# Assessment of the Electrification of the Road Transport Sector on Net System Emissions

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**Abstract**

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As worldwide environmental consciousness grows, electric vehicles (EVs) are becoming more common and despite the incredible potential for emissions reduction, the net emissions of the power system supply side plus the transportation system are dependent on the generation matrix. Current EV charging patterns tend to correspond directly with the peak consumption hours and have the potential to increase demand sharply allowing for only a small penetration of Electric Vehicles. Using the National Household Travel Survey (NHTS) data a model is created for vehicle travel patterns using trip chaining. Charging schemes are modeled to include uncontrolled residential, uncontrolled residential/industrial charging, optimized charging and

optimized charging with vehicle to grid discharging. A charging profile is then determined based upon the assumption that electric vehicles would directly replace a percentage of standard petroleum-fueled vehicles in a known system. Using the generation profile for the specified region, a unit commitment model is created to establish not only the generation dispatch, but also the net $CO_2$ profile for variable EV penetrations and charging profiles. This model is then used to assess the impact of the electrification of the road transport sector on the system net emissions.

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# Chapter 1. INTRODUCTION

In the most recent decade, volatility of fossil fuel prices along with global initiatives looking to reduce carbon emissions have led to a push to explore alternative energy sources and enhance existing vehicle technologies. According to 2013 estimates by the Environmental Protection Agency (EPA) 27% [1] of the US greenhouse gas emissions are produced by the transportation sector making it a key target for state and federal reduction efforts. In addition to these efforts, recent decreases in energy storage prices due to advances in battery technology are making electric vehicles (EVs) more attractive than ever before and excellent candidates to curb emissions from the road transport sector [2]. This is likely to lead to increased consumer electricity demands as well as potential positive environmental impacts as EV adoption grows.

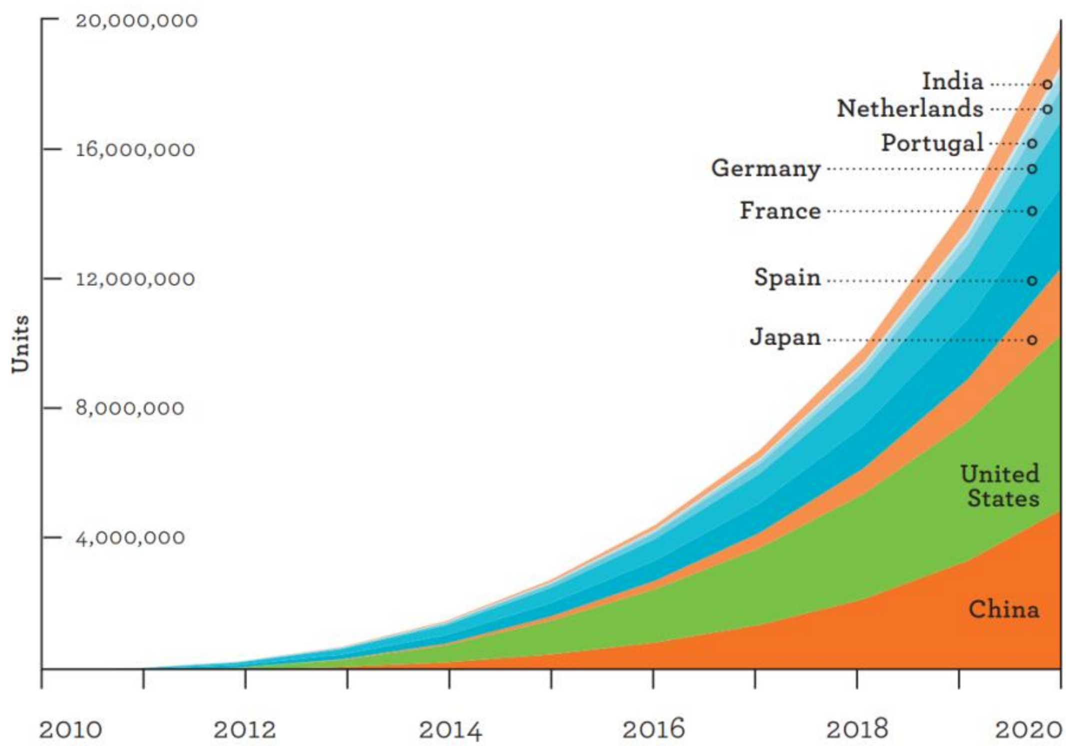


Figure 1 – World Wide Electric Vehicle Inventory Targets [2]

EVs of all varieties are becoming increasingly popular due to low road emissions, increased reliability, efficiency, and affordability, [3]. According to the International Energy Agency (IEA), in 2012 roughly 0.02% of the worldwide passenger vehicle inventory consisted of PEV's representing 180,000 vehicles, [4]. Targets for Electric Vehicle Initiative (EVI) member countries have set an ambitious goal of increasing the number of electric vehicles to 20 million by 2020 as shown in Figure 1, [4]. While current estimates place a more likely total around 5 Million worldwide by 2020, [3], the international community has overwhelmingly shown that increasing PEV penetration is a top priority. Current numbers for total sales since 2011 in the US alone sit at 400,666 with the majority coming from the west coast [5]. This undoubtedly has the potential to cause congestion strain on the existing electrical infrastructure if numbers continue to climb. Using current PEV charging techniques, peak demand will increase and may allow for only a small penetration of PEVs without adapting these uncontrolled charging practices [6]. However, with the aid of smart charging techniques, the grids capacity for electric vehicles has the potential to be greatly increased providing measurable benefits such as a more evenly distributed load profile and reduction in greenhouse gases [6].

## 1.1 Plug – in Electric Vehicles (PEVs)

The first electric vehicles were introduced over 100 years ago with the creation of a rudimentary electric carriage by British inventor Robert Anderson, [3]. At time of their inception electric vehicles were quite popular due to factors such as ease of use, lack of hand crank, and convenience for short in-town commutes. With the rise of Hennery Fords model T and several major improvements to the manufacturing process, internal combustion engines became more practical for the average consumers leading to a decline in the use of electric vehicles. Couple this decline, with the discovery of cheap crude oil sources and the expansion of the interstate highway system, by 1935 electric vehicles were all but extinct for use the residential consumer [3].

Fast forward now to the later part of this century in the 1990's. Environmental concerns begin to arise as well as marked criticism of dependence on petroleum fuels. This leads to the passage of the Clean Air Act amendment in 1990 followed by strict state and federal emission reduction targets bringing about a renewed interest for research in electric vehicles and alternative fuel sources. By 1997 the first mass produced hybrid electric vehicle, e.g. Prius, was being manufactured by Toyota marking the beginning of a new consumer age for electrification of the transport sector [3].

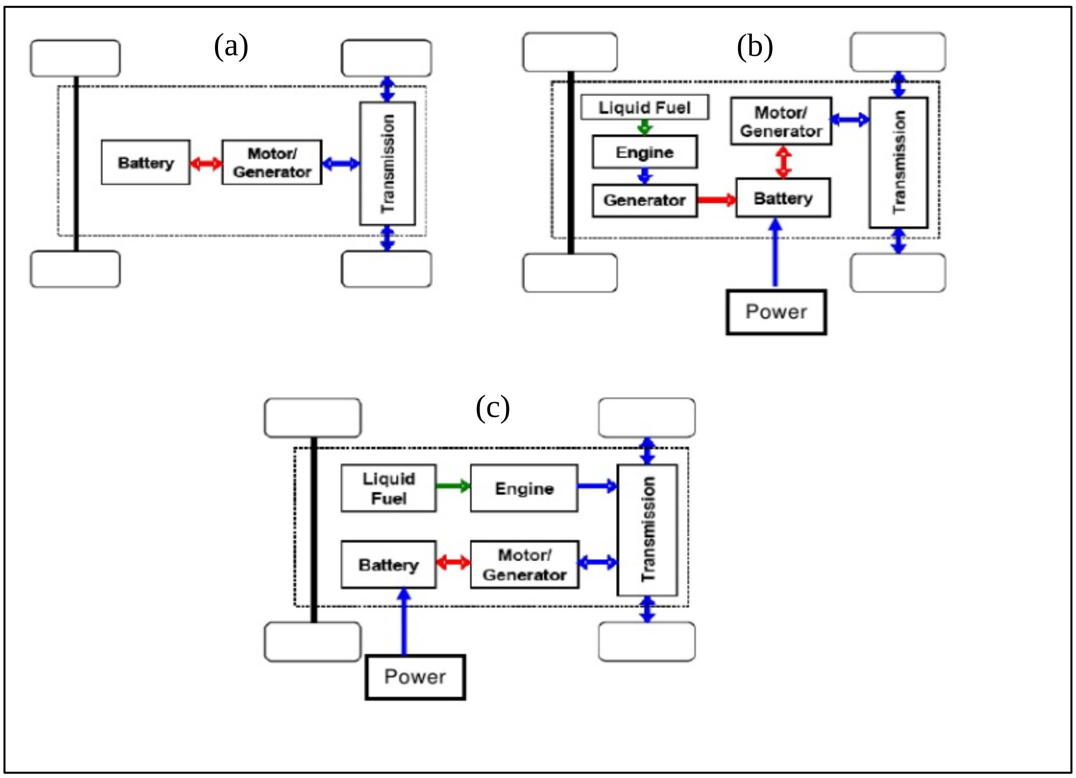


Figure 2 - Visual representation of PEV and PHEV configurations, [16]

Expanding from the introduction of the Prius, there are primarily two types of Plug-In electric vehicles being deployed for passenger vehicle use today:

- Plug in Electric Vehicles (PEVs) – are driven entirely by a single electric motor attached to a traditional drivetrain or separate motors attached to each wheel as shown in Figure 2a. To provide a reasonable commute range between charges, these vehicles are required to be powered by some form of a large stable battery. Due to historically high prices of energy storage capacity large scale electric vehicle integration has been prevented or at the very least slowed as demand out paces existing storage technologies. As the prices of battery storage technology are reduced large scale adoption of all electric vehicles becomes a more likely scenario. [7]
- Plug in Hybrid Electric Vehicles (PHEVs) – use a typically small internal combustion engine (ICE) and an electric motor to power the car. The prime movers are commonly designed in one of two configurations. The first configuration is in parallel where both the IC and electric motor operate at the same time shown in Figure 2c. The second, is in series where the electric motor drives the wheels and the generator recharges the battery, shown in Figure 2b. These vehicles provide several advantages over current all electric vehicles. They have enhance range due to the ability to store a petroleum fuel source and also, due to the electric motor, they can take advantage of the motor characteristics associated with high horse power ICE motors without the increase in weight or fuel consumption [8] [9].

## 1.2 PLUG- IN ELECTRIC VEHICLE CHARGER OPERATION

As PEVs have grown in popularity, several means of charging have been adapted to suit consumer and industrial requirements. This section provides the reader with a practical overview of current charging capabilities as well as nomenclature for later reference.

### 1.2.1 *Charger Classifications*

PEVs owners essentially have three different levels of charger to choose from when it comes to meeting their needs. In general, as a charger increases in power output it also increases in price and difficulty of installation. However, lower cost options may not be able to meet a consumer's overnight travel or commute charging requirements and thus justify the increased cost of adoption.

*Level 1 Charging* – is the most commonly available charger variety requiring no additional professionally installed equipment. It is accomplished through a direct 120V connection to a standard household wall outlet. Recharging rates are typically around 4 miles of travel for each 1 hour of charge time [10]. While this will generally meet the requirements for short local area commutes, charging the battery completely will require 18 - 20 h to fully recharge, [10].

*Level 2 Charging* - utilizes available 220 V residential or 208 V commercial ac electrical service which requires additional equipment to be purchased and professionally installed, thus making it better suited for commercial applications [10]. It is not uncommon however, for residential consumers requiring more rapid charge times than level 1 onboard chargers can provide to have a level 2 charger installed. Recharge times for level 2 chargers vary depending on the capabilities of the specific vehicle. For vehicles with a 3.3 kWh onboard charger a user can expect to gain 15 miles of travel time per hour of charge. As expected, vehicles with a 6.6 kWh on-board charger will receive 30 miles per hour of charge and completely recharge in approximately 7 - 8 h [10].

*Level 3 or dc Fast Charging (DCFC)* – is the least common and most expensive variety of charging available. It requires commercial grade 480V ac service, professional installation, as well a special bypass connector to be installed on the PEV [10]. In this variety, the charger bypasses the onboard charging equipment and interfaces with the vehicles traction batteries directly. The benefit is fast recharge rates, adding 80 – 100 miles of travel with only 20 – 30 minutes of charge time. Although DCFCs have an impressive recharge rate, due to their restrictive size and cost they are limited mostly to pubic or commercial settings, [10]. Table 1 below provides a summary of each charger type and relevant statistics for reference.

Table 1 - PEV Charger Charascteristics [10]

| | Charge Time | Voltage / Amps | Cost | Installation |
|---|---|---|---|---|
| Level 1 | Up to 20 hrs [10] | 120 / 15 | Supplied w/ PEV | Self |
| Level 2 | Up to 7 hrs [10] | 240 / 40 | $1,500-$3,000 [4] | Professional |
| Level 3 / DCFC | Approx. 30 mins [10] | 480 / 125 | $12,000-$35,000 [2] | Professional |

## 1.3 Expected Effects of increased PEV Penetration

While the majority of expected impacts for Electric vehicles are positive there is potential to have a damaging impact on the electric grid if not integrated carefully. This is due to the vehicles directly interfacing with the distribution network which is the most susceptible to large variations in load. Some of these vehicles will be a larger load than a typical home [11] regularly consumes and the effects will compounds as more homes integrate PEVs. In order to fully understand the impact of PEV penetration, charging requirements, and the time of day charging profiles need to be known. Due to the decreasing cost of PEVs and increasing cost of gasoline there is predicted be an increase in PEVs on the road [2]. The numbers estimated can change drastically based on battery costs, gasoline prices, competition from other vehicles, and government policy. The current numbers vary dramatically between 5 million and 40 million in 2030 [11] which makes predicting necessary upgrades difficult. There are however, some intuitively expected effects which must be planned for.

***Effects on the amount of required generation***

As the penetration of PEVs increases, more generation will need to be scheduled. The system will also need to schedule more reserve capacity. As seen in Figure 3a, the number of peak hours would also increase leading to the need for more peaking generation. [6] With coordinated charging, the demand can be flattened allowing for a more even profile which requires less peaking generation and reduces ramping as seen in the bottom optimized graph in Figure 3b.

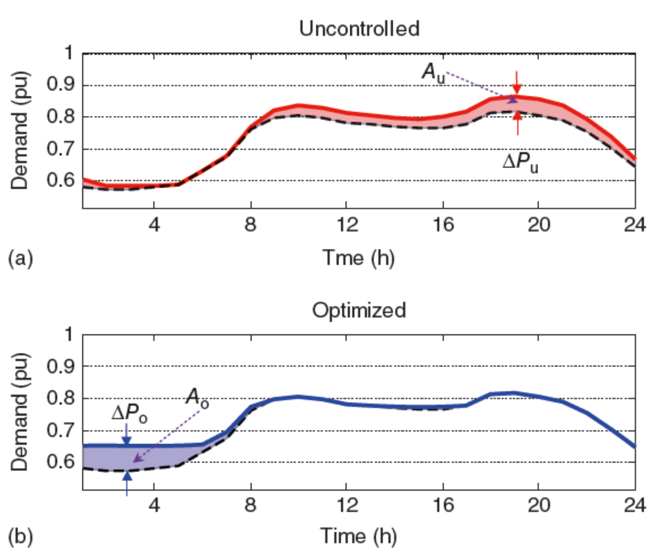


Figure 3 - Uncontrolled and Optimized load profiles [6]

*Market Price of Electricity*

Electric vehicle penetration also has an effect on electricity prices. In Figure 4 an sample supply curve is shown for a region in the US. As shown as demand increases the price in $/MWh increases [12]. If the demand of electricity is low then base generation is used to serve the load and the average price remains low in a market structure.  From the controlled charging case shown in Figure 4 one would expect a lower hourly demand and thus a lower marginal price. If demand for electricity is high, expensive peaking generation will be needed to serve the load and the price of electricy would be higher for the overall system [12].

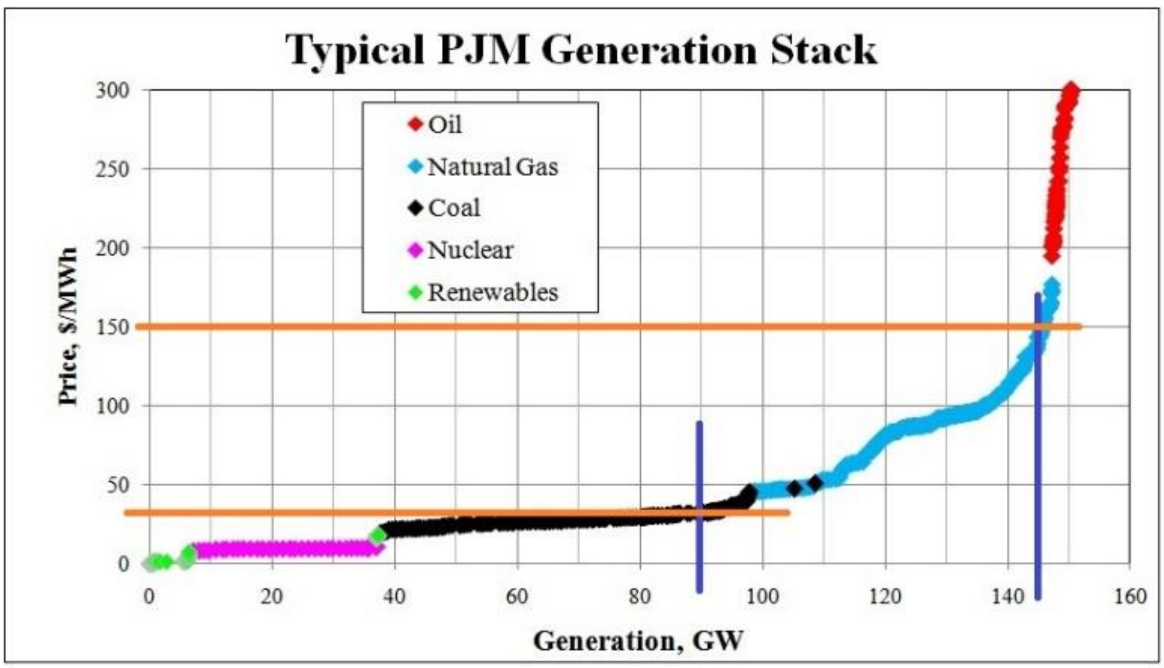


Figure 4 - Sample Generation Supply Curve [12]

***Net Green House Gas Emissions***

Electric vehicle penetration has an impact on emissions for vehicles as well as genration. The on-road emissions from vehicles would be eliminated but the emissions from electricity generation would increase. Current esitmates suggest vehicles with IC engines can expect 15 - 20% efficiency compared to an equivelently sized PEV at around 65 – 75% effecency [8]. These gains in effiecieny should traslate directly into sizeable reductions in fuel consumed for a closed system, [1]. A tradeoff analysis must be preformed by looking at the generation mix of electricity stored in the PEV's battery and the fuel economy of the vehicle being displaced. Aditionally as the $CO_2$ emissions improvement of the PEVs over conventional gasoline decreases as the efficiency of the gasoline vehicle increases [6]. As this margin narrows the gains in effeciecy for PEVs would need to be greatly bolstered by further efficiencies in power production or through the introducion of increased penetrations of green energy sources [6].

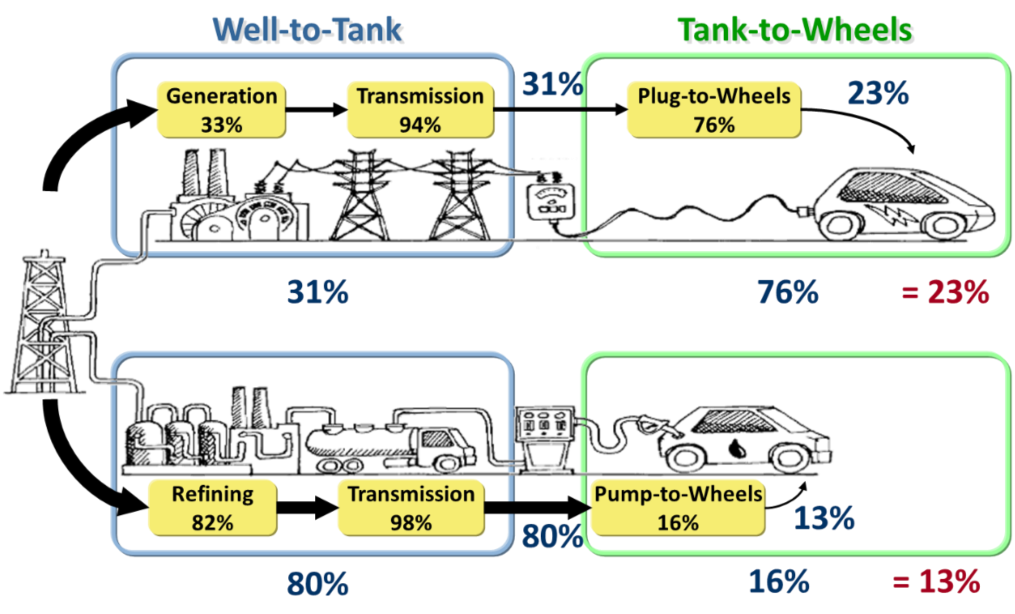


Figure 5 – Comparison of EV vs IC Well to Wheel Efficiencies [20]

## 1.4 RELEVANT CURRENT RESEARCH

**Emissions and Security Constrained Economic Dispatch (ESCED)**

Economic dispatch is the quintessential problem for all power systems and a foundational topic of research in the modern day. It all boils down to the ability to operate a power system cheaply and efficiently while still meeting the needs of the consumer. This is an issue which appears trivial on the surface but becomes significantly more complicated as real world security or safety constraints become a factor. Ideally, as demand grows the cheapest generators would be available to supply power in a moment's notice and the consumer's needs would be immediately fulfilled. Unfortunately, this is not the case. Real world generators cannot act instantaneously and must be scheduled in advance. In addition not all types of generators are suited to every type of load. Some can react immediately for a short period of time while others are suited to provide a consistent base load indefinitely. The addition of these limitations on generation is known as Security Constrained Economic Dispatch. This problem alone has thousands of variables which must be accounted for just to ensure that demand is seamlessly met for all instances of the day. Further complicating this problem is our collect objective as a society to reduce greenhouse gas emissions associated with power generation which account for 31% of greenhouse gases in the US [13].

