price for electricity production at different loads would be different. The thermal efficiency of the units can thus be determined by equation 1 below, where the impact of load factor (f_{load}) is a quadratic function of load factor, and efficiency is highly affected by generation technology. For the parameters considered in this study and over the range of load factors considered, the function is an increasing function. Therefore, a high load factor indicates a higher thermal efficiency. The exact functions and assumptions are detailed in another work [99], and the general equations are as follows.

$$\eta = \eta_0 \times f_{age} \times f_{size} \times f_{water} \times F(f_{load}) \quad (1)$$

η_0: Base thermal efficiency

f_{age}: Age factor, function of generator age

f_{size}: Size factor, function of nameplate capacity

f_{water} : Cooling water factor, function of cooling water

$F(f_{load})$: Impact of load factor, function of load factor

This thermal efficiency can then be translated to the amount of fuel needed per unit of electricity produced, and by extension, the cost of fuel. The marginal bid prices can then be determined by equation 2. As discussed in an earlier section, fuel cost and variable O&M costs are only incurred when generators produce electricity, while fixed O&M costs and financial payments occur no matter if the generators produce electricity or not. Since generators are assumed to recover costs and profits only from market participation, the marginal bid price is then modified by the capacity factor for the generator.

$$P_{bid} = C_{total} \times f_{markup}$$

$$= \left(C_{fuel} + C_{vOM} + \frac{1}{\mathrm{C_f}} \times \frac{C_{fOM}+C_{in}}{\mathrm{C_{name}} \times 8760\ \text{hours}}\right) \times f_{markup} \qquad (2)$$

P_{bid}: Generator bid price

C_{total}: Total per unit cost of electricity generation

f_{markup}: Markup Factor

C_{fuel}: Fuel unit cost

C_{vOM}: Variable O&M cost

C_f: Capacity factor

C_{fOM}: Annual fixed O&M cost

C_{in}: Annual investment cost

$\mathrm{C_{name}}$: Nameplate capacity

In this study, it is also assumed that energy generated from renewable energy sources do not incur marginal variable generation costs since solar and wind energy sources do not consume fuel during electricity generation. Hence it can be assumed that renewable energy generators would be willing to sell any amount of electricity as long as the electricity price is positive. For the purpose of this study then, in order to maximize renewable electricity production, the bid price of electricity is assumed to be zero.

Once the ISO consolidates the bids from the generators, it will generate a merit order stack of the bids, listing the bids from lowest bid price to highest bid price for every hour. It will then schedule the day-ahead hourly electricity production according to the forecasted demand. The bid that just fulfills the demand in the market becomes the marginal price for the hour. The schedule is done for each hour, resulting in 24 marginal prices.

5.3.3.2 Regulation Market

The regulation market acts as the avenue for load balancing in the electricity market. In this study, the regulation market is only cleared once the actual electricity demand is realized. After the market clears for the day-ahead electricity market, generators are invited to submit bids for regulation power for each hour. There are two possible scenarios for regulation – up regulation and down regulation. Up regulation power is required when the realized demand is greater than scheduled production, while down regulation occurs when demand is smaller. The modeled bidding process is similar to the wholesale electricity market, with capacity price pairs submitted by each generator for each time period. The main differences are that the market clears only when the actual electricity demand is realized and the time periods are half-hourly. Up regulation bid pairs are determined using the same set of equations in the previous section and are dispatched through their merit order in the stack. Down regulation is treated slightly different. Since generators can only down regulate if they are already producing electricity, down regulation bids are only available to generators that have been scheduled in the day-ahead market. The down-regulation bid price is determined in equation 3, with a key assumption that the total income for a generator after doing down-regulation should be the same as if it does not participate in down-regulation.

$$P_{down} = \frac{(P_m - C_{before}) \times Ele_{before} - (P_m - C_{after}) \times Ele_{after}}{Ele_{down}} \qquad (3)$$

P_{down}: Down-regulation bid price

P_m: Marginal price of electricity

C_{before}: Cost per MWh of electricity generated before down-regulation

C_{after} : Cost per MWh of electricity generated after down-regulation

Ele_{before} : Electricity production amount before down-regulation

Ele_{after} : Electricity production amount after down-regulation

Ele_{down} : Down-regulation bid amount

Wind and solar generators can also participate in the down-regulation market, and it is assumed that they can curtail generation if needed. Since renewable generators do not have fuel considerations, it is assumed that they would always produce at their capacity; correspondingly, the down-regulation price for wind and solar would be the same as the marginal price of electricity in the market.

5.3.4 Carbon Emissions

Typically, carbon emission calculations have been done through an aggregated manner through aggregating overall electricity generation by generating technology, assuming all generators within the group are equally efficient and applying a standard emissions factor to them. In this study, each individual generating resource is tracked over the course of the simulation through the agent-based model, allowing for more accurate accounting of carbon emissions per generating plant.

For the purpose of this paper, only carbon emissions from the combustion stage in generators are considered. Emissions from upstream processes like fuel processing and power plant construction are not taken into account, therefore, wind and solar resources are considered carbon free. From literature [100], the amount of CO_2 emitted is a function of both the carbon content of fuel and the operational thermal efficiencies of combusting units. Hence, assuming that all the carbon content is oxidized to CO_2, the CO_2 emission per electricity generated is given as:

$$E_{CO_2} = \frac{C_C}{\eta} \times \frac{44}{12} \quad (4)$$

E_{CO_2}: CO_2 emission by fuel type and technology (g/kWh)

Cc: Carbon content of fuel (g carbon/kWh)

$\frac{44}{12}$*:* Ratio of molecular weight of CO2 and carbon atoms

5.3.4.1 Carbon Content of Fuel

The values of carbon content for the fuels used in this study are listed in Table 5.2 [100]. The carbon content of waste is complicated due to the fact that waste is a heterogeneous mixture where single components have different carbon amounts and heat properties. Since waste only accounts for a very small proportion as an energy source in Singapore, we assume that the carbon content of waste is the same as fuel oil.

Table 5.2 Carbon content of the fuels

	Natural Gas	Fuel Oil	Waste
Carbon Content (g Carbon / kWh)	52.6	74.3	74.3

5.3.4.2 Thermal Efficiency

In this study, each individual generating resource is tracked over the course of the simulation through the agent-based model. The operational thermal efficiencies

(Equation 1) of every generator are recorded every fifteen minutes. In order to improve simulation speed, we use the average thermal efficiency $(\frac{1}{2}(\eta_{max} + \eta_{min}))$ for each generator over the course of the simulation to calculate CO_2 emissions.

5.4 Model Validation

As with any simulation study, one of the most important steps in model building is to ensure that this agent-based model can accurately represent the characteristics of the supply side of power system. In this work, we have used the Singapore data from 2012 from the Energy Market Company, Singapore [98], [101] to do validation.

Singapore has slightly over 30 generators, with a combination of CCGT, ST and OCGT generators. The fuel mix for Singapore is predominantly natural gas followed by fuel oil and waste. Table 5.3 gives a summary of the total capacity of each type of generator together with published statistics on electricity generation mix. As can be seen, 92% of electricity consumed in Singapore is generated by CCGT generators, with 8% from ST generators with minimal capacity from OCGT. In order to validate the electricity supply model, generator characteristics and historical forecasted data from 2012 are fed into the agent-based model which generates simulated electricity prices. These simulated electricity prices are then compared to historical data from 2012.

Table 5.3 Generator capacity information for Singapore in 2012

	CCGT	ST	OCGT
Generation Capacity / MW	7874	2215	210
Capacity Ratio / %	73.33	21.76	0.16
Generation Ratio / %	92.29	7.70	0.01
Generation Ratio (Model) / %	91.52	8.41	0.07

Table 5.3 also gives a summary of results obtained from various simulation runs. The averaged simulated energy generation ratios are 91.52%, 8.41% and 0.07% for CCGT, ST and OCGT respectively. These are similar to historical data seen in Table 5.3. The generated price data is also summarized and given in Table 5.4. The historical price information was obtained from the online database [98]. Once again, the model results tracked closely to historical data. Electricity prices are highly temporal in nature and Figure 5.2 shows the average price variation within a day for the Singapore electricity market, showing the two marginal price peaks in a day.

Table 5.4 Average marginal and regulation price for 2012 and model results

	Historical data	Model Results
Average Marginal Price	222.49	221.68
Average Regulation Price	91.50	91.69

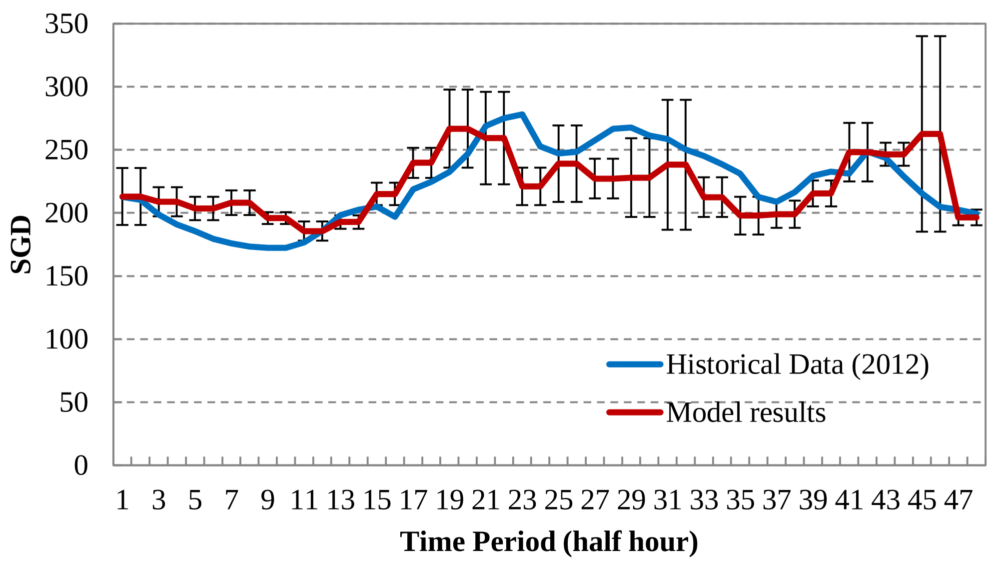

Figure 5.2 Average electricity marginal price across a day

5.5 Results and Discussion

The main thrust of this study is the investigation of a large scale penetration of renewable energy sources in an electricity system. A deregulated electricity system represented by the Singapore electricity market is used as a reference case for the idealized scenarios. We examined different penetration levels of wind and solar energy and determine the effects on the electricity price and carbon emission. Different combinations of wind and solar are examined, equal contributions from wind and solar, pure solar investment and pure wind energy investment. Starting from a base case with no renewables, increasing levels of renewable energy sources are added. In this study, the added renewable energy capacity is the effective capacity, which is the nameplate capacity divided by a capacity factor. The effective capacity of both wind and solar is less than their nameplate capacity. It is assumed that this factor is 0.35 [102]. For example, when adding 200MW effective wind energy, the nameplate capacity needed is 200/0.35=571MW. In the renewable scenarios examined, several permutations of renewable capacities are added. Initially, the same capacity of wind and solar (WS) energy are added into the power system gradually, from (200+200) MW to (1000+1000) MW. Then wind (W) and solar (S) energy are added into the power system separately, both from 400MW to 2000MW. The daily peak electricity demand in Singapore is between 4000 MW to 6500MW [98], [101], so 2000MW is around 30% to 50% of the peak electricity demand in Singapore.

5.5.1 Marginal Price

The effect of renewable energy on electricity marginal price is of great interest to both utilities and customers and throughout this study, the currency of analysis will be the Singapore Dollar (SGD). The average historical marginal price for Singapore in 2012 is 222.49 SGD/MWh, while the marginal price from the energy market model is 221.84 SGD/MWh. As mentioned in the previous section, in order to observe the change of marginal price affected by renewable energy, different scenarios are simulated with multiple levels of renewables. The results are shown in Figure 5.3. A direct observation is that marginal prices seem to be directly correlated with renewable generation capacity increase. In the examined scenarios, the average marginal prices come to 502.80 SGD/MWh, 500.93 SGD/MWh, and 339.97 SGD/MWh, for WS, W and S scenarios respectively for cumulative capacities of 2000 MW. These prices, however, could be influenced by very low utilization units which drive up marginal prices significantly.

As mentioned earlier, the bid price for renewables is assumed to be 0. Intuitively, as the merit order stack becomes populated with more renewables, the marginal price should decrease, as determined in other publications [90]. As discussed in the earlier section, this study assumes that the bid prices are tied to the capacity factors, as the capacity factors of electricity generators get reduced, the bid prices increase. Correspondingly, if we assume that all the generators remain as participants in the electricity market, the marginal price of electricity generation should also increase. Although the price of electricity does increase across all scenarios, the effect of wind is more pronounced than that of solar. This effect can be attributed to the fact that solar power tracks peak usage much better than wind, hence the effect of solar is to displace more marginal generators which already have low capacity factors.