Modern day power system operators have become accustomed to the intricacies of scheduling and meeting system demand, but doing so as environmentally cleanly as possible while still keeping costs to consumers low can be exponentially more complicated. This brings about a new topic of research which is known as Emissions and Security Constrained Economic Dispatch (ECED).

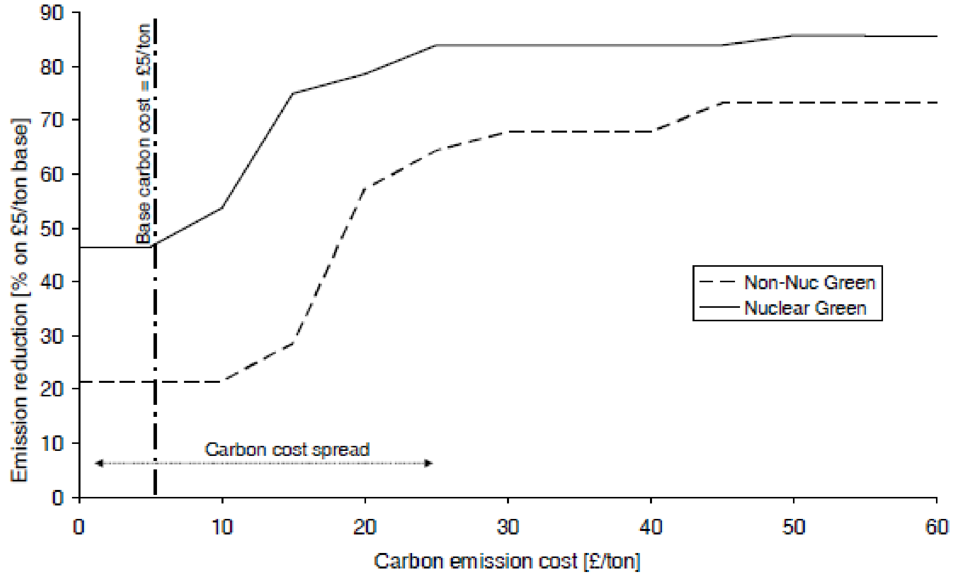


Figure 6 - Reduction in emissions as a function of carbon emission cost [14]

Paper [14] explores adding an incremental tariff to the price for electricity based upon the carbon output of the fuel source. ESCED is then solved for using a unit commitment model which includes all relevant generator constraints. Figure 6 shows that for low tariffs carbon emissions see little reduction in total system emissions. As the tariff is increased a large increase in system emissions is achieved up to the point in which the system is running as cleanly as possible. After this point increasing in tariff has little effect on carbon emission of the system and only serves to increase the net cost.

Table 2 – Emissions Constrained Economic Dispatch Swarm Algorithm Results [15]

| | ED solution without Emission constraints | ED solution with Emission constraints | Difference |
|---|---|---|---|
| $G_{A1}$ (MW) | 88.89 | 25.62 | -63.27 |
| $G_{A2}$ (MW) | 20.61 | 20.00 | -0.61 |
| $G_C$ (MW) | 110.01 | 124.39 | 14.38 |
| $G_D$ (MW) | 40.01 | 40.01 | 0 |
| $G_E$ (MW) | 550.48 | 599.97 | 49.49 |
| $CO_2$ (t) | 860.25 | 843.17 | -17.08 |
| $N_2O$ (kg) | 351.40 | 344.13 | -7.27 |
| Fuel Cost ($) | 21,223 | 21384 | 161 |
| Emission Cost ($) | 15,117 | 14824 | -293 |
| Total Cost ($) | 36,340 | 36,208 | -132 |

Tariffs are an excellent means to significantly reduce system emissions but will likely result in increased costs being passed along to the consumer. In paper [15] a swarm algorithm is used to solve the ESCED with emissions constraints applied as opposed to penalties. It was found that by setting a constant emissions penalty and a target reduction by generation type, both total system cost and emissions output could be reduced using this algorithm. This method was tested on a 5 bus system with 5 generating units. Results from this simulation are shown in Table 2.

***Aggregation of Vehicles Resources***

Taking steps to reduce carbon emissions is a necessary under taking and is becoming a larger part of society's awareness. However, what price is the consumer willing to pay for the long term environmental benefits? At some point the immediately outrageous prices of energy will negate any possible benefits in the long term carbon reductions. With modern advances in technology there is a means to not only significantly reduce carbon emissions but also total system cost.  This is where electric vehicles are perfectly poised to provide a unique energy storage solution.

When studying the effects of electric vehicles on the grid it is important to determine how driver habits will effect energy consumption. For instance, how will the charging will be modeled with respect to each individual's energy consumption based on travel patterns?  In an uncontrolled charging situation it is individuals may begin to charge immediately when they arrive in an area where charging is available or wait until they have a sufficiently low battery. Energy recovered is then a matter of distance traveled, battery state of charge (SOC), time charging begins and time spent charging.

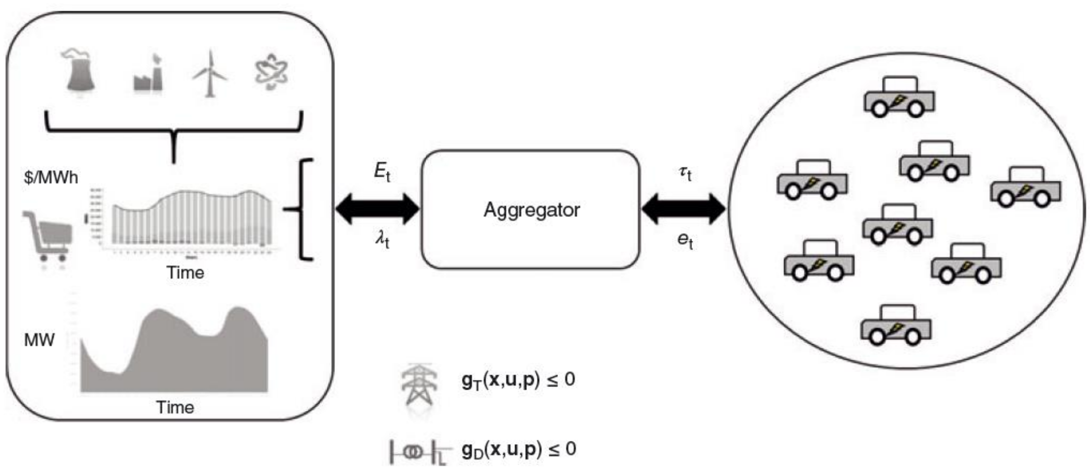


Figure 7- Illustration of a PEV Aggregator Model [6]

In order to model a controlled charging situation two differing strategies can be used.  In one, the vehicle arrives in an area with charging available but a delay is enforced before charging begins [16].  In a second strategy, a third party known as an aggregator acts as a middle man between the system operator and the PEV fleet [6].  The aggregator then controls the discharging or charging of the collective energy for all participating PEVs when convenient for the system operator. Reference [6] looks at using an electric vehicle aggregator to increase PEV penetration without requiring expansion of the supply side. The paper shows that without coordinated charging the maximum possible PEV penetration is limited. On the other hand, when using market based scheduling, the PEV demand is accommodated in the low-price periods, which occur during the demand valleys, leading to the system being able to accommodate significantly larger penetration of the PEVs without resorting to power system reinforcements [6]. The research was performed for a typical U.S. style day-ahead electricity market [6].

### *Effects of Regional Generation Mix on Emissions*

PEVs essentially produce no on road emissions, however the energy used to power the vehicle must be accounted for. Reference [8] looks at the effects of moving emissions from the tailpipe to the power plant. The study shows that particulates from combustion and SOx emissions would increase as a result of increased dispatch of coal-fired power plants [13] [8] Depending on the region studied there are different mixes of coal and natural gas, as well as other fossil-fueled generation that can effect emissions. Volatile organic compounds and carbon monoxide are expected to improve by 93% and 98% respectively, as a result of eliminating the internal combustion engine [17]. Additionally, all the emissions in urban areas are expected to decrease because of the shifting of emissions from the millions of vehicles in population centers to central generation plants that are located away from urban areas. This may not reduce the overall emissions for a closed system but would serve to increase air quality standards for population centers [17].

# Chapter 2. METHODOLOGY

The goal of this research is to create a realistic and reliable model to predict the effect of various PEV charging strategies on the greenhouse gas emissions of any known system. The model incorporates the following features:

- Effect of PEV charging strategy on system Emissions, through the use of
  - State Based Traffic Model
  - Unit Commitment Algorithm
  - Variable Penalization of Generator Emissions Output

These are important aspects not currently combined within available emissions prediction models. By modelling the unit commitment decisions it is possible to observe how the behavior of the generators, concerned with reducing overall cost, effect the generation emission profile. Additionally by incorporating an emissions penalty into the unit commitment model it is possible to establish an optimal penalty for reducing emissions output while still reducing overall system cost through the use of controlled charging strategies. In order to create an adaptable model for a wide variety of systems the following variables are accounted for:

- Vehicle Traffic Patterns
  - Arrival/Departure Times
  - Distance Traveled
  - Vehicle Location / Charging Available
- Unit Commitment / Power Flow Model
  - Generation Mix (e.g. Coal, Natural Gas, Nuclear, among others)
  - Generator Characteristics (ramp rate, min up/down time, among others)
  - Day Ahead - Marginal Cost Curves

- Daily Load Profile

- Emissions Curves
    - Generator input-output characteristics
    - Carbon Intensity Factor of Fuel Source

## 2.1 MODELING OF DAILY VEHICLE MOTION

This section serves to categorize the data set utilized for reader and illustrate its relevance to the research model. A national survey of American households [18] was chosen because of it broad range of data collection and open availability. The data can then be further refined making the model more accurately reflect a specific region or type of traffic (rural against urban for example). For the purpose of this research it is chosen to leave the data set as a general representation of United States passenger vehicle traffic, making the model more widely applicable.

### 2.1.1 *National Household Traffic Survey (NHTS) Data*

In order to accurately predict the offset of tail pipe emissions from the integration of electric vehicles a realistic source of vehicle travel patterns is needed. For this reason, the "trip chains" were established using data from the National Household Traffic Survey (NTHS) [18]. A trip chain consists of all point to point connections for a giving vehicle throughout the course of a single 24 hour period. For each leg of trip a known time and distance can be used to calculate fuel or electrical energy consumption based off of vehicle category.

This data set consists of 1.45 million point to point trip segments from vehicles across the entire 50 states. Entries for the data set are established through random telephone surveys of willing participants. For each household demographic data is given (e.g. income, number of members, married, working, among others), as well as vehicle data (e.g. type, number of miles, primary purpose, among others) and daily trip data. The trip survey data consists of approximately 40 fields, but for the purposes of this model only trip start time, end time, date, week/weekend day, mile traveled, duration, and the purpose for the trip are considered. This data was then combined with additional vehicle data to determine the relative consumption of the vehicle (based on miles per gallon, mpg) and used later in the report to estimate emissions and create daily charging profiles. A sample of pre-sorted trip data from the NTHS [18] is included below in Table 3 as well as descriptions for each column used.

Table 3- Trip Data Sample from the NTHS [18]

| House ID | Vehicle ID | Depart (hhmm) | Arrive (hhmm) | Weekend (2 = yes) | Duration (min) | Distance (mile) | Category (1,2,3) | Type (ref [5]) |
|---|---|---|---|---|---|---|---|---|
| 20000017 | 2 | 955 | 1020 | 2 | 25 | 22 | 3 | 50 |
| 20000017 | 2 | 1022 | 1025 | 2 | 3 | 0.222222 | 3 | 50 |
| 20000017 | 2 | 1120 | 1122 | 2 | 2 | 0.222222 | 3 | 70 |
| 20000017 | 2 | 1130 | 1132 | 2 | 2 | 0.222222 | 3 | 50 |
| 20000017 | 2 | 1310 | 1313 | 2 | 3 | 0.555556 | 3 | 70 |
| 20000017 | 2 | 1330 | 1400 | 2 | 30 | 22 | 3 | 1 |
| 20000017 | 2 | 1750 | 1825 | 2 | 35 | 20 | 3 | 20 |
| 20000017 | 2 | 2000 | 2035 | 2 | 35 | 20 | 3 | 1 |

**House ID** – eight digit identifier for each household participating in the survey.

**Vehicle ID** – Vehicle identifier for each vehicle used in a single house hold.

**Departure** – Time (24 Hr) of departure from last location (assumed to be residential for leg 1.)

**Arrival** – Time of arrival (24 Hr) at new destination.

**Weekend Designation** – Designates if the trip occurred during a weekday (1) or weekend (2).

**Trip Duration** – Length of trip determined from departure and arrival times for computational simplification.

**Vehicle Category** – computed based upon fuel consumption of vehicle. (1 for > 30 MPG , 2 for 20 – 30 MPG, and 3 for < 20 MPG)

**Trip Type** – code corresponding the purpose for that leg of the trip [18]

### 2.1.2 *Modeling Vehicle Location*

In order to improve accuracy, it is necessary to determine locational and movement data relating specifically to PEVs which would be directly replacing equivalent IC engine passenger vehicles. Conveniently, the NTHS is compiled solely from data in which individual households elect to participate and not large fleets or companies. This ensures that all data collected is well within the scope of this research. However, in order to better predict specifically PEV vehicle traffic patterns the 1.45 million trip data set was filtered to remove trips which did not realistically represent PEVs capabilities. Due to the rational that current PEVs are used primarily for short trips and commutes, trip lengths where limited to less than 100 miles total [7]. Additionally trips which contained a “declined to respond” or that happen to be missing any of the information listed in table 2 were rejected (e.g. participants were not required to give information or could respond with an unknown resulting in a negative response code) [18]. This resulted in a total of 464,512 trip segments which contained all applicable survey data from the participants. With the refined data set, trips were then established using a program in MATLAB.

Vehicle motion was established using a discrete-time sample size of 5 minutes similar to the procedure described in [19]. In [19] a discrete time statistical Markov model was used with vehicle locations normalized by number of vehicles transitioning between each state. For the purpose of this research, vehicle locations are derived empirically and normalized along each time vector such that the probabilities for all vehicles locations at each time interval sum to 1.

Four state variables for vehicle location were established: state 0 – "In motion", state 1 – "Parked in a residential area", state 2 – "Parked in an industrial area" and state 3 – "Parked in a commercial or recreational area".

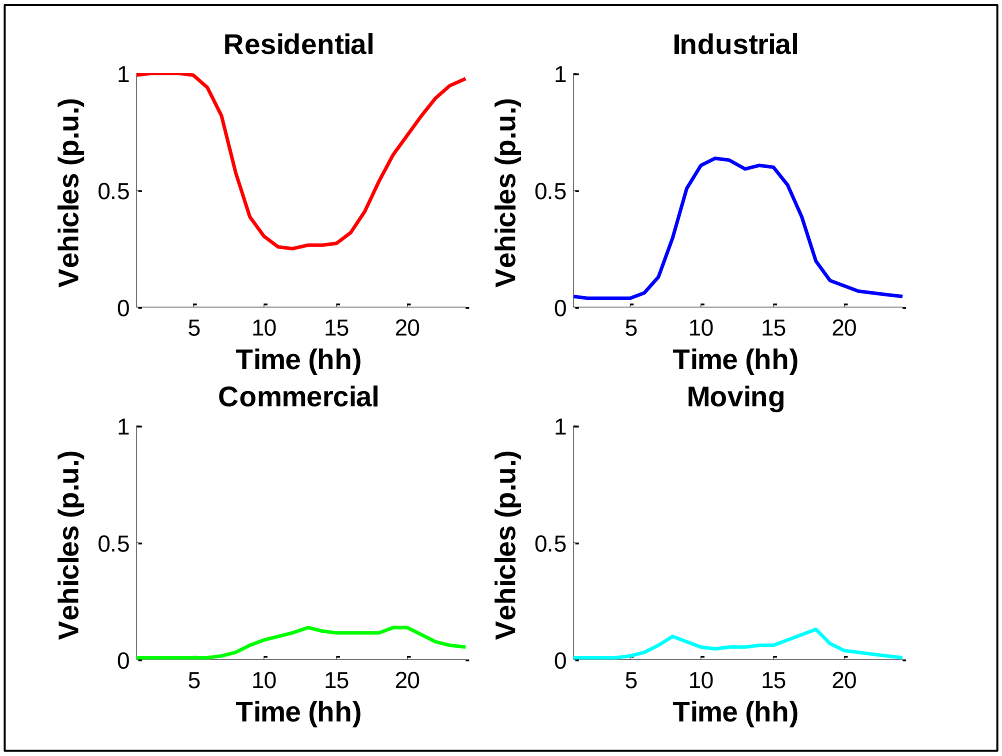


Figure 8- Weekday Vehicle Location for Each Transition State over a 24 hr period

To establish vehicle location profiles it is assumed that all vehicles would start in state 1 and then either transition into a state of motion or remain parked in their current state. Once in motion a vehicle could then transition into any of the other states, excluding the one it just left, or remain in motion. Using the trip chaining technique the 464,512 trip segments were compiled into 104,332 daily trips. The normalized results of the vehicle transitions can be found in Figure 8 with percentage of vehicles in the *y*-axis vs time along the *x*-axis. Figure 9 shows the daily probability distribution for occurrence of a trip of a certain length in 1 mile increments. From this probability distribution, equation (2.1) is used to establish and average daily distance traveled of **25.15 miles**:

$$d_{ave} = \frac{1}{N}\sum_{i=1}^{100} n_i * d_i \tag{2.1}$$

Where, $N$ is the total number of segments, $n_i$ is the number of occurrences, and $d_i$ is the segment distance traveled.

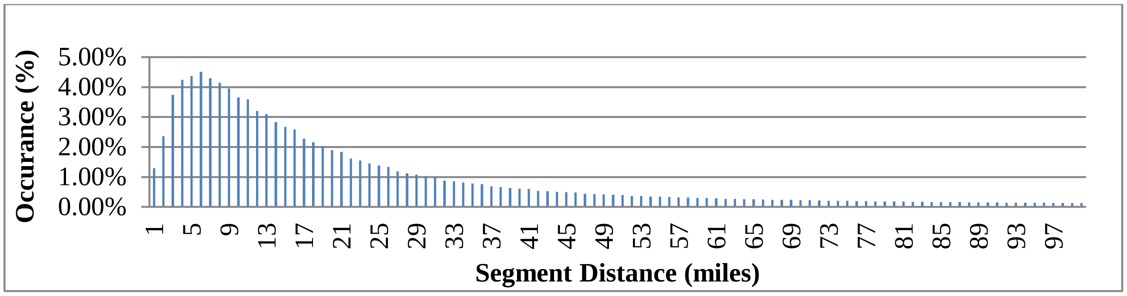


Figure 9 – Distance Probability Distribution for NTHS Data

The vehicle transition data is then used to establish vehicles transition probabilities as shown in Figure 10 for comparison with the statistically derived model [19]. This estimates the most likely destination of a vehicle in motion for a specific hour of the day. For example if a vehicle is traveling from 0400 h to 0700 h on a weekday there is roughly a 70 % chance it is arriving at work. Conversely, as it gets later in the evening it becomes increasingly likely that the vehicle is arriving at a residence. Travel to a commercial or recreational area is shown to be most likely occurring from around 1100 h to 2000 h Comparing the resulting trip data to the probabilistically derived data in [19] it can be seen that the data set realistically models an average weekday motion profile in an US Household. The data is now converted from it raw state of individual trip chains into a more consumable form which can be used as a basis for the remainder of this research.