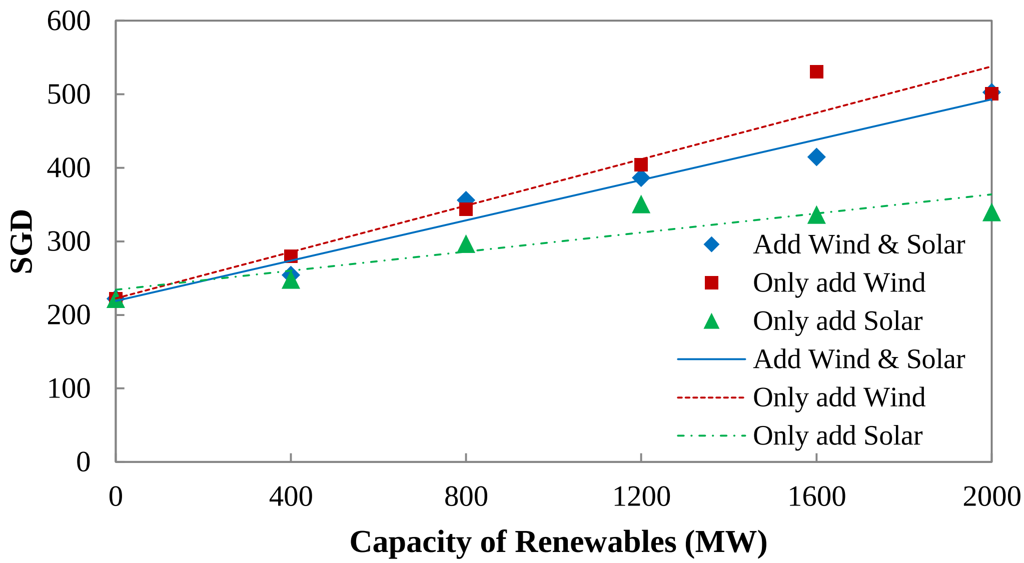

Figure 5.3 Marginal price for electricity for different renewable scenarios

5.5.2 Retired Generators

With the increasing penetration of renewable energy sources, the marginal bid prices will continue to increase as capacity factors decrease. This poses significant problems as these prices may result in untenable scenarios such as the California electricity crisis [103]. In Singapore, the upper limit of marginal price bids is 4500 SGD / MWh [98], [101]. As the level of renewable generation increases in the energy system, the capacity factors of marginal generators in the electricity market start to decrease to the point such that the bid prices of the generators may increase beyond 4500 SGD / MWh. It then stands to reason that the generators would not be able to recoup their costs such that they would leave the market. As a modification to the scenarios described in the previous section, generators that must bid marginal prices above 4500 SGD / MWh would be retired from the market and removed from the system.

The generators that are first removed are the OCGT generators and the small capacity ST. When the added renewable energy sources reach 2000MW, the small scale CCGT generators are also retired, while the biggest ST generators (600MW) remain in the market. The summary of retired capacities is shown in Table 5.5.

Table 5.5 The summary of retired capacities when adding renewable energy

Renewable Capacity (MW)		400	800	1200	1600	2000
Add Wind & Solar (WS)	Retired Capacity (MW)	676	908	908	1158	1408
	Type	OCGT, ST	OCGT, ST	OCGT, ST	OCGT, ST, CCGT	OCGT, ST, CCGT
Add Wind (W)	Retired Capacity (MW)	676	908	908	908	1408
	Type	OCGT, ST	OCGT, ST	OCGT, ST	OCGT, ST	OCGT, ST, CCGT
Add Solar (S)	Retired Capacity (MW)	0	676	676	676	908
	Type		OCGT, ST	OCGT, ST	OCGT, ST	OCGT, ST

The results for marginal prices are shown in Figure 5.4 to Figure 5.7. When compared to the previous scenarios where generators are not retired, the marginal prices for the various scenarios tend to be lower. However, significant amounts of renewable energy sources still tend to increase the marginal cost of electricity when compared to the base case. Comparing across the different scenarios, at installed capacity of 2000MW, the marginal price of electricity is 369.41 SGD/MWh, 393.89 SGD/MWh, and 303.08 SGD/MWh, respectively.

It can also be seen that for the different renewable energy source scenarios, the rate of increase of marginal prices are significantly different. In fact, when only solar capacity is added to the system, the marginal price increase is almost negligible. Conversely, wind energy contributes a high degree of uncertainty and affects electricity generation costs much more drastically. This reinforces the short term empirical observations and arguments with regards wind energy effects on energy system stability [87]. A complementary argument can be made that a relatively high penetration of solar resource can be added to the energy system and not significantly impact marginal electricity prices. However, even then, the model results do not indicate a decrease in marginal prices, just the effect of maintaining status quo in the electricity market.

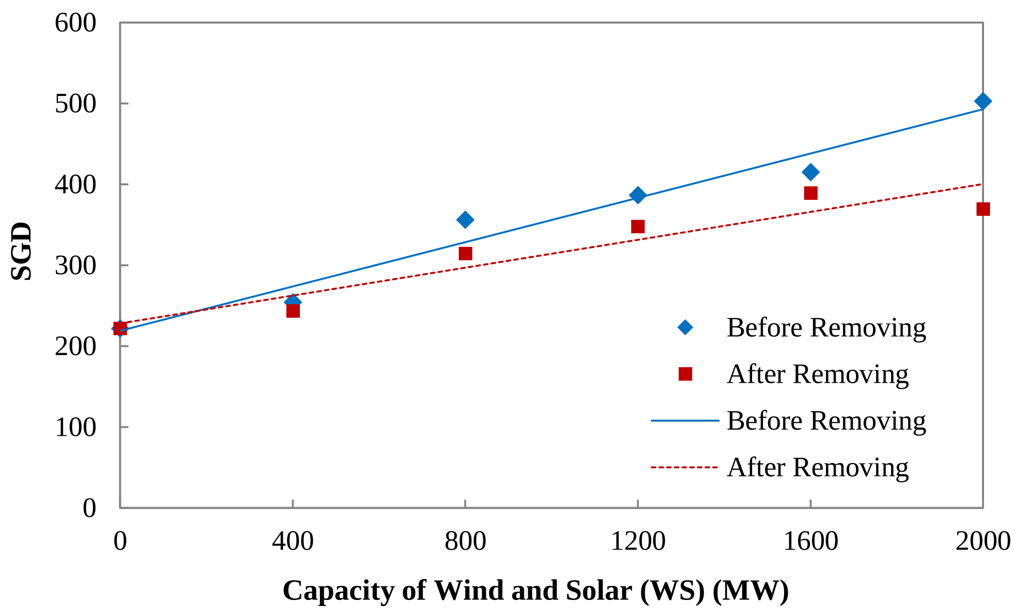

Figure 5.4 Marginal price profile before and after removing retired generators when adding wind & solar