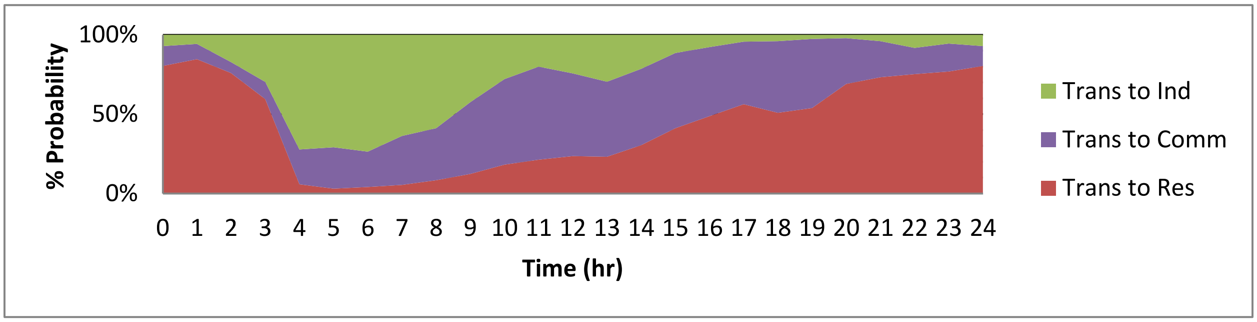


Figure 10- Transitional Probability for Vehicles Traveling on a Weekday

## 2.2 Establishing Uncontrolled Charging Profiles

After establishing generic traffic patterns from the NTHS data set charging behaviors are then simulated. For this research charging profiles are established based upon a specified penetration of electric vehicles directly replacing equivalently sized passenger vehicles. PEV penetration is defined as:

$$PEV\ Penetraion = \frac{\#\ PEV}{\#\ Vehicles\ in\ System} \tag{2.2}$$

The penetration percentages of 0% (base case), 20%, 40%, 60%, 80% and 100% (complete integration) are considered. These penetrations are chosen to give a broad spectrum view of PEV potential should wide scale adoption take place. Along with the different penetrations of electric vehicles there are several modes of operation considered. These modes of operation are used to determine charging and discharging characteristics for the PEV battery:

1. *PEV circulating:* The Plug in Electric Vehicles (PEV) are not connected to the power grid and are consuming the electrical energy previously stored in their batteries. Energy consumed is at a

rate based upon the size of the vehicle relative to the petroleum power equivalent which it replaces [17] .

2. *PEV charging:* The PEVs are plugged in and are charging their batteries with energy from the power grid, [17]. Charging can occur at either level 1 or level 2 based upon the vehicles parked location. Charging can be interrupted at any point to continue on next leg of the trip. If a PEV is parked at a residence it will wait until it has completed all trips for the day to begin charging.

3. *PEV parked and not charging*: The PEV is parked and the battery is neither receiving power nor using power. This occurs either when the vehicle has reached the maximum specified charge capacity for the battery or when the vehicle is parked in a commercial or recreational setting. This mode can also be interrupted at any point as the vehicle continues in motion, [17].

Using the above modes for vehicle operation the following strategies are considered for vehicle charging:

*Uncontrolled Home Charging* – in this strategy the user is free to charge their vehicle once they arrive at a residential state after the last trip of the day. Charging occurs at a level 1 rate shown in Table 4 [10]. The vehicle continues to charge until it has recovered its energy from motion. Once energy from motion is recovered the PEV remains at a state of charge of 100% [2].

*Uncontrolled Home/ Work Charging* – in this strategy the user is free to charge their vehicle once they arrive at an industrial state and at a residential state after the last trip of the day. Charging is discontinued once the vehicle departs from the industrial state. If the vehicle returns after errands it resumes recuperating energy up to 100% of full capacity. Any remaining deficit is recovered once it reaches its final trip of the day and is parked in a residential state, [2].

**Vehicle Charging Profiles**

Utilizing the vehicle motion profiles in conjunction with the distance traveled by each vehicle during its trip a charging profile is created. To begin, vehicle consumption is modeled assuming a petroleum powered vehicle is directly replaced with an equivalently sized electric vehicle based upon the information given by the NTHS [18]. Three categories are used to represent small, medium, and large passenger vehicles. Small vehicles (> 30 MPG) are represented with and 80 kW motor approximating a vehicle similar to the Chevy Volt Hybrid [20]. Medium vehicles (20-30 MPG) are represented with a 115 kW motor approximating a Nissan leaf BEV [20], and large vehicles (< 20 MPG) are represented with a 150 kW motor [2]. Using these motor sizes a kW per mile rating is assigned: 0.33 kWh/mi for small, 0.37 kWh/mi for medium and 0.4 kWh/mi for large [6]. The distance driven is then directly converted into an energy consumption from the battery in kW. The following battery capacities are used: 16 kWh for small, 18kWh for medium and 34 kWh for large [6]. This is believed to be a safe assumption based on the restriction that trip chains longer than 24 hours and further than 100 miles are not considered [16]. Figure 11 shows the algorithm flow programmed using MATLAB to model charging. Table 4 converts the charging levels to specific consumptions per charging increment. Vehicle states are sampled in 5 minute time increments.

Table 4- Conversions for Vehicle Charging levels

| Chagrining Level | Power Consumption | Charge time for empty 24 kWh Battery |
|---|---|---|
| Level 1 | 1.3 kWh | 18.5 h [10] |
| Level 2 | 3.3 kWh | 7.3 h [10] |

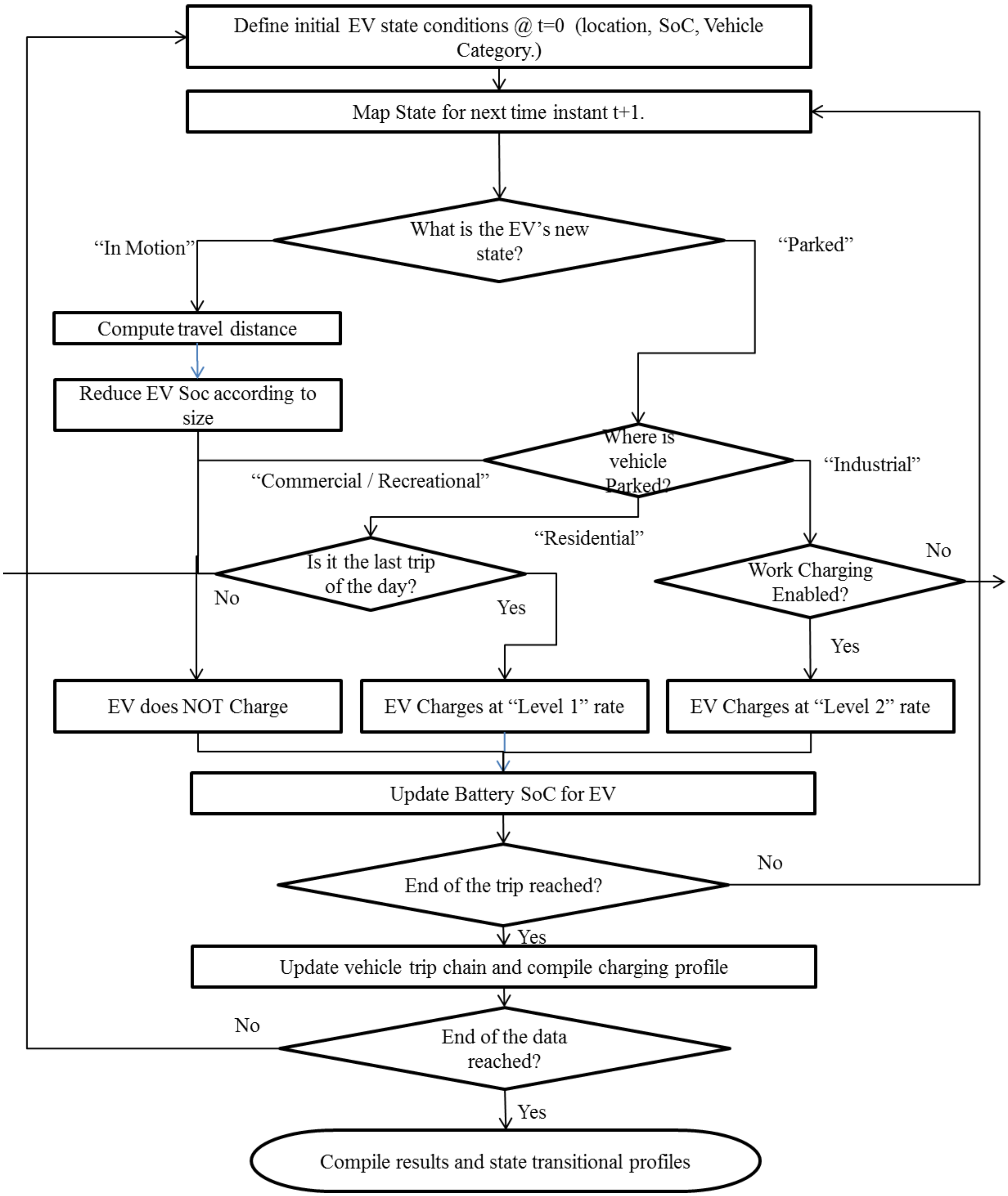


Figure 11 – Flow diagram to detemine how is a PEV charging

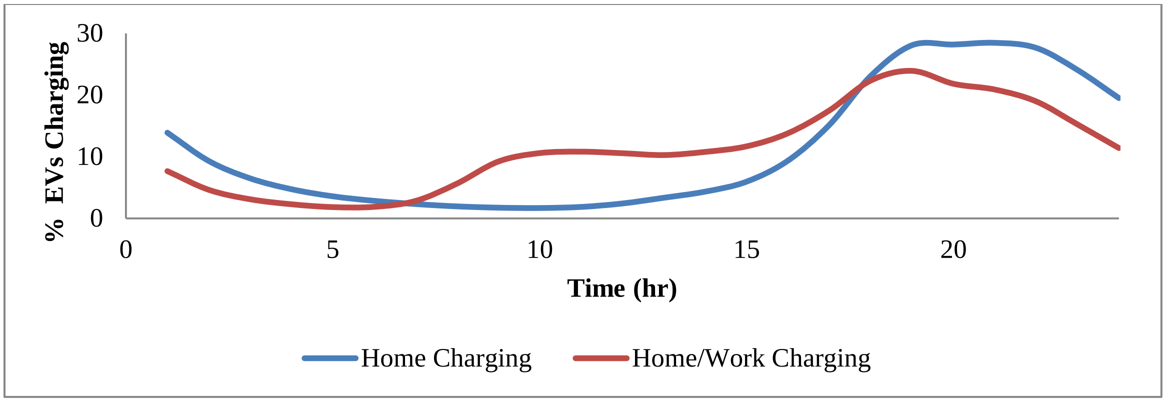


Figure 12 – Weekday EV Charging Profiles

The first profile created is based upon an uncontrolled parked residential charging scheme. In actuality, PEV owners may choose to charge between trips while at home but it was assumed the worst case would likely occur if they did not choose to spread it out over the day. Based upon the available charging technologies all chargers are assumed to be a level 1 charger with a 1.3 kW/h charge rate. The resulting charging profiles for this this strategy are shown by the blue lines in Figure 12 for weekdays and Figure 13 for weekends.

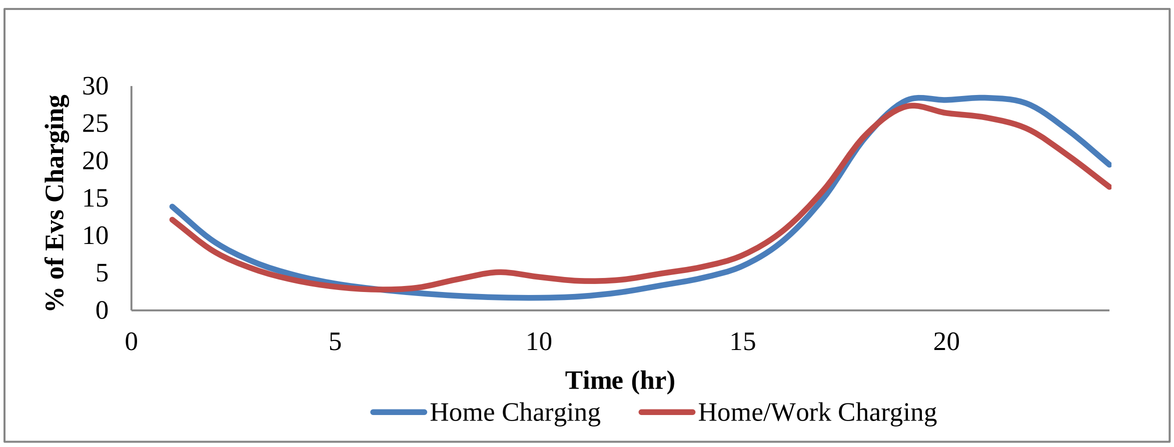


Figure 13 – Weekend EV Charging Profiles

The second profile created is for uncontrolled residential charging and it is assumed that the PEV's would also be allowed to charge while at work. This profile assumed that as soon a vehicle arrived at work or returned home from the last trip of the day it began charging. It is modeled such that all industrial chargers are a level 2 charger with a 3.3 kW/h charge rate and all residential charging occurs at a level 1 rate of 1.3 kW/h. The resulting charging profiles for this this strategy are shown by the red lines in Figure 12 for weekdays and Figure 13 for weekends.

## 2.3 Test System Characteristics and Set Up

This section provides details and rational for the creation of the test system. The test system is crafted to be easily replicable and provide consistent and repeatable results for future research. To that end, the structure of the test system is based on the 3-area 1996 IEEE Reliability Test System (RTS) [21] with some adaptations which are be explained further in later sections. It is chosen due to the wealth of unit commitment research papers available as well as it being a standard in the power research community. Additionally the RTS is not representative of any particular system and it can model a wide variety of generation, making it ideal to compare multiple systems of interest. This chapter starts with a discussion of the Unit Commitment (UC) model formulation followed by input values used in the simulation. Additional rational for the creation of the controlled charging profiles are explained as well as a proposed method for the inclusion of emissions in the UC.

### 2.3.1 *Unit Commitment Model*

The (UC) model is an important tool for analyzing power systems and is used to minimize system cost while enforcing to the generation and system constraints. It is an inherently a large-scale, non-linear and non-convex problem with potentially thousands of constraints and variables making it a popular topic of study in the power community over the past few decades. As computational power grows, computer based optimization of the mathematical constraints allows for increasing large systems to be analyzed in reasonable computing times. This study uses a Mix Integer Linear Programming (MILP) solver for the UC. The UC formulation uses 3 binary variables as described in [22]. This approach is chosen as it is currently the "State of the Art" method when it comes to computational intensity and community accepted solution accuracy [22]. From this model specified generator characteristics (i.e. heat rate, ramp rate, min up and down times, fuel usage, among others) are used to determine the most optimal way for load combined with PEV charging to be served.

**Indices**

For the problem formulation the following indices will be used:

*b* Index of generating unit cost curve segments, 1 to B

*i* Index of generating units, 1 to I

*j* Index of generating unit start-up costs, 1 to J

*l* Index of lines, 1 to L

*s* Index of buses, 1 to S

*t* Index of hours, 1 to T

**Objective Function**

The goal of the unit commitment problem is to find the minimal cost of the system given the applicable generator characteristics. The objective function for this model is constructed shown, where $C_i(t)$ is defined as the Operating cost of generator i at time t ($):

$$Minimize \sum_{t=1}^{T}\sum_{i=1}^{I} C_i(t) \tag{2.3}$$

**Generator Cost Function**

The cost function for a given generator is derived based upon the type of fuel consumed and the rate at which that fuel is consumed for a specified power production. These functions are non-convex but can be approximated using a convex quadratic equation. In this form it would not be possible to use a MILP method for solving the UC, so an additional approximation must be made to covert the convex quadratic into a linear piece wise function for incorporation into the UC [13]. Figure 14 shows the linearization of a quadratic cost curve into three piecewise sections.

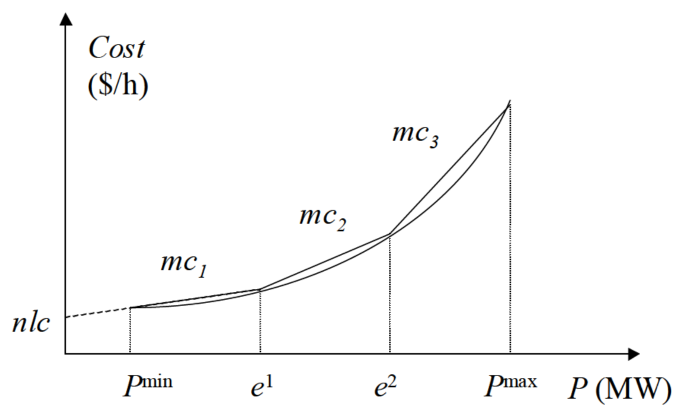

Figure 14- Linearization of a quadratic cost curve

Using this formulation the linearized cost function for the generators is analytically written as follows:

$$k_i^t(p_i^t) = nlc_i + mc_i^1 p1_i^t + mc_i^2 p2_i^t + mc_i^3 p3_i^t \tag{2.4}$$

Where, $k_i$ is the cost curve of generator *i* ($/MW), $P_i^{max}$ is the rated capacity of generator *i* (MW), $P_i^{min}$ is the minimum stale output of generator *i* (MW), $pb_i^t$ , is the output of generator *i* at time *t* in segment b (MW), $mc_i^b$ is the slope of the segment *b* of the cost curve of generator *i* ($/MW) and $nlc_i$ is the no load cost of generator *i* ($).

Once an acceptable approximation of the each of the generator cost curves has been established start-up costs are included. This feature of the UC model takes into account the balance between bringing generation online which may have a lower marginal cost but is expensive to start and synchronize with the grid. For this model a fixed startup cost will be incurred only once a generator is synchronized with the grid using the constraints:

$$suc_i(t) = K_i \, (x_i(t) - y_i(t)) \qquad 2.5$$

where, $Ki$ is a constant associated with starting a generating up i ($), $x_i(t)$ is a binary variable equal to 1 if generator *i* is producing at time *t*, and 0 otherwise, and $y_i(t)$ is a binary variable equal to 1 if generator *i* is started at the beginning of time *t*, and 0 otherwise.

Equation 2.5 is then subject to the following inequality constraints ensuring the start-up cost is only enforced when a generator synchronizes and it has been uncommitted in the previous time period:

$$y_i(t) \le x_i(t) \qquad 2.6$$

$$y_i(t) \le x_i(t-1) \qquad 2.7$$

$$y_i(t) \ge x_i(t) + x_i(t-1) - 1 \qquad 2.8$$

The linearized cost function combined with the startup cost formulation can then be used to establish the total generation cost function used in the objective function minimization. Additionally total generation must sum to the amount of generation occurring in each cost segment for each generator:

$$C_i(t) = nlc_i\, x_i(t) + \sum_{b=1}^{B}(k_{i,b}\, g_{i,b}(t)) + suc_i(t) \qquad \forall t \leq T, i \leq I \tag{2.9}$$

$$g_i(t) = \sum_{b=1}^{B} g_{i,b}(t) \qquad \forall t \leq T, i \leq I \tag{2.10}$$

Where, $nlc_i$ is the fixed production cost of generator $i$ (\$), $x_i(t)$ is a binary variable equal to 1 if generator *i* is producing at time *t*, and 0 otherwise, $k_{i,b}$ is the slope of the segment *b* of the cost curve of generator *i* (\$/MW), $g_i(t)$is the generator *i* output at time *t* (MW), $g_{i,b}(t)$ is the generator *i* output at time *t* occurring in segment b (MW), and $suc_i(t)$ start-up cost of generator *i* at time *t* (\$).

**Physical Constraints**

A key component for the accuracy of this proposed UC model requires not only reasonable approximations of costs, but also that physical system parameters are realistically enforced. The following equations express the mathematical representation of the power balance, so as to ensure that system demand is met the synchronized generation:

$$\sum_{i=1}^{I} g_i^t = \sum_{s=1}^{S} d_s^t \tag{2.11}$$

Where, $g_i(t)$ is the generator *i* output at time *t* (MW) and $d_s(t)$ is the demand at bus *s* (MW).

Limits on maximum and minimum outputs as well as ramping limits are required when considering thermal generating units [13]. These formulations are used to ensure that the limits of the generators are accounted for and equipment safety/longevity standard are not violated. Minimum and Maximum stable generating output are constrained by:

$$g_i(t) \geq g_i^{min} * \; x_i(t) \tag{2.12}$$

$$g_i(t) \leq g_i^{max} * \; x_i(t) \tag{2.13}$$

Where, $x_i(t)$ is a binary variable equal to 1 if generator *i* is synchronized at time *t*, and 0 otherwise; $g_i^{max}$ is the rated capacity of generator *i* (MW), $g_i^{min}$ is the minimum stable output of generator *i* (MW), $g_i(t)$ is the generator *i* output at time *t* (MW), and $x_i(t)$ is a binary variable equal to 1 if generator *i* is producing at time *t*, and 0 otherwise.

The following ramping constraints are used to limit the amount a generator can increase or decrease in single time period:

$$-ramp_i^{down} \leq g_i(t) - \; g_i(t-1) \tag{2.14}$$

$$ramp_i^{up} \geq g_i(t) - \; g_i(t-1) \tag{2.15}$$

Where, $ramp_i^{down}$ ramp-down limit of generator *i* (MW/h), $ramp_i^{up}$ ramp-up limit of generator *i* (MW/h) and $g_i(t)$ is the generator *i* output at time *t* (MW).