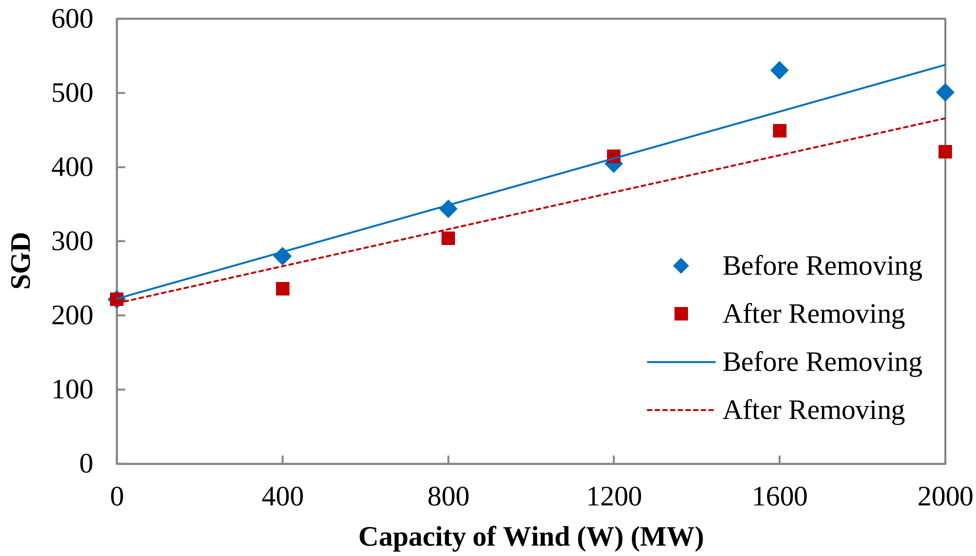

Figure 5.5 Marginal price profile before and after removing retired generators when only adding wind

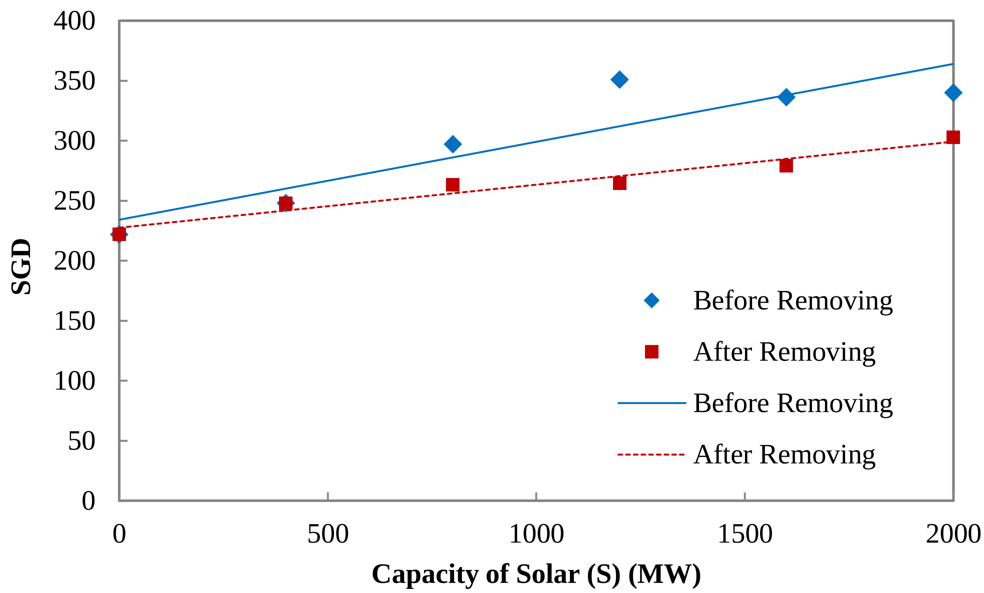

Figure 5.6 Marginal price profile before and after removing retired generators when only adding solar

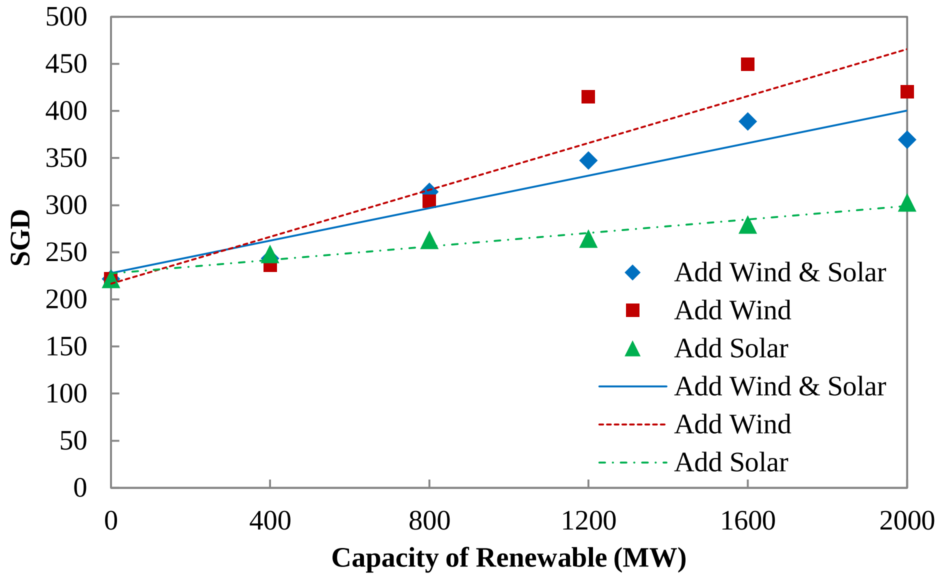

Figure 5.7 Marginal price profile after removing retired generators

5.5.3 Carbon Emissions

The effect of renewable energy sources on CO_2 emissions is a key benefit of renewable energy sources. As discussed in section 5.2, with the increasing penetration of renewable energy sources, generators which are not able to compete competitively could start to exit the market. That translates to fossil fuel generation being replaced by carbon free energy sources. On the other hand, the increase penetration of renewable energy would also affect the load factor and operational thermal efficiency of the other generators which are still in the market. This change of operational thermal efficiency will then also affect CO_2 emission.