Additionally, it must be guaranteed that if a generator has been started that it will not be immediately shut down for time period $t_i^{up-min}$. Conversely if generator has been shut down it will need to remain off for a specified period of time before it can be restarted $t_i^{down-min}$. Unit commitment equations for minimum up and down times are formulated according to paper [23] in which optimal spinning reserve is calculated for the unit commitment model. The minimum up time for generators is enforced by:

$$x_i^m = 1 \qquad \forall m \in \left[1, \dots, t_i^{up-min} - t_i^H\right], t_i^{up-min} > t_i^H > 0 \tag{2.16}$$

$$x_i^{t-1} - x_i^t \le x_i^{t+1} \tag{2.17}$$

$$x_i^{t-1} - x_i^t \le x_i^{t+2}$$

$$\vdots$$

$$x_i^{t-1} - x_i^t \le x_i^{min\left\{t+t_i^{up-min}-1,T\right\}} \qquad \forall t = 2,3 \dots, T-1$$

$$x_i^m = 0 \qquad \forall m \in \left[1, \dots, t_i^{dn-min} + t_i^H\right], t_i^{dn-min} < t_i^H < 0 \tag{2.18}$$

$$x_i^{t-1} - x_i^t \le x_i^{t+1} \tag{2.19}$$

$$x_i^{t-1} - x_i^t \le x_i^{t+2}$$

$$\vdots$$

$$x_i^{t-1} - x_i^t \le x_i^{min\left\{t+t_i^{dn-min}-1,T\right\}} \qquad \forall t = 2,3 \dots, T-1$$

where, $x_i(t)$ is a binary variable equal to 1 if generator *i* is synchronized at time *t*, and 0 otherwise and $t_i^H$ indicates the number of time periods generator *i* has been committed for.

### 2.3.2 *System Load Profile*

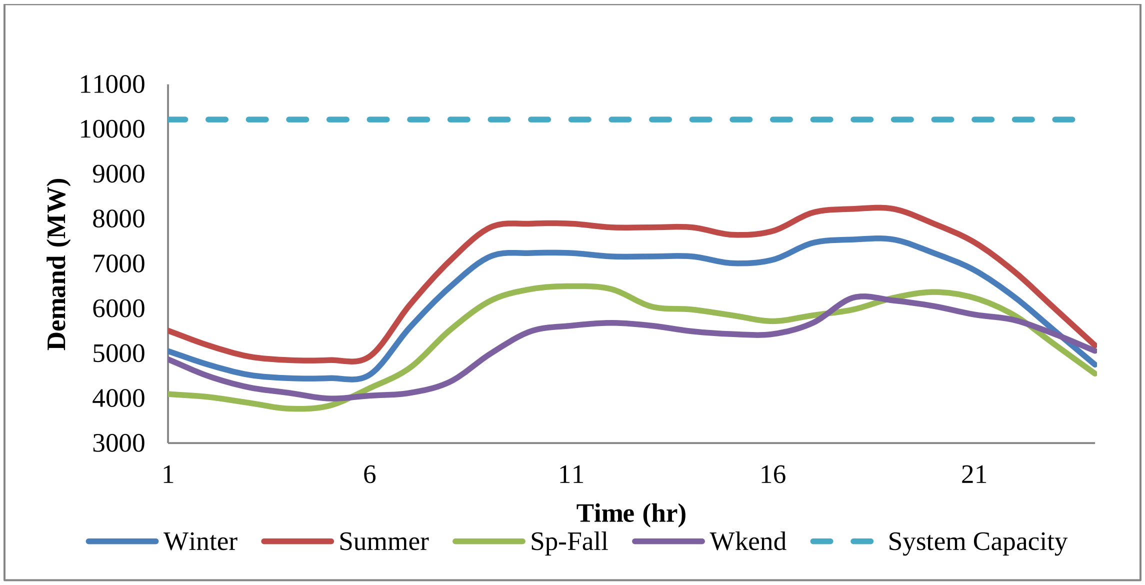


Figure 15- 96 RTS Yearly Load Composition Profiles [12]

The load profile for this this system is as in the 1996 RTS 3-Area [21] with an additional scaling adaptation by season [22]. Load profiles for the RTS are given as weekly peak load for each of the 52 weeks of the year and then scaled daily based upon a percentage of that week's peak. Using this method the data required is an annual peak value representative of the system of interest which is then scaled accordingly. The load profiles used for this research are scaled according to a method in which representative seasonal and weekend loads are chosen to represent a 365 day year for a summer peaking system. A representative winter load is chosen using the RTS scaling factors, [21], as the first day (93% of weekly peak load) of the 26$^{th}$ week (86.1% of annual peak load) assuming a 10% increase in the annual peak load (9045 MW). This results in a daily winter peak load of 7,540 MW. Fall and spring loads are chosen as the first day (93% of weekly peak load) of the 41$^{st}$ week (74.3% of annual peak load) resulting in a daily fall and spring peak load of 6,499 MW. A representative summer load is chosen as the first day (93% of weekly peak load) of the 47$^{th}$ week (94.0% of annual peak load), resulting in a daily summer peak load of 8,221 MW. A single representative weekend load is chosen as the 6th day (77% of weekly peak load) of the first week (86.2.0% of annual peak load), resulting in a weekend peak load of 6,242 MW for Saturdays and Sundays across the year. Load distribution among buses is as provided in [21]. Although this method may not be perfectly representative of all areas and loads it gives an accepted standard base line off which all data sets can be compared. Figure 15 depicts the seasonal and weekend load profiles using the RTS scaling factors. Table 5 contains the normalized hourly weekday values used in the simulation for comparison.

Table 5– 96 Normaized Daily Load Profile

| Hour | Load (p.u.) | Hour | Load (p.u.) | Hour | Load (p.u) | Hour | Load (p.u.) |
|---|---|---|---|---|---|---|---|
| 1 | 0.67 | 7 | 0.74 | 13 | 0.95 | 19 | 1 |
| 2 | 0.63 | 8 | 0.86 | 14 | 0.95 | 20 | 0.96 |
| 3 | 0.6 | 9 | 0.95 | 15 | 0.93 | 21 | 0.91 |
| 4 | 0.59 | 10 | 0.96 | 16 | 0.94 | 22 | 0.83 |
| 5 | 0.59 | 11 | 0.96 | 17 | 0.99 | 23 | 0.73 |
| 6 | 0.6 | 12 | 0.95 | 18 | 1 | 24 | 0.63 |

The additional PEV load for uncontrolled charging is created by scaling these profiles to a representative size for a specific level of PEV penetration. For scalability of vehicles based upon the representative size of system generation capacity, the Northwest Power Pool (NWPP) region of the Western Electricity Coordinating Council (WECC) is chosen. According to a 2015 report published by [24] the NWPP has a summer peak load of 68,000 MW and a total generation capacity of 115,000 MW. Comparing this system with the scaled RTS winter peak load of 8,221 [22] and total capacity of 10,215 MW a scaling factor of 12% is chosen. This is chosen based upon the peak load value as it represents a higher penetration of PEVs affecting the system and is the scaling method used in [6] to establish relative system size. A representative system size for NWPP is then established using the 2013 database for motor US motor vehicle registrations [25]. Using specifically passenger vehicles registrations for all or major portions of the states of Washington, Oregon, Idaho, Wyoming, Montana, Nevada, and, Utah, as well as a small portion of Northern California a system size of 10.73 million vehicles is established. This is then scaled for simulation to a representative system size of 1,288,000 [9] vehicles. The resultant load profiles for a 20% PEV penetration are shown in Figure 16 combined with the total base load for the test system. The red line represents the total load with uncontrolled residential charging and the green line represents uncontrolled charging with charging allowed while at work and residential locations. From the Figure 16, it can be seen that the load associated with the relatively small addition of the electric vehicle charging coincides with the daily peak load of the system. This demonstrates, as discussed previously, not only increased the peak load of the system but also a region where additional rapid ramping generation will be required as PEV penetration is increased [17].

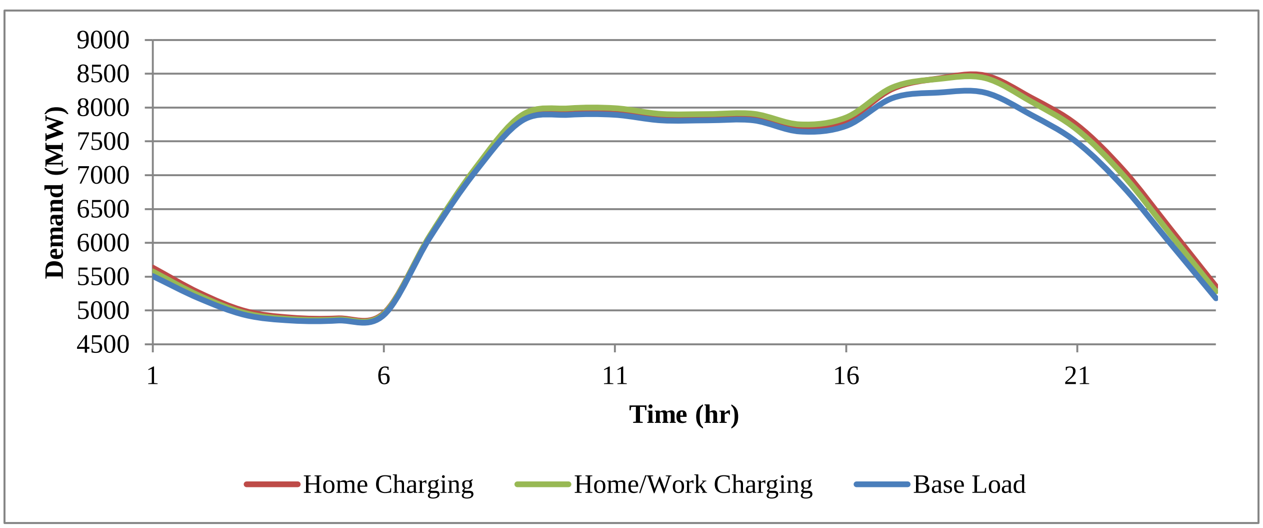


Figure 16 – Winter RTS Load Profile Combined w/ Simulated Charging

### 2.3.3 *Test System Topology and Generation*

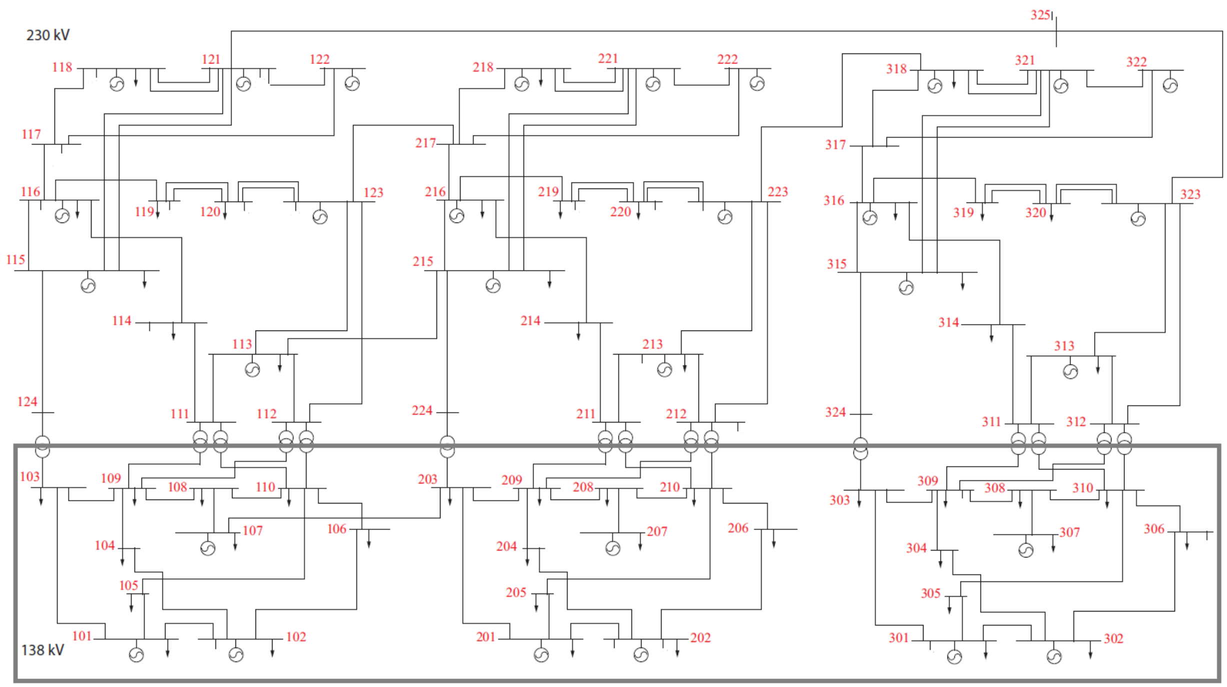


Figure 17 – 96 IEEE 3 Area Test System Topology

To establish PEV charging emissions profiles, two distinct variations of the 96 RTS Test system are analyzed. Both systems have the same general layout as the original RTS as shown in Figure 17. The system shown is made up of three 24 bus areas with 96 generating units, 51 loads, and 121 lines, [21]. For both systems hydroelectric plants have been removed and replaced with additional thermal generating units. This is done for the sake of simplicity to eliminate the need for hydro thermal scheduling (HTS). HTS requires several additional regional assumptions and would add an unnecessary. The complete data sets for both test systems are included in Appendix A with pertinent information extracted.

**Test System #1**

This system shares identical location and group nomenclature as the original IEEE 96 RTS [21]. The primary difference results from Group U50 (originally Hydroelectric generators) being replace with additional 50 MW Coal / Steam plants sharing the same characteristics as group U76. System 1 is composed mostly of coal at 46.2% followed by 30.3% fuel oil providing peaking and ramping and finally 23.5% nuclear supplying base load. For a regional reference this system most closely models power generation found in the Mid or Southern Atlantic Regions of the Eastern United States. Table 6 contains the generation make-up used for system 1 [21].

Table 6 - Test System 1 Generation Make-up

| Group | Number of Units | Type of Unit | Capacity (MW) |
|---|---|---|---|
| U12 | 15 | #6 Oil – Steam | 12 |
| U20 | 12 | #2 Oil - OCGT | 20 |
| U50 | 18 | Coal – Steam | 50 |
| U76 | 12 | Coal – Steam | 76 |
| U100 | 9 | #6 Oil- Steam | 100 |
| U155 | 12 | Coal – Steam | 155 |
| U197 | 9 | #6 Oil- Steam | 197 |
| U350 | 3 | Coal – Steam | 350 |
| U400 | 6 | Nuclear | 400 |

Generator characteristics and initial conditions for this system are derived from a 2006 paper [23]. All generator characteristics can be found in Appendix A for reference. Cost curves for each generation block are shown below in Figure 18.

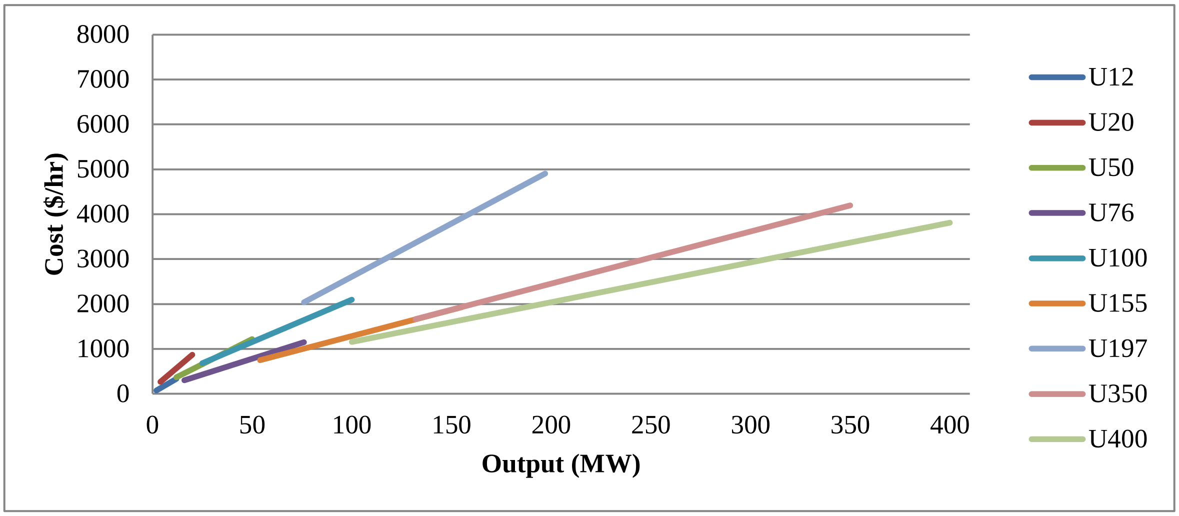


Figure 18- Test System 1 Generation Cost Curves

**Test System #2**

The second system constructed again shares identical location and group nomenclature as the original IEEE 96 RTS [22]. In this test system an effort is made to update the original RTS with somewhat "modern" generation technologies according to [22]. In this system the following technologies have been added Open Cycle Gas Turbines (OCGT), [26] Combined Cycle Gas Turbines (CCGT) [26], as well as Integrated Gasification Combined-Cycle generators [27]. As with test system 1, Group U50 (originally Hydroelectric generators) is replaced, but in this system with 50 MW CCGTs. Table 7 contains the generation make-up used for system 2 [22].

Table 7 - Test System 2 Generation Make-up

| Group | Number of Units | Type of Unit | Capacity (MW) |
|---|---|---|---|
| U12 | 15 | #2 Oil – OCGT | 12 |
| U20 | 12 | #2 Oil - OCGT | 20 |
| U50 | 18 | NG – CCGT | 50 |
| U76 | 12 | NG – CCGT | 76 |
| U100 | 9 | NG – CCGT | 100 |
| U155 | 12 | Coal – IGCT | 155 |
| U197 | 9 | NG – CCGT | 197 |
| U350 | 3 | Coal – Steam | 350 |
| U400 | 6 | Nuclear | 400 |

Generator characteristics and initial conditions for this system are derived from a 2012 paper [22]. All generator characteristics can be found in Appendix A for reference. Cost curves for each generation block are shown below in Figure 19.

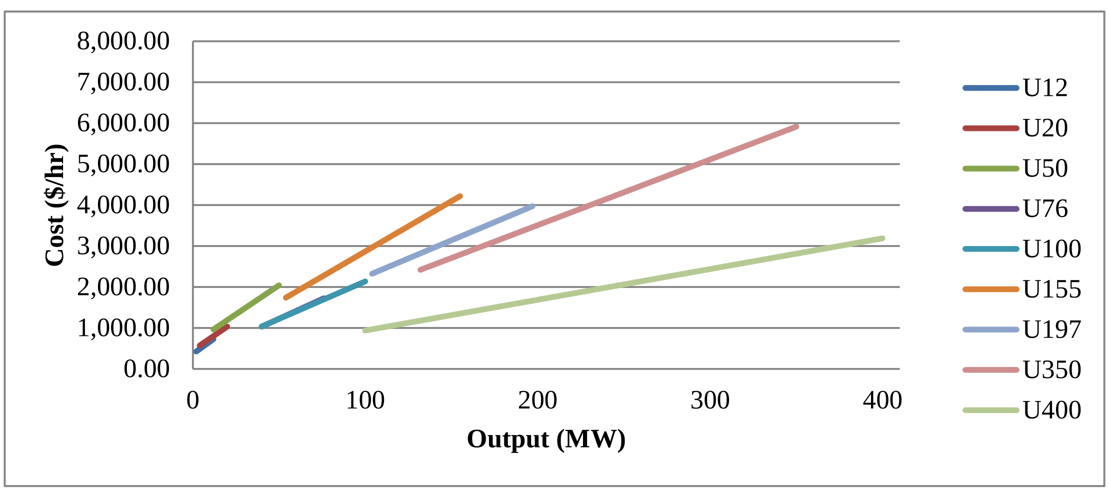


Figure 19 - Test System 2 Generation Cost Curves

## 2.4 OPTIMIZED CHARGING PROFILES

This section discusses the process used to model the optimized charging for a specific penetration of PEVs. In the uncontrolled charging scenario, PEVs charging is simply treated as an additional time-varying load in the system. This requires no additional formulation to implement as the system operator schedules and dispatches the available generation to meet the resulting net demand. On the other hand, in the optimized case the PEV aggregator interfaces the population of PEVs with the system operator allowing for control over how and when the vehicles are charged in order to minimize the overall cost of running the system. The aggregator deals with the clustered effects of all batteries as discussed in [6]. Individual vehicle dynamics are forgone and an average is used for the values established in Chapter 2.2. Charging and discharging rates are based upon an assumption of 95% roundtrip efficiency. These assumptions are made to reduce the size and complexity of the UC problem to a realistic level, since it is not expected for each individual PEV to participate in the system scheduling process. Table 8 shows the parameters assumed for the aggregator in the controlled charging models:

Table 8 - PEV Aggregator Data

| PEV parameter | PEV Size | | | Simulation Value |
|---|---|---|---|---|
| | Small | Medium | Large | |
| PEV Fleet Composition (%) | 7 | 43 | 48 | 100 |
| Battery Capacity (kWh) | 16 | 24 | 34 | 27.80 |
| Energy Consumption (kWh /mi) | 0.33 | 0.37 | 0.4 | 0.374 |
| Average distance Traveled (mi) | | | | 25.15 |
| Average Daily Consumption (kWh/Day) | | | | 9.41 |
| Charge/ Discharge rate (kW/h) | | | | 3.13 |
| Total number of PEVs | | | | 1,288,000 |

There are two controlled charging scenarios which are implemented in this study:

*Optimized Charging* – In this scenario charging occurs in only one direction. That is, charging occurs when an PEV is stationary and it is most beneficial for the system operator to charge the vehicle. This occurs when the marginal price of electricity is the lowest. It is assumed for this scenario that all vehicles share the similar travel patterns and are charged at the same rate. Also, the motion profile established in chapter 2.1.2 is used to ensure the similar total amounts of energy are consumed between the controlled and uncontrolled charging cases [2].