Therefore, in order to investigate the change of CO_2 emissions affected by the impact of renewable energy, detailed calculations that track individual generating units as detailed in section 5.3.4 have been done. These results are shown in Table 5.6 and Figure 5.8. The most obvious trend is that as renewable capacity increases, carbon emissions decrease. This is expected and not surprising.

Another observation is that the effects of the different renewable sources on the magnitude of decrease of carbon emissions are different. It can be seen then that for a same effective capacity, wind power decreases carbon emissions to a bigger extent when compared to solar energy. The average CO_2 emissions per day for different levels of renewable generation are given in Table 5.6. At a penetration level of 2000 MW, pure wind investments result in an average reduction of 21930 metric tons of CO_2 per day, corresponding to a reduction of 43% of CO_2 emissions; while pure solar investments result in only a 21% in emissions or 10811 metric tons of CO_2 per day. This serves as an interesting counter point to the previous section where solar generation has a less significant effect on marginal electricity prices.

Table 5.6 CO2 emission with the increase of renewable and retired generators (metric tons/day)

Capacity of Renewable (MW)	0	400	800	1200	1600	2000
Add Wind & Solar (WS)	50636	46345	42214	38989	40584	32713
Add Wind (W)	50636	45428	40205	36424	32737	28716
Add Solar (S)	50636	47866	45265	43576	41643	39825

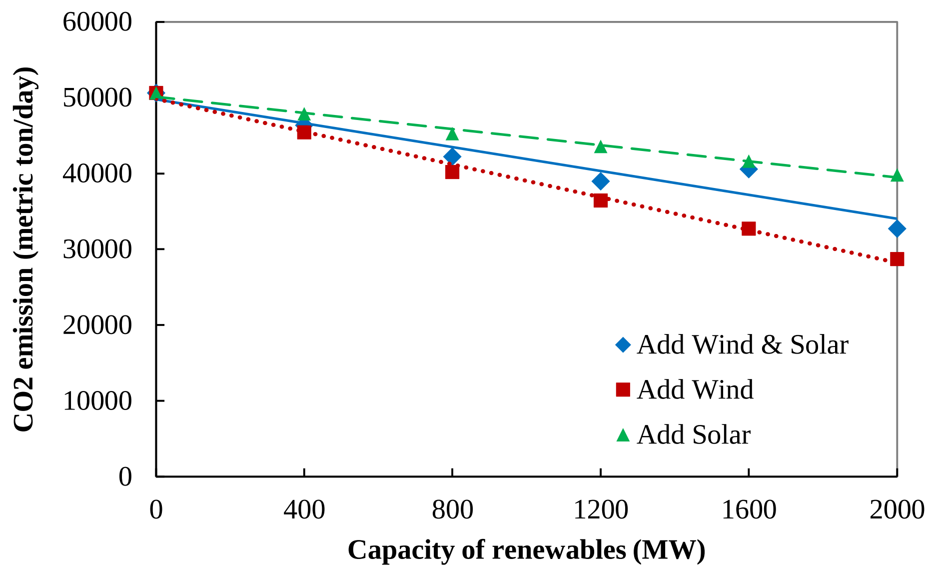

Figure 5.8: CO2 emission with the increase of renewable after removing retired generators

Figure 5.9 to Figure 5.12 display daily generation profiles and resultant CO_2 emissions on a typical day in the system examined. Figure 5.9 represents the reference case for the model where the current electricity generation profile is examined. It shows a typical assignment of the generators that are operating in Singapore where the expensive oil generators are only used during peak periods. Cases in Figures 10 to 12 are all with 2000 MW effective capacity of renewables, with uncompetitive generators retired.

In general, the emission profiles are consistent with fossil fuel consumption, CO_2 emissions decrease with renewable electricity production. Solar energy generation peaks during midday (Figure 5.12), representing minimum CO_2 emission during daytime (around 1pm). While there is no well-defined peak for wind energy, generally, wind energy production is higher during night time (Figure 5.11). It is obvious then, from these figures that solar energy more readily displaces smaller generators that only operate during peak demand. These generators may not have much influence over the production of carbon emissions, but in a system where these generators are marginal generators, they are still significant factors on marginal electricity prices. Similarly, wind generators generate throughout the day, while the displacement of marginal generators still occur, they do not exclusively displace these, hence the effect on the marginal electricity prices would then be lower than solar energy sources.

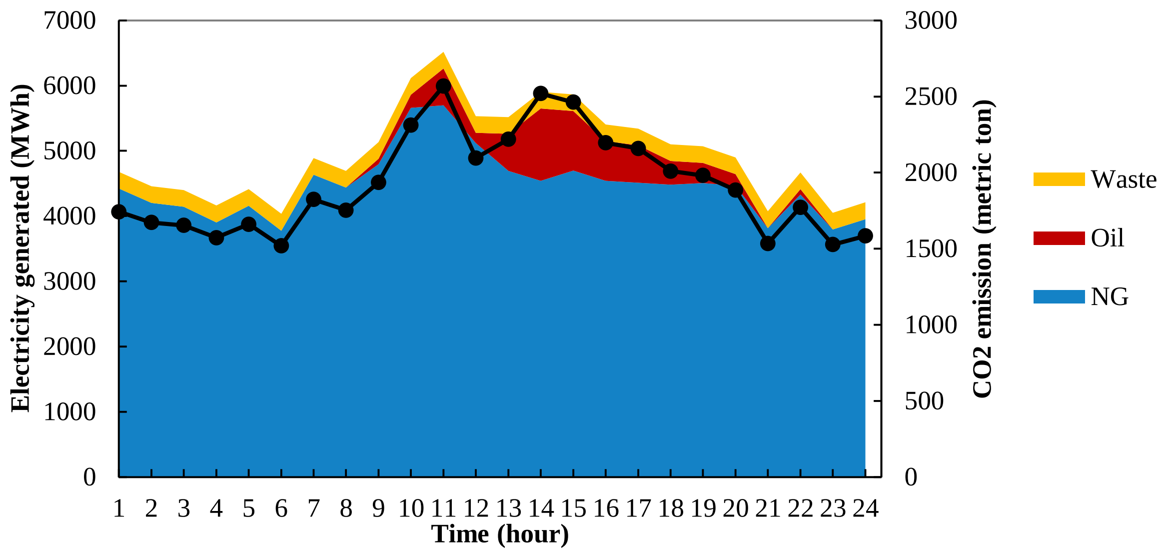

Figure 5.9 Daily electricity generation by fuel sources and CO2 emission without renewables

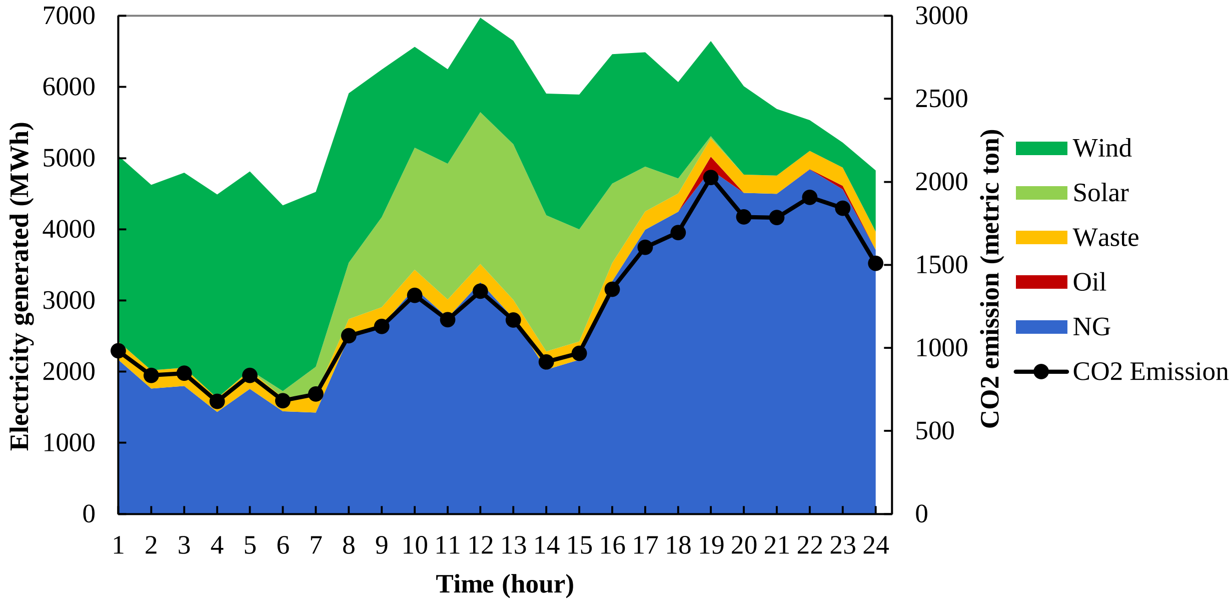

Figure 5.10 Daily electricity generation by fuel sources and CO2 emission when adding 2000 MW solar & wind

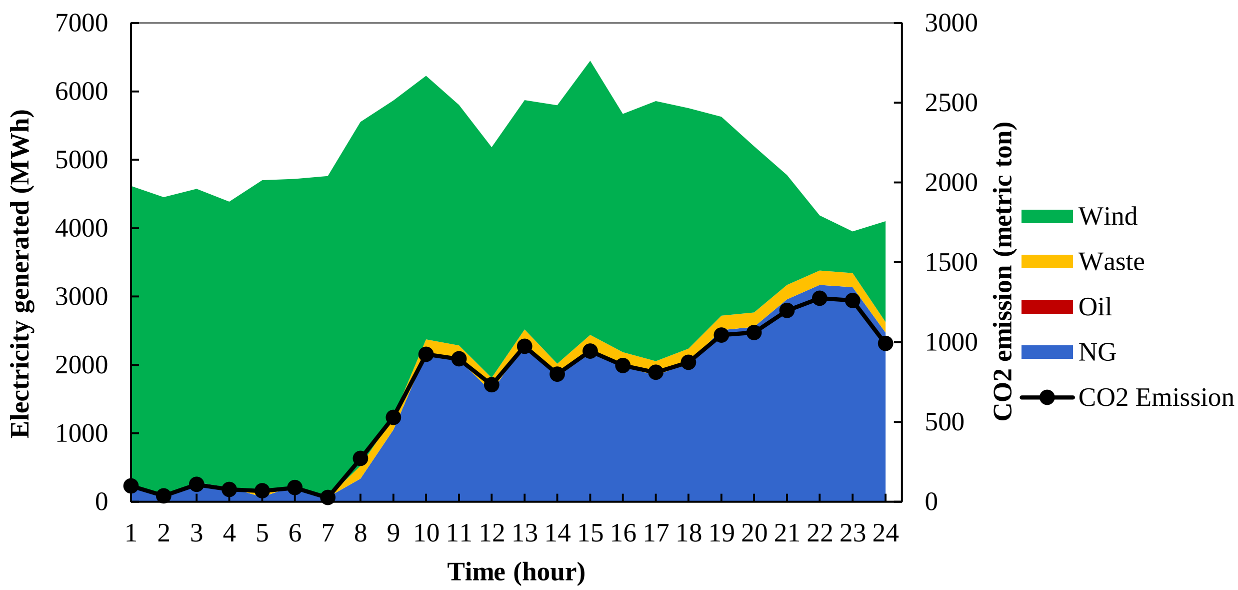

Figure 5.11 Daily electricity generation by fuel sources and CO2 emission when adding 2000 MW wind