*Optimized Charging with* (V2G) – In this charging scenario the system operator is allowed to utilize the aggregated energy of the vehicles in order to support the grid. Again energy consumed through motion is accounted for through the vehicle charging, however bidirectional flows are now considered. In other words, vehicles are now available the provide power injections back into the grid when they are parked, if there is a benefit in doing so. Although this creates additional complexity, it allows the system operator increased flexibility when scheduling generation. During times when energy is inexpensive vehicles can be charged to their maximum capacity and then discharged when periods of peak generation would be required [2].

The two charging scenarios require additional equations to be added to the UC model in order to allow for system control over the charging. Source [6] lays out a foundation for the inclusion of vehicle charging and discharging in the UC. The model used for the sake of this study ignores the portions of the equations pertaining to reserve services and renewable energy generation. The energy consumed or provided by the PEVs now need to be accounted for in the power balance equation:

$$\sum_{i=1}^{I} g_i^t + EV_{dsg}^t = \sum_{s=1}^{S}(d_s^t) + EV_{chg}^t \qquad (2.20)$$

where, $g_i(t)$ is the generator $i$ output at time $t$ (MW), $d_s(t)$ is the demand at bus $s$ (MW), $E_{chg}(t)$ is a variable for the demand from PEV charging at time t (MW) and $E_{dsg}(t)$ is a variable for the energy from PEV injections at time t (MW).

In addition, limitations must be placed on the batteries of the PEVs not only to prevent over charging but to ensure enough energy is conserved to allow for daily vehicle motion and emergency reserve (anxiety range). For the sake of simplicity an aggregated population of PEVs is modeled as an average state of charge for all vehicles in the system. This varies based on the number of vehicles in the system and thus the capacity of storage. Also, the amount of energy required for charging increases as the penetration of PEVs increases. Equation 2.21 is included in the UC to account for the PEVs average SOC:

$$SoC_{ev}^{t} = SoC_{ev}^{t-1} + \frac{EV_{chg}^{t}}{EV_{Total}} - \frac{EV_{dsg}^{t}}{EV_{Total}} - \eta * \frac{V_m^t}{\sum_{t \in T} v_m^t} \tag{2.21}$$

Where, $SoC_{EV}(t)$ is the average SoC for the PEV batteries at time $t$ (MW), $E_{chg}(t)$ is a variable for the demand from PEV charging at time $t$ (MW) $E_{dsg}(t)$ is a variable for the energy from PEV injections at time $t$ (MW), $EV_{total}$ is the total number of vehicles available and $V_m(t)$ is the number of vehicles in motion at time $t$, $\eta$ is the average energy consumption for PEVs (MW). The motion profiles used for weekdays and weekends are shown in Figure 20.

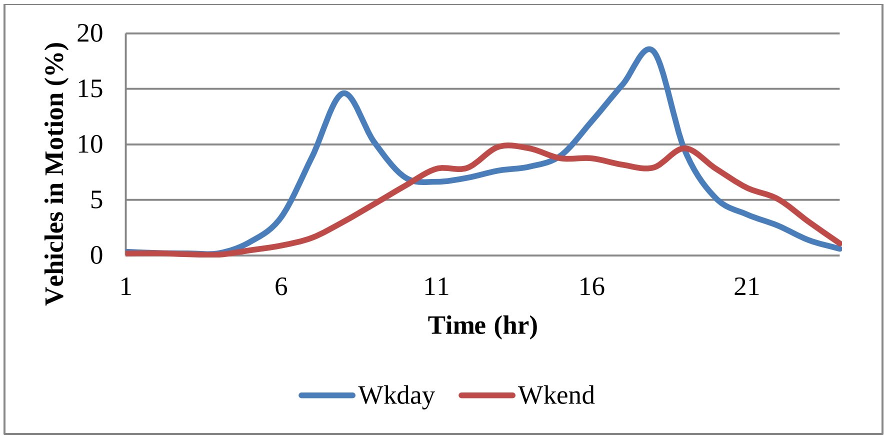


Figure 20 - Daily Vehicle Motion Profiles

Additional equations are required to ensure the physical limits for the battery are not violated and that conservation of energy is maintained from day to day. Equation 2.22 and 2.23 are required to ensure that charging is limited to parked vehicles:

$$EV_{chg}^{t} \leq EV_{prk}^{t} * EVchg\_rate \qquad (2.22)$$

$$EV_{dsg}^{t} \leq EV_{prk}^{t} * EVchg\_rate \qquad (2.23)$$

where, $E_{chg}(t)$ is a variable for the demand from PEV charging at time t (MW), $E_{dsg}(t)$ is a variable for the energy from PEV injections at time t (MW), $EV_{prk}(t)$ is the total number of vehicles available for charging or discharging, and $EVchg\_rate$ is rate at which power can be transferred (MW/h).

Equations 2.24 and 2.25 ensure that the battery is not charged or discharged beyond the limits specified by the vehicle aggregator:

$$SoC_{Ev}^{t} \leq Bat_{Cap\_max} \qquad (2.24)$$

$$SoC_{Ev}^{t} \geq Bat_{Cap\_min} \tag{2.25}$$

where, $SoC_{EV}(t)$ is the average SoC for the PEV batteries at time t (MW), $Bat_{cap\_max}$ is a constant specifying the maximum battery capacity (MW), and $Bat_{cap\_min}$ is a constant specifying the minimum battery capacity (MW).

Equation 2.26 is needed to ensure that the vehicles start and end each charging period with the same amount of energy:

$$SoC_{Ev}^{t=24} = SoC_{Ev}^{t=0} \tag{2.26}$$

Equation (2.26) prevents against scheduling energy gains or losses by the PEV fleet that cannot be maintained over consecutive optimization horizons.

## 2.5 EMISSIONS

In this section it is discussed how generation emissions are modeled for each of the generator types as well as the formulation to include the emissions in the UC framework. The emissions associated with power generation are a product of several factors, of which the most obvious is fuel source. Other factors to consider include transportation of the fuel source, efficiency of the generator and life cycle construction of the power plant. Simulations for this study are focused on emissions as a direct result of PEV penetration and ignore emissions associated with transportation of fuel and construction of plants.

**Emissions from Power Generation**

To model the impact of PEV penetration and charging strategy, emissions must be associated with the generation matrix for each test system. This requires first that a heat rate curve be established for each type of generator to be modeled in the UC [28]. Using the heat rate for each generator fuel consumption and plant efficiency can then be modeled. Developing these curves is done in a similar way to the method used for creating cost curves with a separate scaling factor for fuel $CO_2$ content. Again, these curves are non-linear and non-convex so they must be converted into a linear approximation to use the MILP UC solver.

Using the heat rate curves for various modern generator technologies an emissions curve is developed. This method combined with characteristic curves in [19] and 2013 measurement for the carbon content of various fuel sources, as reported by the EIA [29], is used to construct an emissions curve for each generator technology. Over the relatively short ranges of generator capacities used it this study it was determined that using a strictly linear fit $(\beta)$, a worst case closeness of fit $R^2$ value of 0.94 is attained. By adding an additional term $(\gamma_i)$ for the no-load emissions of each generator type $i$ a worst case $R^2$ value of 0.9945 is attained. This indicates a tight fit with little scatter for emissions values using a linear regression fit and is the method used to estimate each generators output. Equation 2.26 is incorporated into the UC model to represent emissions by generation source. Table 9 shows the coefficients used in equation 2.27 converted from lbs/kWh to tons (short)/ MWh:

$$CO_{2i}^{t} = \beta . g_i^t + \gamma_i \tag{2.27}$$

Where, $g_i(t)$ is the generator *i* output at time *t* (MW), $CO_{2-out}(t)$ is the hourly $CO_2$ output from generator i at time t (tons (short) $CO_2$/h), $\beta$ is the variable $CO_2$ coefficient for generator $i$, and $\gamma$ is the no-load $CO_2$ coefficient for generator *i*.

Table 9 – Generator Greenhouse Gas Coeefficients

| Generation Technology | $\beta\ (\frac{tons\ CO_2}{MW})$ | $\gamma(tons\ CO_2)$ |
|---|---|---|
| Coal - Steam | 1.06 | 0.4 |
| Gasified Coal – IGCT | 0.682 | 0.2 |
| #6 Oil – Steam | 0.9 | 0.2 |
| #2 Oil – OCGT | 0.835 | 0.1 |
| Natural Gas - CCGT | 0.481 | 0.3 |
| LWR – Nuclear | N/A | N/A |

Once a $CO_2$ output for each generating unit is established a variable penalty can then be applied to each individual block of generators to determine a cost of carbon emissions ($C^t_{co2\_i}$ ). Equation 2.28 is then added to the UC solver and equation 2.29 shows the modified objective function:

$$C^t_{co2\_i} = CO^t_{2i} \, . \varphi \tag{2.28}$$

$$Minimize\ \sum_{t=1}^{T} \sum_{i=1}^{I} C_i(t) + \ C^t_{co2\_i} \tag{2.29}$$

Where, $CO_{2-out}(t)$ is the hourly $CO_2$ output from generator *i* at time *t* (tons (short) $CO_2$ /hr), and $\varphi$ is the penalty for emitting $CO_2$ for generator *i (*$/ton*)*.

**Emissions from Offset Road Transportation**

Emissions from road transportation are modeled as static value used for comparison as a direct offset by electric vehicles. Total system capacity is scaled to 1,288,000 vehicles and road vehicles removed are replaced with the corresponding percentage of PEVs. All PEVs added are in the percentages established through an average of the sample set for simplicity of comparison. According to 2014 estimates by the EPA 8,887 g of $CO_2$ are produced by each gallon of gasoline burned [30]. Using equations 2.30 [30] and the vehicle make-up of the traffic data a net $CO_2$ daily output can be established for comparison:

$$Daily\ CO_2\ Emissions = \frac{CO_2 per\ Gallon}{Vehicle\ MPG} \cdot miles \qquad (2.30)$$

In section 2.1.2 an average round trip travel distance of 25.15 miles is established. Fuel economies are given in three ranges > 30 MPG, from 20 – 30 MPG and < 20 MPG. Based off of the EPA 2016 Fuel Economy Guide, a value of 16 MPG is assigned to large passenger vehicles, 26 miles per gallon for midsize vehicles and 35 miles per gallon for small vehicles [31]. Note fuel economy values for PHEVs and BEVs where not considered in the selection. Using the percentages associated with the sample data, a value of 22.3 mpg is established as compared to the 2014 EPA estimated average of 21.6 mpg [31]. The resulting net greenhouse gas production is determined to be 14,230 tons of $CO_2$ per day for the scaled 1,288,000 vehicle system size.

# Chapter 3. RESULTS AND ANALYSIS

In this chapter the results of the MILP UC optimization, described in chapter 2 section 3.1, are discussed. The effect of PEV charging strategy on net system emissions is evaluated for both test systems over a 1 year period. To begin, a discussion of the base case optimal generation solution for each system and season is examined. This serves to establish the yearly emissions profile for each system with no PEVs included. Then test scenarios for both uncontrolled charging strategies discussed in chapter 2.2 and controlled charging strategies described in chapter 2.4 are evaluated for their effect on net system emissions using security constrained economic dispatch as PEV penetration increases. Finally, the effect of an emissions penalty included in the UC model and it is then evaluated for its effect on net system emissions.

## 3.1 BASE CASE EMISSIONS RESULTS

For the base case systems the UC is solved using the Generic Algebraic Modeling System (GAMS) set to a stopping optimality gap of 0.5%. The generators in each test system use the linearized cost approximations found in Appendix A for reference. All generators are set to the initial conditions and subject to the constraints found in Appendix B. The load profiles established in chapter 2 section 2.3.2 are used to represent seasonal weekdays and weekends.

**Test System 1**

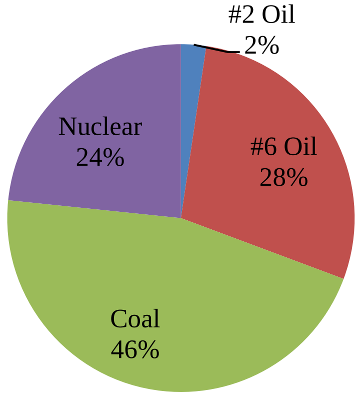


Figure 21 - System 1 Percentage of Total Generation Composition

In order to accurately compare the effect of increased PEV penetration in each of the test systems a base line is established for each system on a seasonal basis. As shown in Figure 21 test system 1 is dominated primary by coal with flexible fuel oil plants serving the system's peaks and rapid ramping requirements. A small percentage of expensive OCGT plants using #2 Oil exist, but are expensive and serve primary to increase system head room (i.e. adequacy and security, which are beyond the scope of this thesis). Base load is served predominantly by nuclear and coal technologies due to their low marginal cost of production, with larger penetrations of more expensive oil peaking plants being committed during higher demand seasons (summer and winter). The seasonal weekday and weekend results for system 1 are shown in Figure 22. Results are itemized by the percent make-up that each of the 9 generator technologies contribute to the total generation. For visual reference base generation technologies start at the bottom of the stack with more efficient and expensive peaking generation at the top of the legend.

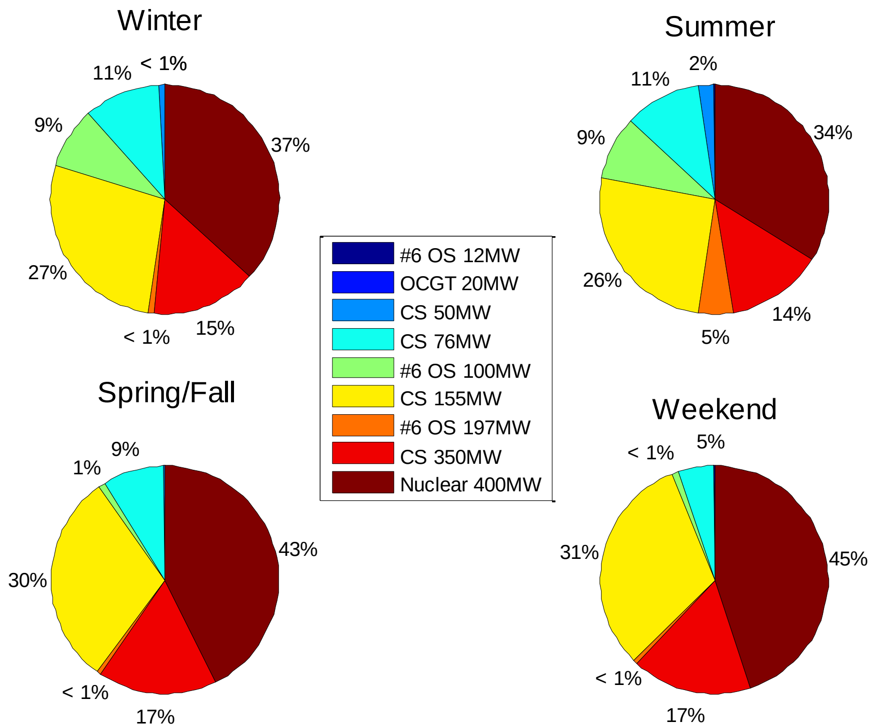


Figure 22 – Generation Composition for System 1

As expected, during periods of the year with lower total demand such as autumn, the spring and weekends, the generation make up for the system is more heavily dominated by the nuclear generation and inexpensive coal technologies. As the load shifts higher to a higher level, oil peaking generation is more frequently used and accounts for a larger portion of the total generation mix. Notice in the base case for this system the most expensive peaking generation is rarely used aside from a small percentage occurring in summer months.

**Test System 2**

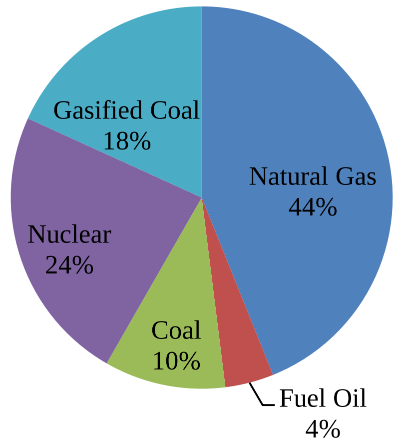


Figure 23 - System 2 Percentage of Total Generation Capacity

The second system is composed by a more diverse generation mix which results in greater overall system flexibility. Nuclear generation again serves the base load with a smaller percentage of inexpensive coal. The system is natural gas heavy with OCGT technologies responding as to provide peak and ramping support. Additionally IGCT technologies are added to support the mid to high demand periods. As in the case in system 1; system 2 shows an increased amount of more expensive generation during periods of higher demand. Base demand is served by coal steam and nuclear technologies with increased CCGT plants synchronizing during summer and winter seasons.

Seasonal and weekend results for system 2 are shown in Figure 24. Results are itemized by the percent make-up that each of the 9 generator technologies contributes to the total generation. For visual reference base generation technologies start at the bottom of the stack with more efficient and expensive peaking generation at the top of the legend. Table 10 displays the resulting seasonal and weekend total daily generation, costs, and emissions for future reference.

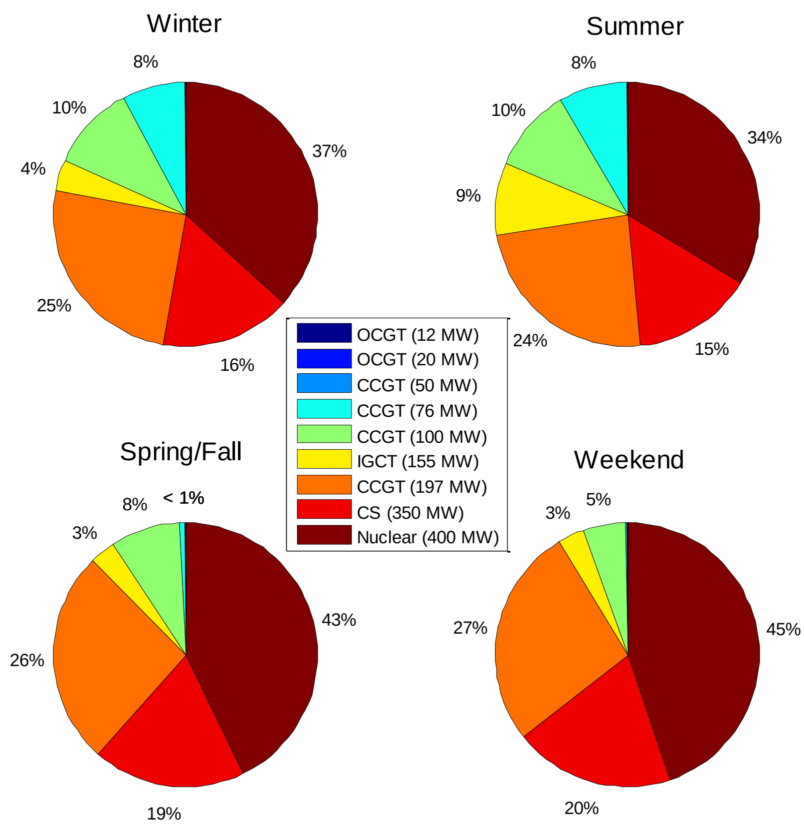


Figure 24– Generation Composition for System 2

Table 10 – UC Daily Seasonal and Weekend Day System Results Comparison

| | Winter | Summer | Spring – Fall | Weekend |
|---|---|---|---|---|
| Daily Demand (MW) | 145,439 | 158,599 | 124,906 | 119,231 |
| System 1 Cost ($) | 2,066,197.43 | 2,366,090.61 | 1,663,388.10 | 1,578,753.70 |
| System 2 Cost ($) | 2,608,054.40 | 2,963,683.59 | 2,143,906.12 | 2,032,863.17 |
| | Emissions (tons $CO_2$) | | | |
| System 1 Output | 91,714 | 104,212 | 74,461 | 68,429 |
| System 2 Output | 59,063 | 67,137 | 48,848 | 46,058 |

## 3.2 EMISSIONS ASSOCIATED WITH INCREASING PEV PENETRATION

For the both systems the UC is solved using GAMS set to a stopping optimality gap of 0.5%. The generators in each test system use the linearized cost approximations found in Appendix A for reference. All generators are set to the initial conditions and subject to the constraints found in Appendix B. The Load profiles established in chapter 2 section 3.2 are used to represent seasonal weekdays and weekends.

### 3.2.1 *PEV Influence on Daily Demand*

The additional hourly demand from PEVs in the uncontrolled case is added to the system load using the charging profiles established in chapter 2.2. In the controlled charging scenarios, the equations established in chapter 2.4 are enabled in the UC allowing the system to optimize when the PEV demand is met. In the optimized charging with V2G scenario the system is also allowed to discharge energy back into the system when vehicles are available for charging. Vehicles in the optimized case begin and end the day at midnight with an aggregated battery level of 25% charge. The UC solver can then choose to charge the aggregated battery level up to 100% but cannot allow the battery level to fall below 15% for to avoid rapid degradation and irreversible changes in the battery, as well as for emergency travel purposes (i.e. range anxiety) [32]. For both controlled and uncontrolled scenarios, the same net amount of energy is consumed to ensure the vehicles replenish energy consumed during motion. The motion profiles shown in section 2.4 Figure 20 are used to determine how many vehicles are traveling and consuming energy. The remaining vehicles are available for charging and for discharging in the V2G mode. An example of the controlled charging cases is shown in Figure 25.

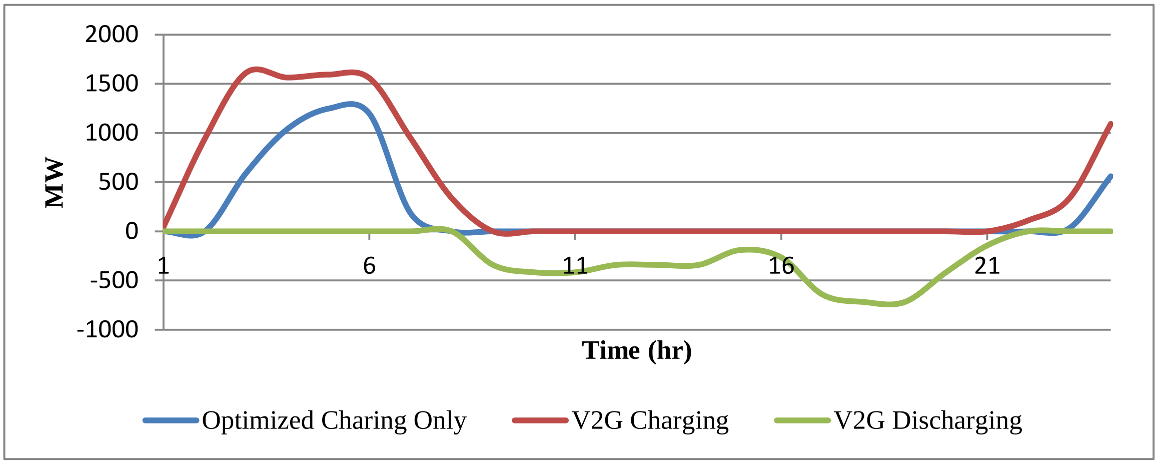


Figure 25 – Controlled Charging (Winter Day for 40% EV penetration)

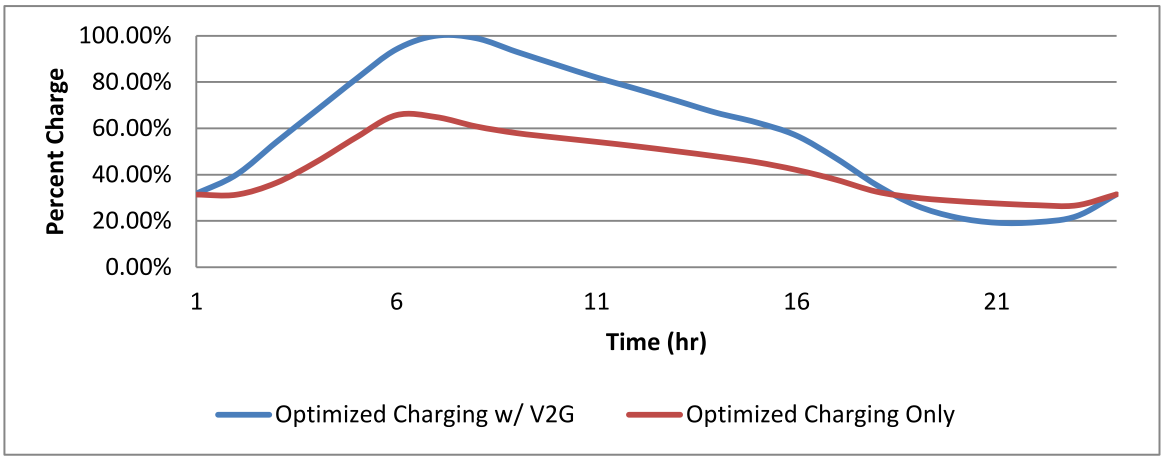


Figure 26 - Aggregated Battery SoC (Winter day @ 40% EVs)

Figure 25 shows that for the optimized charging scenario the energy required for motion is recovered during the night when energy is at its cheapest. Note that only the amount of energy needed for the next day's motion is consumed as shown by the battery state of charge in Figure 26. In the controlled charging scenario with V2G allowed the system charges the vehicles to the maximum extent possible and then used the available excess energy to reduce the demand during periods where energy prices are highest such as peak demand. In this way the system operator is able to achieve the lowest overall system operating cost while still meeting the travel demands of the aggregated PEV fleet. As penetrations of PEVs increase, the system has a greater overall capacity with which it can influence demand in the system.

The effect of these charging profiles drastically changes the daily load profile as shown in Figure 27. Note, although not immediately clear to the naked eye, the additional demand created by all charging scenarios is identical over the course of a day. Notice for the uncontrolled cases peak demand is further increased as well as sharply increasing areas requiring rapid ramping. In the controlled charging only case, the "valley" during periods of low demand is filled creating a gradual ramp up to higher afternoon demand. In the controlled charging with V2G scenario demand throughout the day is flattened creating a more even load profile with a lower flat peak and a shallower ramp rate. These changes to the load profile have varying effects on the generation mix used for each system as shown in Figure 29 and Figure 28.

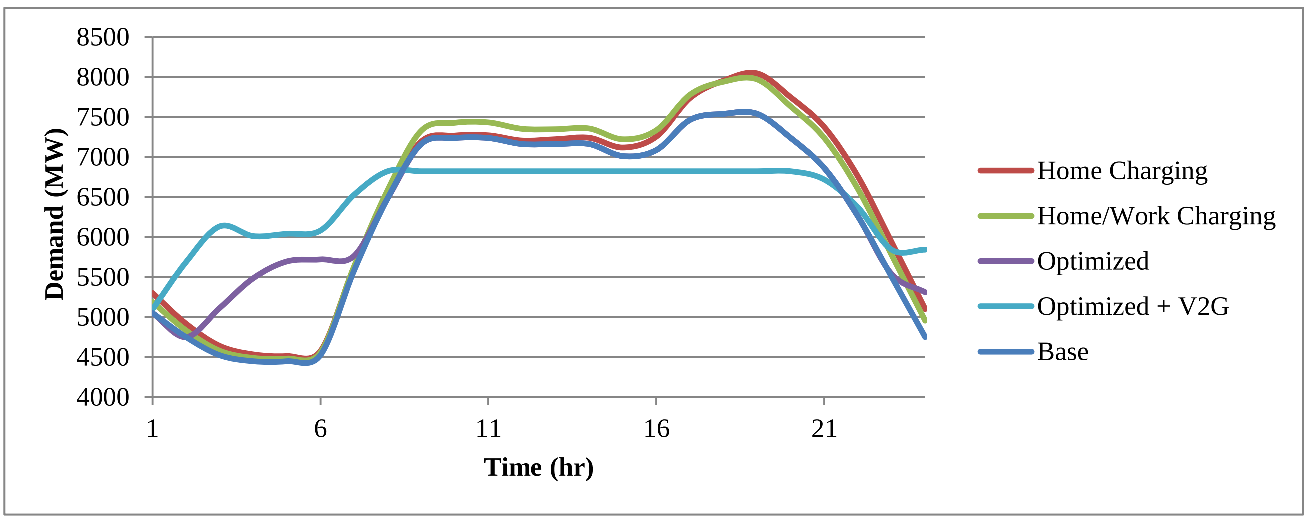


Figure 27 – Hourly System Demand (Winter day @ 40% EVs)

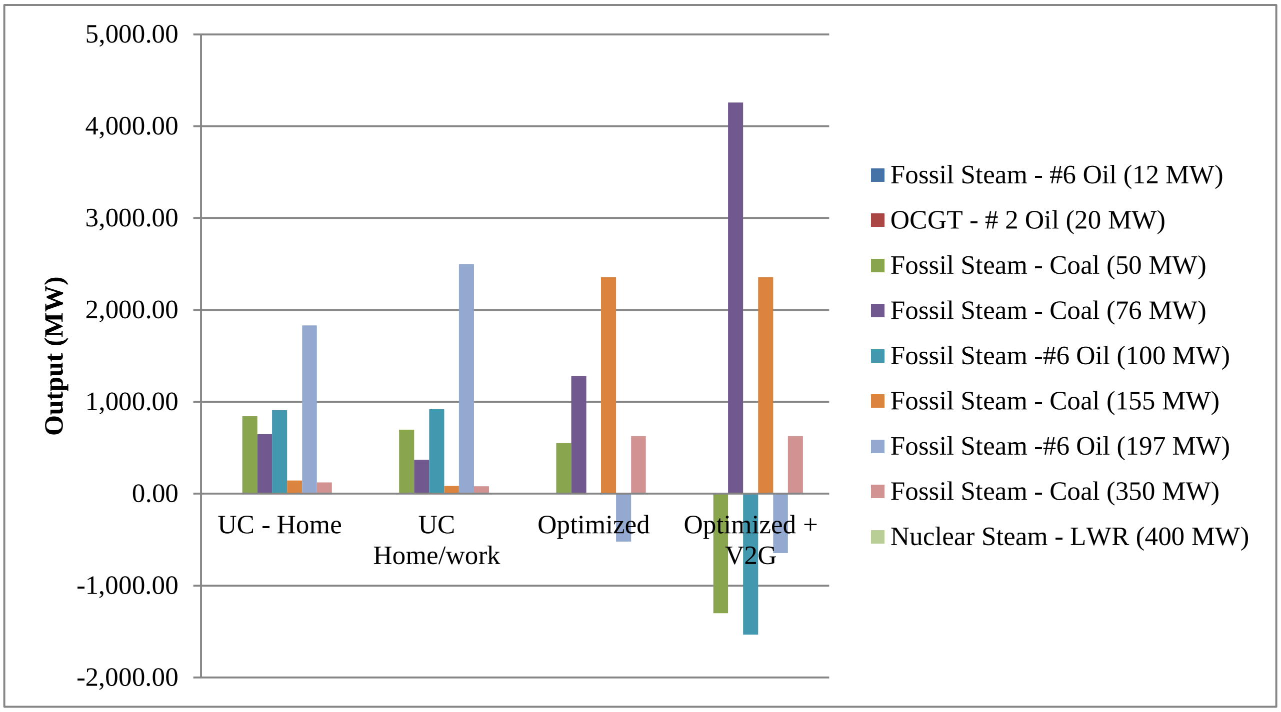


Figure 28 - System 1 Generation change vs base case (Winter day with a 40% EV penetration)

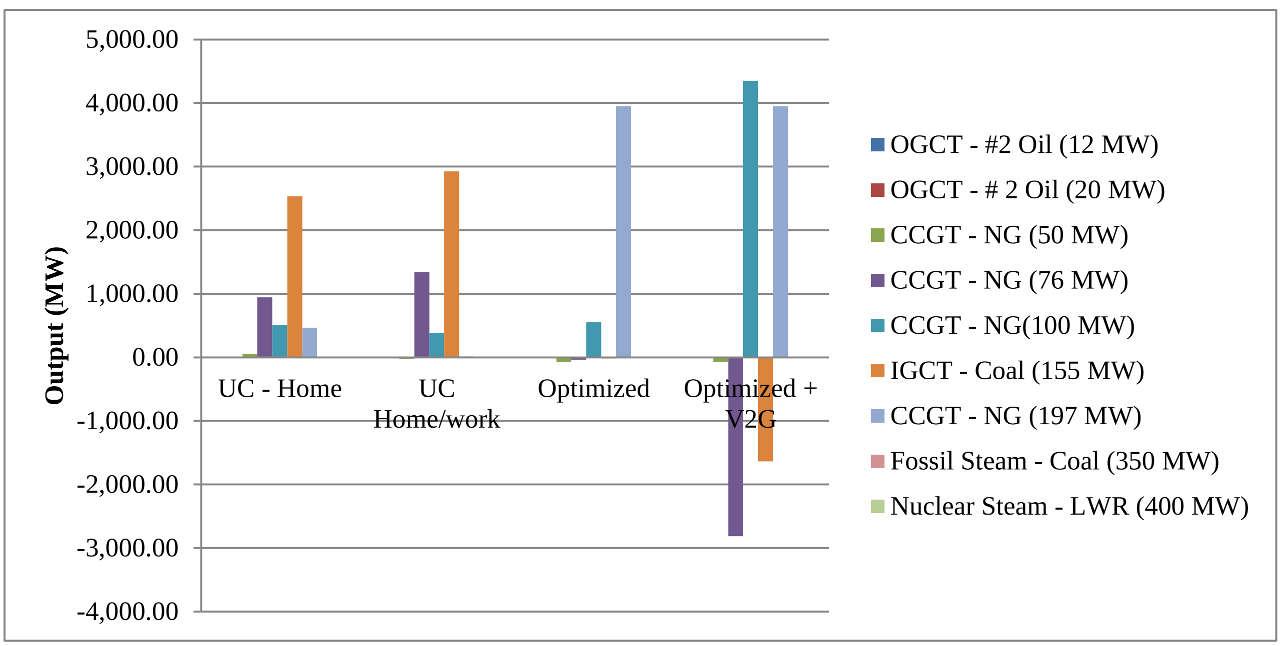


Figure 29 – System 2 Generation change vs base case (Winter day with a 40% EV penetration)

Note that in the uncontrolled charging scenarios increased amounts of expensive generation are needed to accommodate the increased ramping and peak demand created. However, in the controlled charging case, base generation is used to supply the entire demand created by the PEVs. Additionally in the controlled charging with V2G scenario ramping and peaking generation technologies are almost entirely removed and replaced with lower cost base generation. The effect these changes have on emissions varies depending on the season and penetration of PEVs. These results are discussed in detail in the following section.

### 3.2.2 *Emissions Results*

In this section the results of the UC solver are used to establish and compare the net system effects of increased PEV penetration for each of the test systems. Seasonal weekday and weekend results are shown in Figures 30 – 34. For ease of comparison system results are shown side by side with net emissions in the top graphs and the increase in system cost in the lower graphs. Net system emissions are established by adding the increased emissions from PEVs, for each charging strategy, to the emissions from internal combustion engine (ICE) vehicles remaining on the road. For example in a situation with 20% PEV penetration, 80% of the net system emission are coming from ICE vehicles and the remainder is replaced by the emissions from PEVs. In a 100% PEV penetration scenario, all of the emissions is the system are produced from generation required to charge PEVs and no emissions are coming from ICE vehicles. For each of the emissions plots, the remaining emissions contributions from ICE vehicles are represented by the blue dashed line.

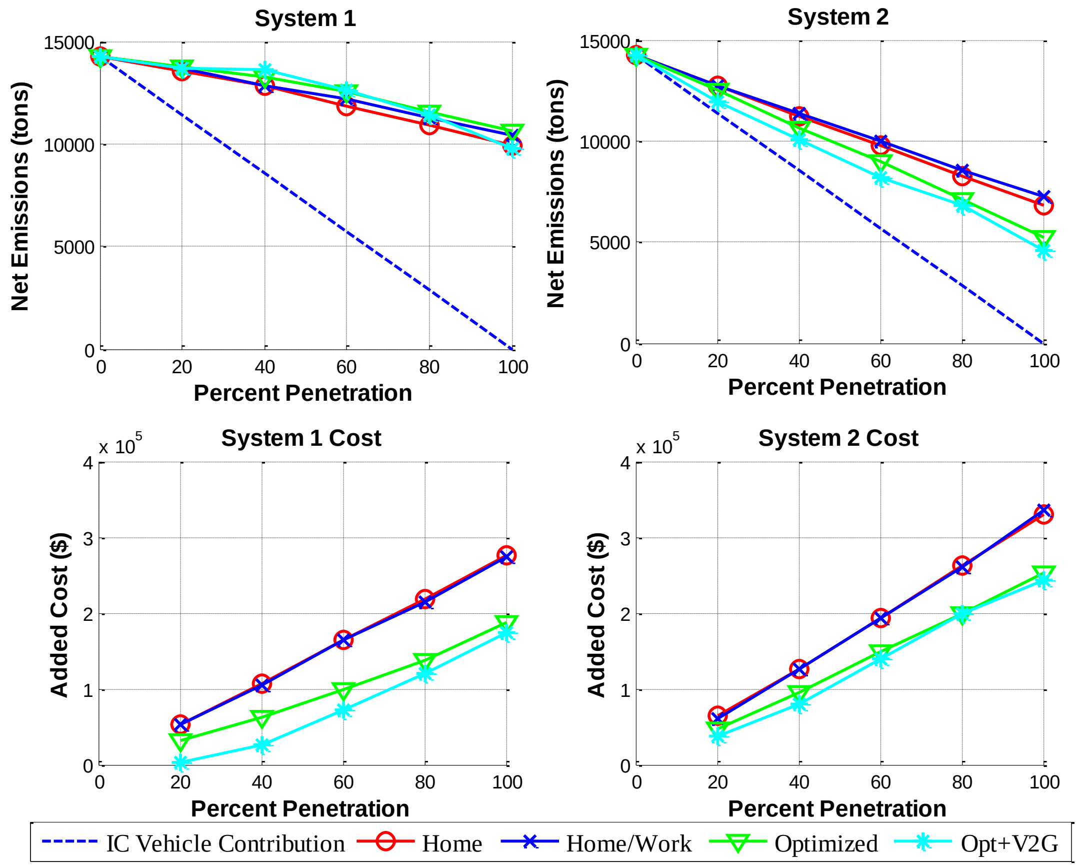


Figure 30 – Winter Weekday Emissions Comparison

In the winter emissions comparison shown in Figure 30, it is found that system 2 is able to achieve the greatest overall emissions reduction primarily due to the cleaner mid-level generation. System 1 has more modest reduction is $CO_2$ but with a substantially lower cost increase. Note that in System 1, with a 20% PEV penetration the cost increases only slightly when using the optimized charging strategy with V2G discharging allowed. This is due to the shifting of what would have been expensive peaking generation to cheaper base generation. As the penetration of PEVs increase for this season, emissions created in the controlled charging cases are slightly increased over the uncontrolled charging cases. This is due to the removal of what would have been higher cost but less emission intensive generation.

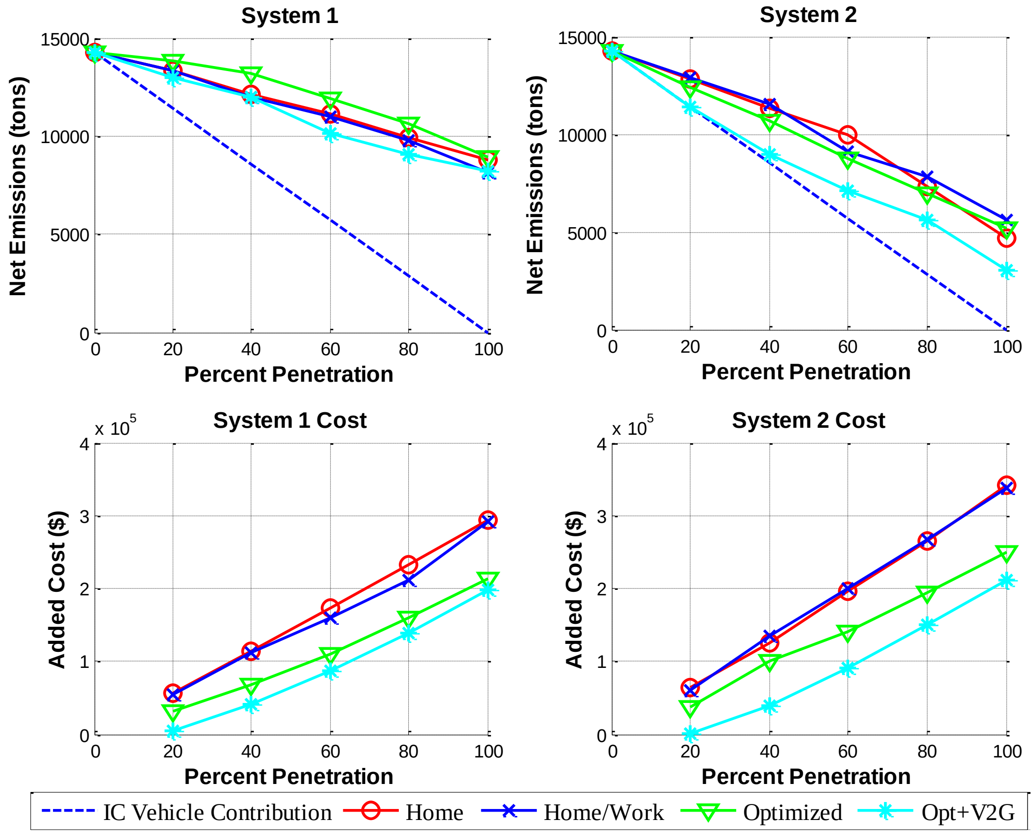


Figure 31- Summer Weekday Emissions Comparison

Again in the summer emissions comparison shown in Figure 31, system 2 is able to achieve the greatest overall emissions reduction but costs for the uncontrolled cases are substantially increased as the peak load nears the total capacity for the system. System 1 has more modest reductions and as PEV penetration grows, emission reductions begin to coverage. In the summer and winter seasons the base load is larger and the diversity of the available generation in system is diminished. Thus although cost is still reduced by displacing demand, emission are not as greatly affected by charging strategy. System 2 on the other hand again has cleaner mid-level generation and less emissions intensive ramping generation resulting in the best reductions coming from the controlled charging cases. Costs for System 2 are higher resulting from more expensive but efficient peaking generation.