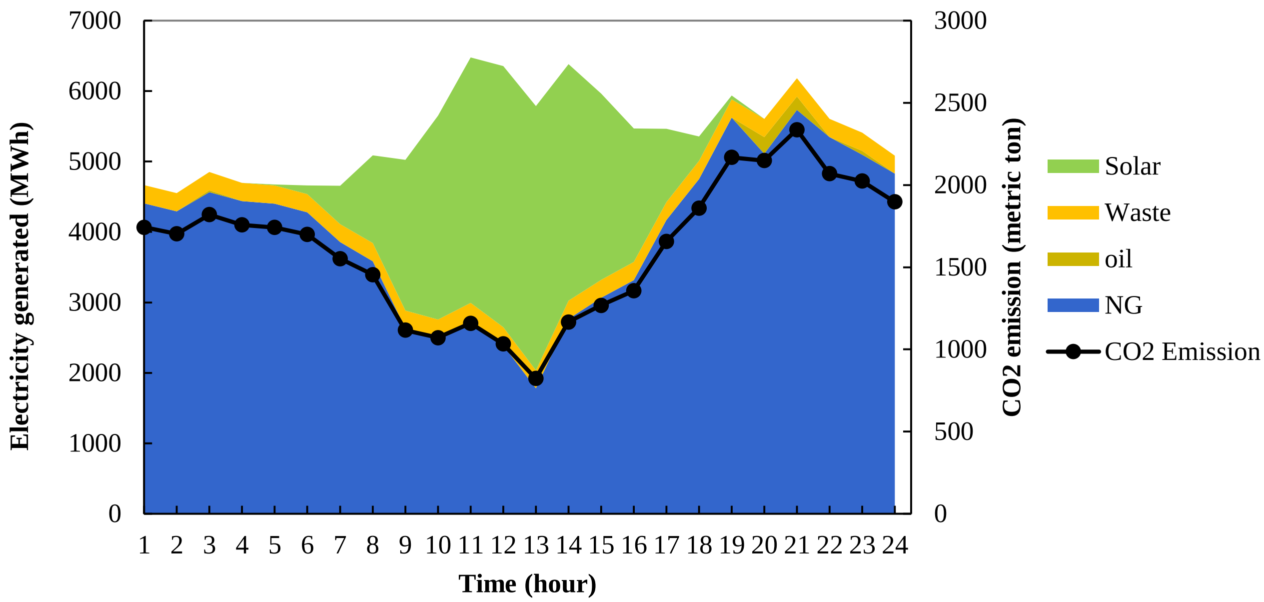

Figure 5.12 Daily electricity generation by fuel sources and CO2 emission when adding 2000 MW solar

5.6 Conclusion

In this study, a detailed energy system model based on the city of Singapore is presented to examine the effects of high renewable penetration on the system. Both marginal electricity prices and carbon emissions were quantified for three different penetration scenarios of wind and solar energy: a balanced mix of wind and solar energy sources (WS), a scenario of only wind capacity (W) and just solar (S). It is assumed that generators consider the effect of capacity factor when calculating bid prices. When low capacity factors for generators force units to bid at prices that are above the allowed price caps, the generators are then assumed to be retired from the system. It can be seen from the model results that the wind and solar generation affect the assumed electricity system very differently. In general, wind generation would reduce carbon emissions more than similar effective capacity of solar energy sources.

However, in terms of marginal costs of electricity generation in the Energy Market, wind energy increases marginal electricity prices more than equivalent solar capacities. It is then interesting to note that from a system perspective, different renewable energy resources should be favored differently for different system objectives.

CHAPTER 6. CONCLUSION AND FUTURE WORK

6.1 Conclusion

In this thesis, both energy demand sector and energy supply sector are analyzed based on several subsystems. On demand sector, both transportation system and solar PV micro-generation system are studied. For transportation system, a model-based methodology is developed to quantify EV battery lifespan. Using this methodology, battery life distributions arising from various driving behaviors are generated based on realistic drive cycles in Indianapolis. Besides Indianapolis, this methodology can be applied to any regions for battery life studies, and provide insights for EV companies to design battery warranties. For solar PV micro-generation system, a laboratory simulation tool is developed for solar PV systems for both research and education purposes. This tool has been published on line, and is free for everyone to use. On supply sector, an agent-based model is developed and validated to simulate the Singapore power system. Using this model, in-depth understanding was gained for wind and solar energy associated with electricity prices and CO2 emission. Besides Singapore, this model can be applied to any power systems and to provide detailed information for policy makers to develop strategies for utilizing various types of renewable energy.

6.2 Future work

This work can be extended or improved in several ways.

6.2.1 Public Charging Effects

In this study, charging effects are neglected in the EV battery lifespan investigation. It is reasonable to ignore charging effects if EV only charges at home with level 1 or level 2 chargers. With the development of EVs and related infrastructures, public charging stations are going to be a significant part of transportation system. Therefore, this work can be extended to integrate public charging effects on battery lifespan on the one hand. On the other hand, public charging effects on electricity demand and transmission should also be studied in future work.

6.2.2 Integration of Solar PV System with EV

In this study, EV and solar PV micro-generation system are analyzed as two separated systems. Actually, both EV and solar PV can be considered as household appliances. EV is an electricity consumer and energy storage device, while solar PV is an electricity generator. A model which combines EV, solar PV, and household energy demand should be developed to answer various types of what-if questions.

6.2.3 Integration of Demand Sector with Supply Sector

In this study, both energy demand sector and energy supply sector are analyzed. Energy system is an integrated system which includes energy demand and supply. Energy supply sector provides energy through transmission system to match total energy demand. Both sectors' behaviors will affect each other. In this study, for the sake of simplicity one sector is assumed to be ideal when the other sector is studied. In future work, a model which combines both energy demand sector and supply sector should be developed. This proposed model can simulate the whole energy system more accurately. It can provide detailed information for policy makers to develop strategies for making various policy portfolios.

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APPENDICES

Appendix A Solar PV System Survey Results from Purdue University

Total participants: 23

Gender: Female: 8 Male: 15

Statistics for each question:

1. Using Solar PV systems would reduce electricity consumption.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	3	6	8	6	0
After	2	2	4	15	0

2. Solar PV system would reduce the peak demand of electricity for household.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	3	2	14	4	0
After	3	1	7	2	0

3. Individual consumers will benefit from the installation of solar PV systems.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	0	3	14	5	1
After	0	2	16	4	1

4. Local utility companies will benefit from the installation of solar PV system.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	1	7	9	5	1
After	2	6	10	5	0

5. Solar PV system is safe to use.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	0	0	18	4	1
After	0	0	10	12	1

6. Solar PV system is reliable to use.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	2	8	12	0	1
After	1	5	10	6	1

7. Solar PV system is easy to maintain.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	1	13	7	0	2
After	1	9	8	3	2

8. Solar PV system can help to reduce CO2 emission.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	0	1	7	15	0
After	0	0	12	11	0

9. Solar PV system would be too expensive for the average household.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	0	2	13	7	1
After	0	9	8	5	1

10. Batteries can help to improve the efficiency of solar PV systems.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	0	4	15	4	0
After	0	0	6	17	0

11. Batteries can help to reduce the peak demand of electricity for households.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	1	4	15	3	0
After	1	1	8	13	0