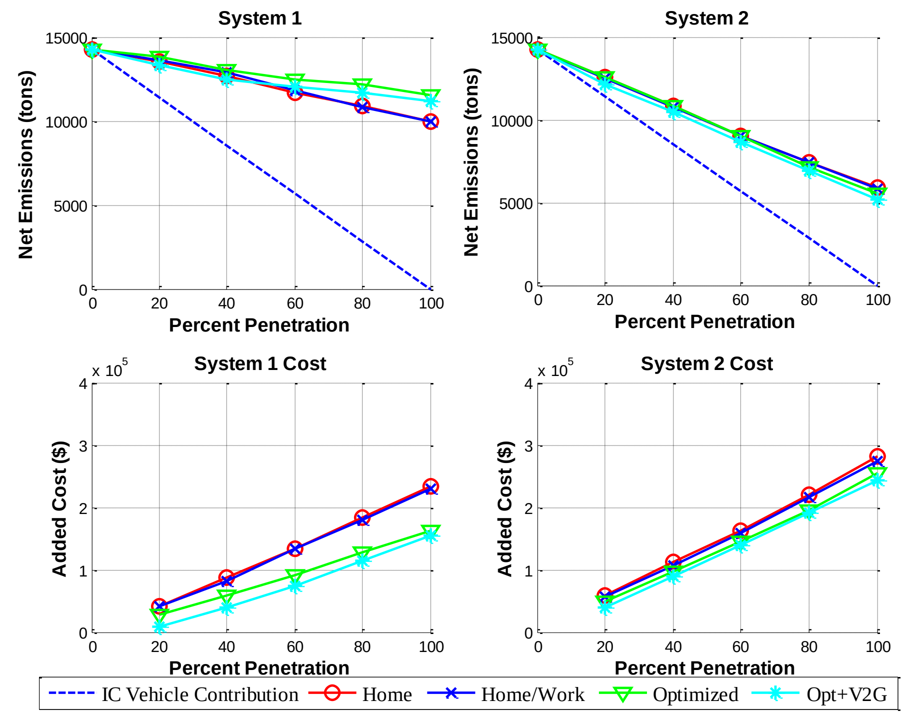


Figure 32 – Spring and Autumn Weekday Comparison

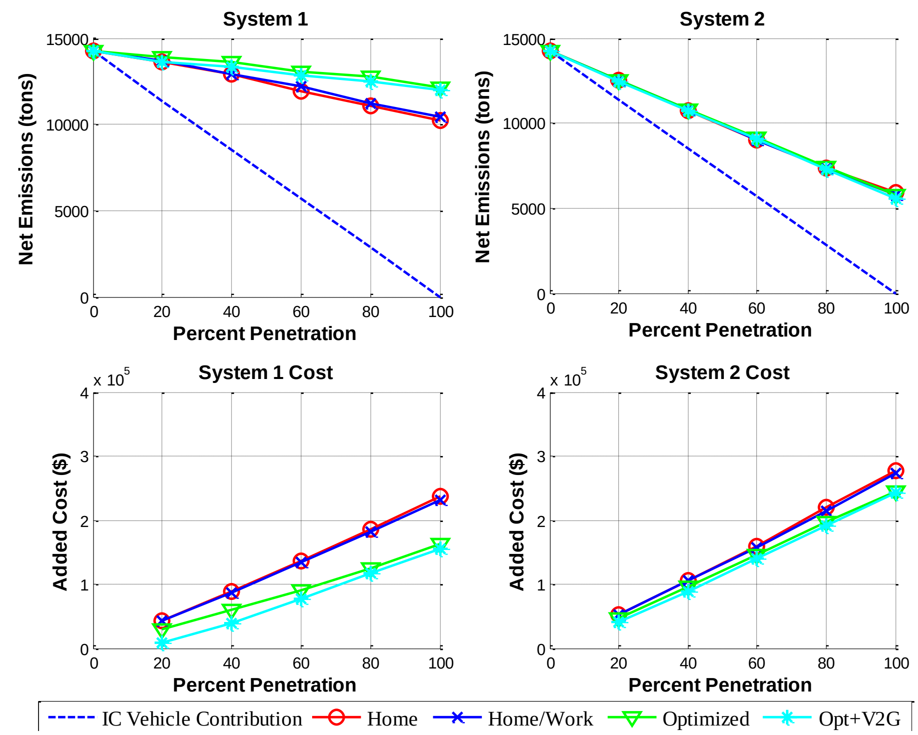


Figure 33 – Weekend Emissions Comparison

During the spring and autumn weekdays shown in Figure 32 as well as weekends shown in Figure 33, the peak daily base load is low resulting in lower cost increases for both systems. In system 1 the optimized charging cases replace expensive peaking generation with cheaper coal steam generation. This results in higher emissions output but at a lower added cost. System 2 does not undergo an appreciable decease in cost between the controlled and uncontrolled cased due to the groups of mid-tier CCGT technologies. Prices for generation in system 2 are more competitive in this region thus we do not see the large cost decrease associated with optimized charging as shown in the previous cases.

Using the established seasonal emissions profiles for each system a comparison over the course of a year is made. For a 365 day year the following composition is used: 63 winter weekdays, 68 summer weekdays, 66 spring weekdays, 64 fall weekdays, and 104 weekend days. Total emissions and cost increase for each seasonal day and weekend are used to determine the total emissions for each charging strategy for each system over the course of a non-leap year. System 2 shows a roughly 50% increase in emissions reductions over system 1 across all comparable charging strategies for only a 20% increase in cost as shown in Figure 34 and Figure 35.

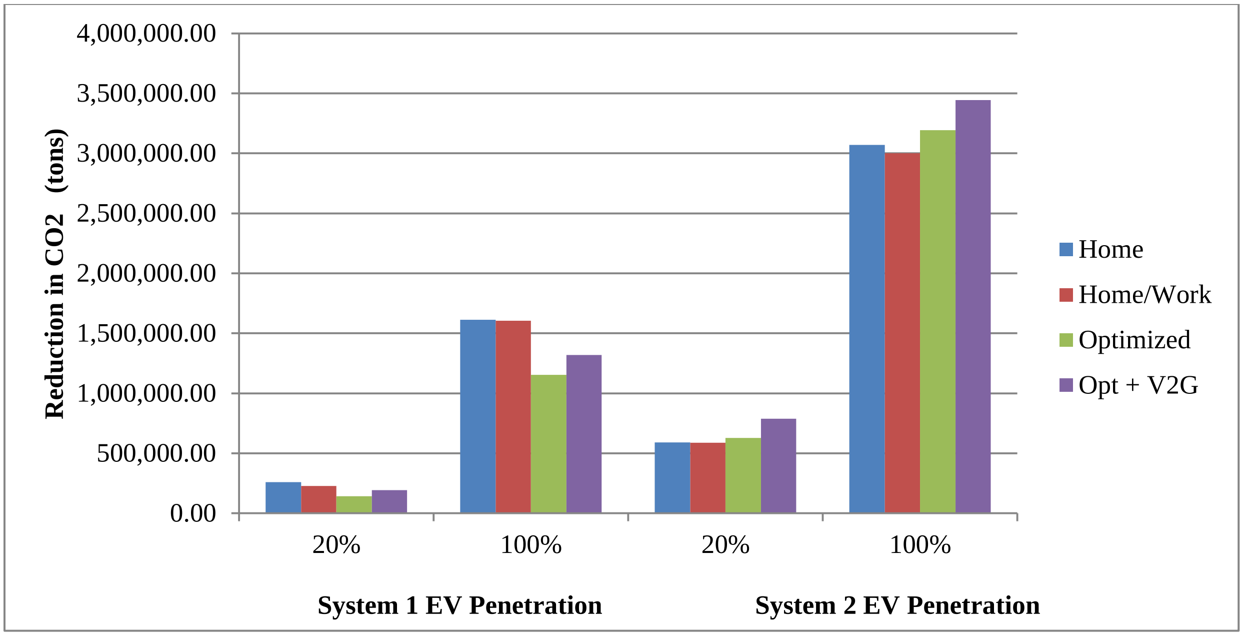


Figure 34 – Yearly Emissions Reduction by Charging Strategy

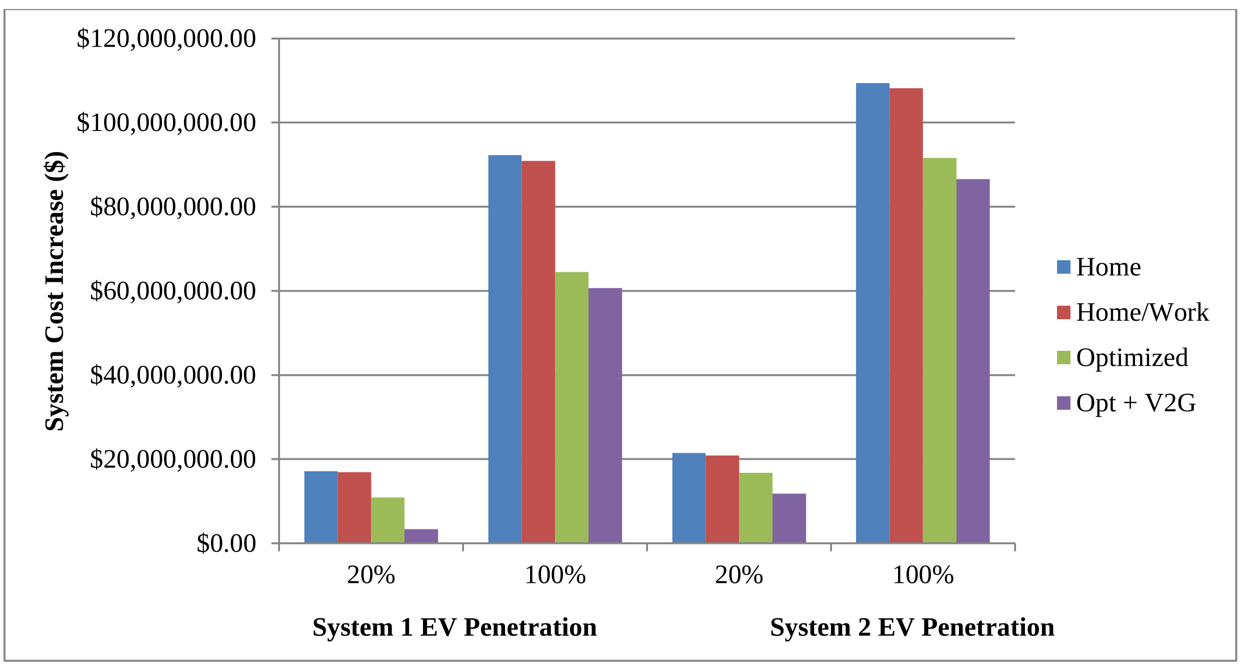


Figure 35 – Yearly System Cost Increase by Charging Strategy

In general optimizing charging achieves the lowest increase in cost of generation especially for lower penetrations of PEVs. However, optimized charging has a varying effect on emissions depending on the generation mix of the system. In the system 2, having less carbon intensive mid-tier generation, it is found that optimized charging has a beneficial effect on emissions. For the predominately coal steam generation mix found system 1, controlled charging shows a slight increase in system emissions over the uncontrolled cases. When we compare the reduction in road transport emissions to the cost increase in power generation it is found that the optimized charging with V2G enabled achieves the greatest reduction in emissions for the lowest increase in system cost in. This benefit diminishes as penetration of PEVs increases. Figure 36 shows a comparison of the reduction in emissions over ICE vehicles per dollar of generation cost increase.

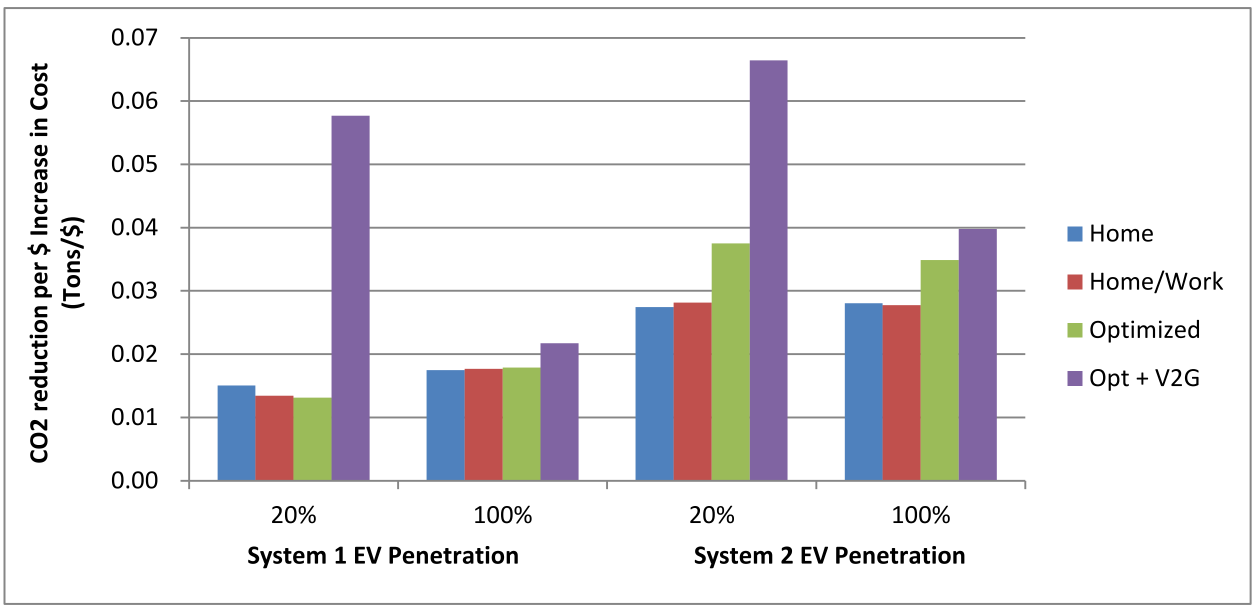


Figure 36 - Performance Comparison by Charging Strategy

## 3.3 EFFECT OF EMISSIONS PENALTY IN THE UC MODEL

In chapter 3.3, it is shown that the electrification of the road transport sector is most effective from an emissions perspective, in power systems with cleaner mid-level generation technologies. Although these systems come with higher total costs, the efficiencies in generation provide higher reductions in emissions for the equivalent cost increase. It is also shown that the flexibility provided by controlled charging can greatly reduce system costs while still providing moderate emissions reductions for lower penetrations of PEVs. Ideally there should be a means of leveraging this trade off in a lower cost but more emissions intensive system.

In this chapter the effect of an emissions penalty incorporated into the UC is examined. With the inclusion of a variable penalty on emissions, more carbon intensive fuels become economically prohibitive making more efficient generation more attractive. In this study the 40% PEV penetration winter weekday scenario is examined for System 1. This scenario incorporates low enough penetration of PEVs to allow for a diverse selection of generation but high enough penetration to provide some flexibility with controlled charging strategies.

The UC is again solved using GAMS set to a stopping optimality gap of 0.5%. The generators in each test system use the linearized cost approximations found in Appendix A for reference. All generators are set to the initial conditions and subject to the constraints found in Appendix B. The Load profiles established in chapter 2 section 2.3.2 are used to represent seasonal weekdays and weekends. The emissions penalty is varied from 5 to 50 \$/ton of $CO_2$ in 5 \$/ton increments. The effect is then established for the base system (no PEVs) as well as for all charging strategies. Figure 37 shows the reduction in emissions achieved vs penalty. Figure 38 shows the increase in system cost associated with the added penalty.