12. I am interested in learning about solar PV systems.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	0	1	15	7	0
After	0	2	10	10	1

13. I have access to adequate amount of information about solar PV systems.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	0	6	15	1	1
After	0	3	12	8	0

14. I am interested in pursuing further studies in an area related to solar PV systems.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	2	8	12	1	0
After	2	6	10	5	0

15. I am interested in conducting research on solar PV systems.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	4	7	10	2	0
After	3	8	10	2	0

16. If given the opportunity, I would use solar PV systems.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	0	1	13	5	4
After	1	0	14	8	0

17. I would still use solar PV systems in my house even if solar electricity is expensive than the electricity from power grid.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	2	14	4	3	0
After	3	10	5	4	1

18. I am willing to use solar PV systems in the future.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	0	1	13	9	0
After	0	1	11	11	0

19. I think solar PV systems will become one of the most popular electricity sources in the future.

	Strongly Disagree	Disagree	Agree	Strongly Agree	Not Applicable
Before	1	4	13	5	0
After	1	4	8	10	0

20. In how many years do you think solar PV systems will become one of the most popular electricity sources?

	10years	20years	30years	50years	Not Applicable
Before	0	14	6	3	0
After	3	10	7	1	2

21. Do you think governments should subsidize solar PV systems? Why?

	Yes	No	NA		
Before	13	8	2		
After	16	5	2		

22. Do you think governments should support solar energy related research? Why?

	Yes	No	NA		
Before	22	1	0		
After	21	2	0		

23. How would you describe your current knowledge/understanding of solar PV systems?

	High	Medium	Low	NA	
Before	0	4	17	2	
After	2	13	8	0	

24. Based on what you have learned in this project, are you more likely to accept solar PV systems?

	Yes	No	NA		
Before					
After	21	2	0		

Appendix B Solar PV System Survey Results from United States Military Academy

Total participants: 3

Gender: Female: 0 Male: 1

Comparison of the average results before and after the project:

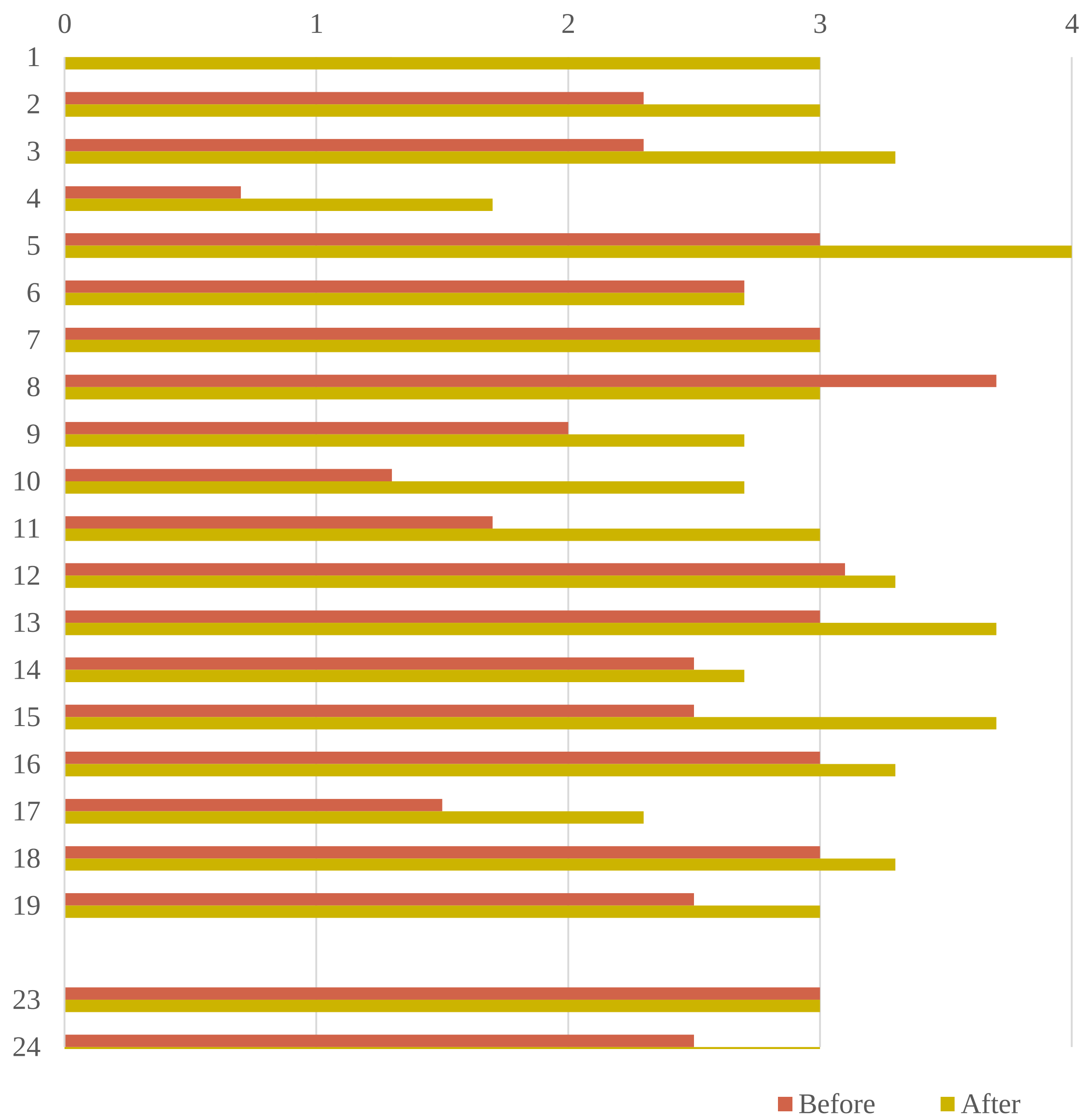

Figure B1 Results comparison from United States Military Academy at West Point

VITA

VITA

Xiaohui Liu received her Bachelor degree of Chemical Engineering from Tsinghua University in Beijing, China, in 2009. She then joined Professor Shanying Hu's research group to continue her Master study at Tsinghua University. Her Master research is about industrial ecology. She got her Master degree of Chemical Engineering in 2011 from Tsinghua University. After that, she enrolled in the PhD program at Purdue University (West Lafayette, Indiana) in the school of Chemical Engineering in August 2011. Her advisors are Professor Joseph Pekny and Professor James Dietz. She obtained her PhD in Chemical Engineering in the May of 2016.