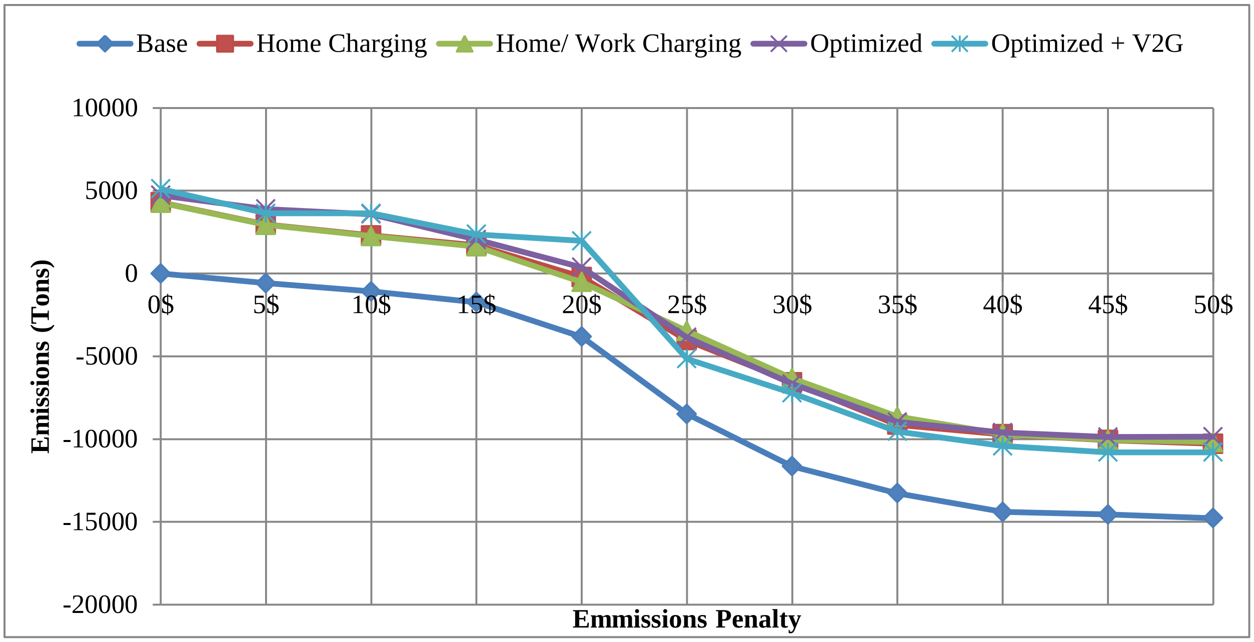


Figure 37 - Emissions Reduction vs Penalty Imposed

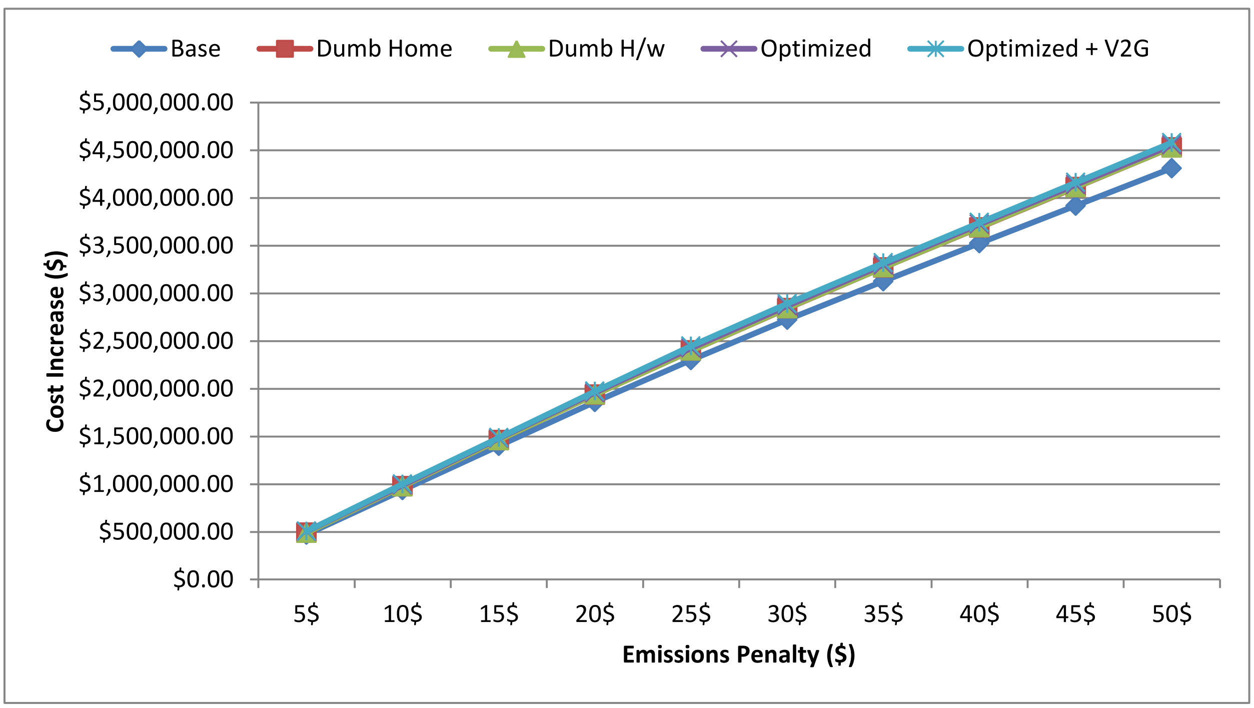


Figure 38 - Cost Increase over the Un-penalized Case

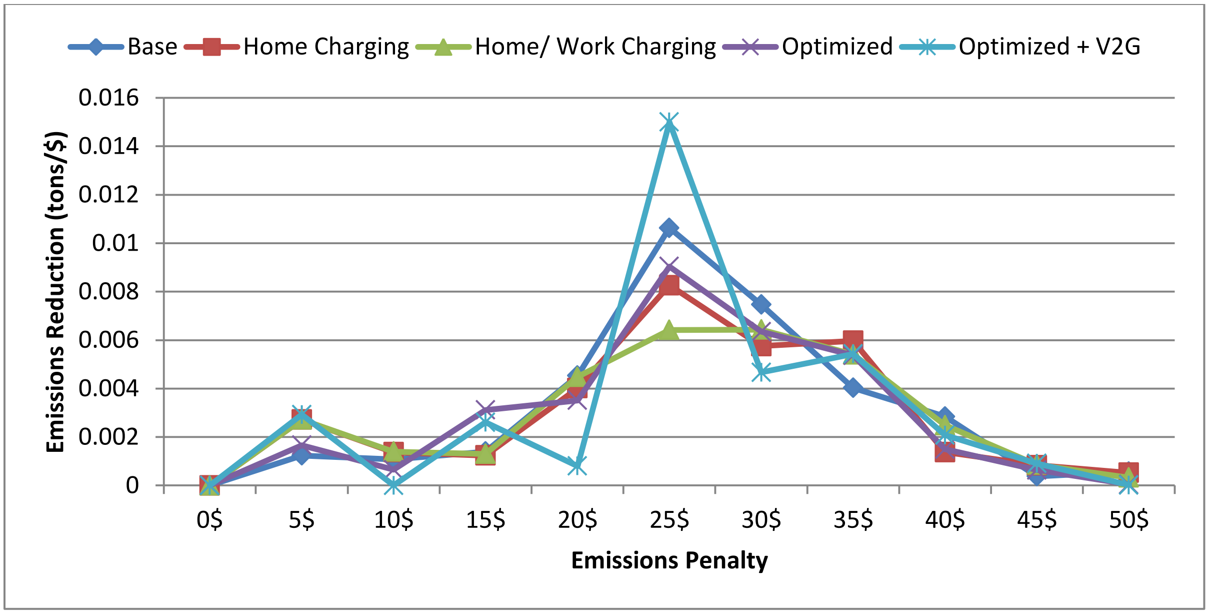


Figure 39 – Emissions Reduction as a function of the increase in system cost

Similarly to [14], which is discussed in the introduction, lower penalties from 10 to 15 $/ton seem to have little effect on emissions reduction. As the penalty is increased to around 20 $/ton the model begins to show a rapid decline in emissions up to a saturation point beginning around 35 $/ton. Costs for all charging strategies increase linearly with respect to the un-penalized case. The more interesting comparison occurs when costs are normalized by the amount of emissions reduction per dollar increase in the system cost shown in Figure 39. The highest reductions in emissions per dollar increase in system cost are shown to occur sharply at around 25 $/ton for all cases. The uncontrolled charging strategies increase peak demand which more tightly restricts available generators. This limits the ability to avoid using carbon intensive sources during time of peak demand. In the controlled charging strategies the system has more flexibility over the types of generation and respond rapidly when the increase in cost from the penalty reaches the 25 $/ton threshold.

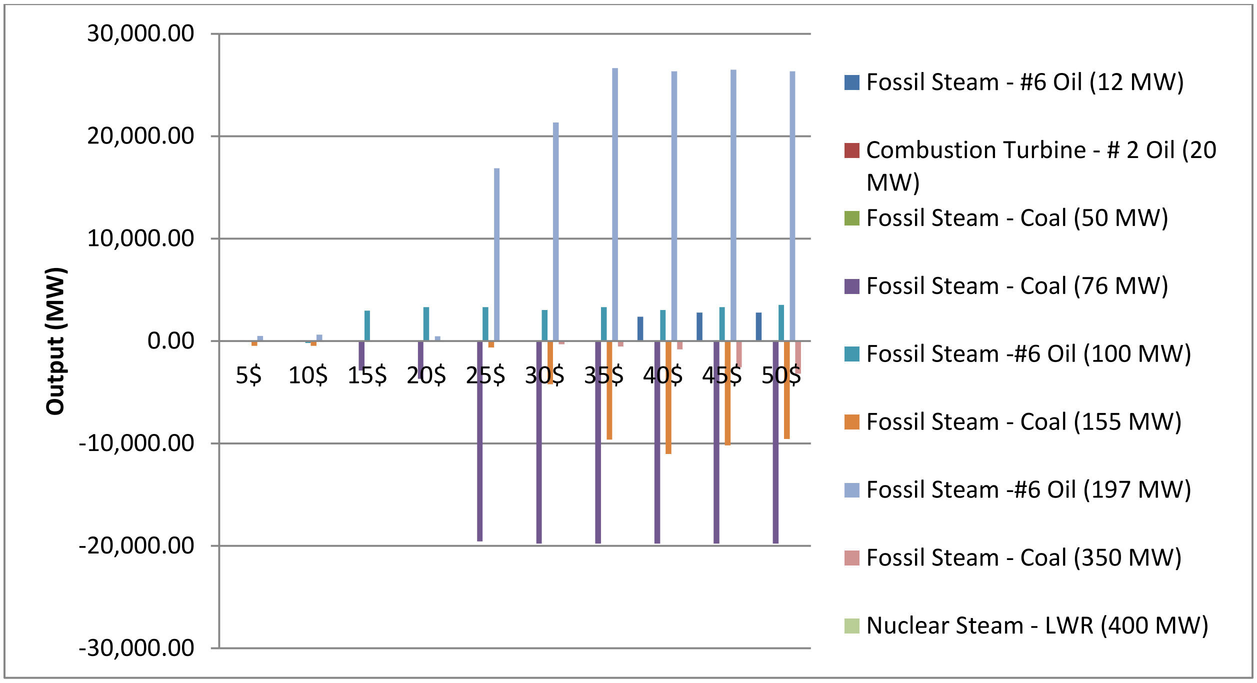


Figure 40 - Generation Output (Optimized + V2G Case) as a function of the emissions penalty

One particular instance of note is for the optimized plus V2G case at 25 \$/ton $CO_2$ penalty. Here the system is able to reshuffle the generation profile resulting in emissions reductions beyond the results achievable in the uncontrolled cases. Figure 40 shows the difference in generation technologies used for each penalty in the system in the Optimized V2G case. Note that there is little change in generation until the price penalty reaches a breaking threshold. At this point the 76 MW Coal Steam plants are largely removed and replaced with more expensive oil generation. It can be concluded from this that the optimized plus V2G charging case is flexible and has the potential to exceed the emissions reduction of the other charging strategies once an adequate penalty have been imposed.

# Chapter 4. CONCLUSION

As worldwide environmental consciousness grows, electric vehicles are becoming more common and despite the incredible potential for emissions reductions, the net emissions of the power system supply side plus the transportation system are dependent on the generation matrix. To assess the potential environmental impact of the electrification of the road transport sector a unit comment model is developed. This model is then used to study the effects of various charging strategies on net system emissions. The results show that the efficiency of generation mix of the system largely dictates the effectiveness of PEVs in reducing emissions offset by removing internal combustion vehicles from the road. Uncontrolled PEVs charging patterns tend to correspond directly with the peak consumption hours which increases demand sharply, potentially limiting the penetration of electric vehicles. Optimized charging strategies create opportunities to reduce system costs and increase capacity for PEVs, but in carbon intensive systems they may increase overall emissions output by favoring lower cost fuel sources. The cost saving and flexibility associated with these charging strategies has the potential to further curb emissions when a penalty is added on carbon output.

The secondary purpose of the proposed model is to evaluate the effect off adding a penalty on carbon emissions output as suggested in [14]. It was found that by imposing an emissions penalty emissions could be reduced beyond net zero for carbon penalty of around 25 $/ton of emissions. Controlled charging with V2G was shown to produce the best results once an adequate penalty was reached. Although these results vary by system and generation mix the model frame work can be applied to establish a starting point for a target penalty.

# Chapter 5. FUTURE WORK

The background information and model developed for this research will serve as a foundation to establish emissions offset from the road transport sector through the integration of electric vehicles. This model takes into account primary the economic dispatch and environmental aspect of emissions while simplifying behavioral aspects associated with real world system. For example by adding line constraints and congestions to this system it would be possible to find the optimal PEV charging locations to reduce system congestion and determine the environmental and safety impacts this has on the system.

Another feature the current model lacks is the inclusion of consumption factors for PEVs based upon regional temperature profiles for a specific area. Unlike internal combustion vehicles which used waste heat from the engine to warm the cabin in the winter, PEVs must expend additional energy from the battery to produce heat. Also the battery of electric vehicles will have different performance characteristics based up its starting and surrounding temperature. These additions to this model would help more accurately predict regional emissions

Other improvements which need to be added are the incorporation of renewables into the generation mix. These features would make the model more specific to a location of interest as well as provide a platform to study the interactions between increasing renewable penetrations and increasing electric vehicle penetrations. One possible study is in systems where controlled charging is used in conjunction with coincidental wind generation.

# Chapter 6. REFERENCES


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# APPENDIX A

## A.1 TEST SYSTEM 1 – PIECEWISE LINEAR COST APPROXIMATION

| Group | Unit | Pmin (MW) | e1 (MW) | e2 (MW) | Pmax (MW) | nlc ($/MW) | mc1 ($/MWh) | mc2 ($/MWh) | mc3 ($/MWh) |
|---|---|---|---|---|---|---|---|---|---|
| U20 | 1 | 4 | 7 | 13 | 20 | 117.31 | 37.71 | 37.84 | 37.97 |
| | 2 | 4 | 7 | 13 | 20 | 117.64 | 37.83 | 37.97 | 38.10 |
| U76 | 3 | 15 | 25 | 51 | 76 | 76.41 | 13.77 | 14.13 | 14.48 |
| | 4 | 15 | 25 | 51 | 76 | 76.47 | 13.81 | 14.17 | 14.53 |
| U20 | 5 | 4 | 7 | 13 | 20 | 117.95 | 37.96 | 38.10 | 38.25 |
| | 6 | 4 | 7 | 13 | 20 | 118.29 | 38.08 | 38.23 | 38.39 |
| U76 | 7 | 15 | 25 | 51 | 76 | 76.56 | 13.84 | 14.21 | 14.58 |
| | 8 | 15 | 25 | 51 | 76 | 76.60 | 13.88 | 14.26 | 14.64 |
| U100 | 9 | 25 | 33 | 67 | 100 | 210.11 | 18.47 | 18.78 | 19.09 |
| | 10 | 25 | 33 | 67 | 100 | 210.69 | 18.56 | 18.87 | 19.17 |
| | 11 | 25 | 33 | 67 | 100 | 211.31 | 18.65 | 18.95 | 19.25 |
| U197 | 12 | 55 | 66 | 131 | 197 | 239.19 | 23.47 | 23.69 | 23.91 |
| | 13 | 55 | 66 | 131 | 197 | 239.64 | 23.57 | 23.79 | 24.01 |
| | 14 | 55 | 66 | 131 | 197 | 239.94 | 23.68 | 23.90 | 24.12 |
| U12 | 15 | 2 | 4 | 8 | 12 | 24.05 | 25.75 | 25.91 | 26.07 |
| | 16 | 2 | 4 | 8 | 12 | 24.06 | 25.89 | 26.06 | 26.23 |
| | 17 | 2 | 4 | 8 | 12 | 24.26 | 26.03 | 26.21 | 26.39 |
| | 18 | 2 | 4 | 8 | 12 | 24.38 | 26.16 | 26.34 | 26.52 |
| | 19 | 2 | 4 | 8 | 12 | 24.50 | 26.29 | 26.47 | 26.66 |
| U155 | 20 | 54 | 52 | 103 | 155 | 120.67 | 11.35 | 11.66 | 11.97 |
| | 21 | 54 | 52 | 103 | 155 | 120.50 | 11.39 | 11.71 | 12.02 |
| U400 | 22 | 100 | 133 | 267 | 400 | 271.20 | 8.08 | 8.46 | 8.85 |
| | 23 | 100 | 133 | 267 | 400 | 272.91 | 8.09 | 8.48 | 8.87 |
| U50 | 24 | 12 | 17 | 33 | 50 | 100.10 | 22.40 | 22.50 | 22.60 |
| | 25 | 12 | 17 | 33 | 50 | 100.20 | 23.10 | 23.20 | 23.40 |
| | 26 | 12 | 17 | 33 | 50 | 100.30 | 22.60 | 22.70 | 22.80 |
| | 27 | 12 | 17 | 33 | 50 | 100.40 | 25.10 | 25.30 | 25.60 |
| | 28 | 12 | 17 | 33 | 50 | 100.50 | 26.10 | 26.20 | 26.40 |
| | 29 | 12 | 17 | 33 | 50 | 100.60 | 27.00 | 27.30 | 27.60 |
| U155 | 30 | 54 | 52 | 103 | 155 | 120.41 | 11.42 | 11.74 | 12.07 |
| | 31 | 54 | 52 | 103 | 155 | 120.40 | 11.45 | 11.78 | 12.10 |
| U350 | 32 | 70 | 117 | 233 | 350 | 132.08 | 11.40 | 11.61 | 11.83 |
| U20 | 33 | 4 | 7 | 13 | 20 | 120.83 | 38.84 | 38.97 | 39.11 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 34 | 4 | 7 | 13 | 20 | 121.17 | 38.97 | 39.11 | 39.24 |
| U76 | 35 | 15 | 25 | 51 | 76 | 78.71 | 14.18 | 14.55 | 14.92 |
| | 36 | 15 | 25 | 51 | 76 | 78.77 | 14.22 | 14.60 | 14.97 |
| U20 | 37 | 4 | 7 | 13 | 20 | 121.49 | 39.10 | 39.25 | 39.40 |
| | 38 | 4 | 7 | 13 | 20 | 121.83 | 39.22 | 39.28 | 39.54 |
| U76 | 39 | 15 | 25 | 51 | 76 | 78.86 | 14.26 | 14.64 | 15.02 |
| | 40 | 15 | 25 | 51 | 76 | 78.90 | 14.30 | 14.69 | 15.07 |
| U100 | 41 | 25 | 33 | 67 | 100 | 216.42 | 19.02 | 19.34 | 19.66 |
| | 42 | 25 | 33 | 67 | 100 | 217.01 | 19.12 | 19.43 | 19.75 |
| | 43 | 25 | 33 | 67 | 100 | 217.64 | 19.21 | 19.52 | 19.82 |
| U197 | 44 | 55 | 66 | 131 | 197 | 246.37 | 24.17 | 24.40 | 24.63 |
| | 45 | 55 | 66 | 131 | 197 | 246.83 | 24.28 | 24.51 | 24.73 |
| | 46 | 55 | 66 | 131 | 197 | 247.13 | 24.39 | 24.62 | 24.85 |
| U12 | 47 | 2 | 4 | 8 | 12 | 24.77 | 26.52 | 26.69 | 26.86 |
| | 48 | 2 | 4 | 8 | 12 | 24.78 | 26.66 | 26.84 | 27.01 |
| | 49 | 2 | 4 | 8 | 12 | 24.99 | 26.81 | 26.99 | 27.18 |
| | 50 | 2 | 4 | 8 | 12 | 25.11 | 26.94 | 27.13 | 27.14 |
| | 51 | 2 | 4 | 8 | 12 | 25.24 | 27.08 | 27.27 | 27.45 |
| U155 | 52 | 54 | 52 | 103 | 155 | 124.29 | 11.69 | 12.01 | 12.33 |
| | 53 | 54 | 52 | 103 | 155 | 124.11 | 11.73 | 12.06 | 12.38 |
| U400 | 54 | 100 | 133 | 267 | 400 | 279.34 | 8.32 | 8.72 | 9.12 |
| | 55 | 100 | 133 | 267 | 400 | 281.10 | 8.33 | 8.73 | 9.13 |
| U50 | 56 | 12 | 17 | 33 | 50 | 101.10 | 23.40 | 23.50 | 23.60 |
| | 57 | 12 | 17 | 33 | 50 | 101.20 | 24.10 | 24.20 | 24.40 |
| | 58 | 12 | 17 | 33 | 50 | 101.30 | 25.60 | 25.70 | 25.80 |
| | 59 | 12 | 17 | 33 | 50 | 101.40 | 26.10 | 26.30 | 26.60 |
| | 60 | 12 | 17 | 33 | 50 | 101.50 | 25.10 | 25.20 | 25.40 |
| | 61 | 12 | 17 | 33 | 50 | 101.60 | 23.00 | 23.30 | 23.60 |
| U155 | 62 | 54 | 52 | 103 | 155 | 124.02 | 11.76 | 12.10 | 12.43 |
| | 63 | 54 | 52 | 103 | 155 | 124.01 | 11.79 | 12.13 | 12.47 |
| U350 | 64 | 70 | 117 | 233 | 350 | 136.04 | 11.74 | 11.96 | 12.18 |
| U20 | 65 | 4 | 7 | 13 | 20 | 124.35 | 39.97 | 40.11 | 40.25 |
| | 66 | 4 | 7 | 13 | 20 | 124.70 | 40.10 | 40.25 | 40.39 |
| U76 | 67 | 15 | 25 | 51 | 76 | 81.00 | 14.60 | 14.97 | 15.35 |
| | 68 | 15 | 25 | 51 | 76 | 81.06 | 14.64 | 15.02 | 15.41 |
| U20 | 69 | 4 | 7 | 13 | 20 | 125.03 | 40.24 | 40.39 | 40.54 |
| | 70 | 4 | 7 | 13 | 20 | 125.38 | 40.37 | 40.53 | 40.69 |
| U76 | 71 | 15 | 25 | 51 | 76 | 81.15 | 14.67 | 15.06 | 15.46 |
| | 72 | 15 | 25 | 51 | 76 | 81.20 | 14.71 | 15.11 | 15.51 |
| U100 | 73 | 25 | 33 | 67 | 100 | 222.72 | 19.58 | 19.91 | 20.24 |
| | 74 | 25 | 33 | 67 | 100 | 223.33 | 19.67 | 20.00 | 20.32 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 75 | 25 | 33 | 67 | 100 | 223.98 | 19.77 | 20.08 | 20.40 |
| U197 | 76 | 55 | 66 | 131 | 197 | 253.55 | 24.88 | 25.11 | 25.35 |
| | 77 | 55 | 66 | 131 | 197 | 254.02 | 24.98 | 25.22 | 25.45 |
| | 78 | 55 | 66 | 131 | 197 | 254.33 | 25.10 | 25.33 | 25.57 |
| U12 | 79 | 2 | 4 | 8 | 12 | 25.49 | 27.30 | 27.47 | 27.64 |
| | 80 | 2 | 4 | 8 | 12 | 25.50 | 27.44 | 27.62 | 27.80 |
| | 81 | 2 | 4 | 8 | 12 | 25.72 | 27.59 | 27.78 | 27.97 |
| | 82 | 2 | 4 | 8 | 12 | 25.84 | 27.73 | 27.92 | 28.12 |
| | 83 | 2 | 4 | 8 | 12 | 25.98 | 27.87 | 28.06 | 28.25 |
| U155 | 84 | 54 | 52 | 103 | 155 | 127.91 | 12.03 | 12.36 | 12.69 |
| | 85 | 54 | 52 | 103 | 155 | 127.73 | 12.07 | 12.41 | 12.74 |
| U400 | 86 | 100 | 133 | 267 | 400 | 287.47 | 8.56 | 8.97 | 9.38 |
| | 87 | 100 | 133 | 267 | 400 | 289.28 | 8.57 | 8.99 | 9.40 |
| U50 | 88 | 12 | 17 | 33 | 50 | 102.10 | 23.50 | 23.70 | 23.90 |
| | 89 | 12 | 17 | 33 | 50 | 102.20 | 24.60 | 24.80 | 25.00 |
| | 90 | 12 | 17 | 33 | 50 | 102.30 | 25.30 | 25.70 | 25.90 |
| | 91 | 12 | 17 | 33 | 50 | 102.40 | 28.53 | 29.48 | 30.72 |
| | 92 | 12 | 17 | 33 | 50 | 102.50 | 26.00 | 26.50 | 26.70 |
| | 93 | 12 | 17 | 33 | 50 | 102.60 | 28.51 | 29.46 | 30.70 |
| U155 | 94 | 54 | 52 | 103 | 155 | 127.63 | 12.11 | 12.45 | 12.79 |
| | 95 | 54 | 52 | 103 | 155 | 127.62 | 12.14 | 12.48 | 12.83 |
| U350 | 96 | 70 | 117 | 233 | 350 | 140.00 | 12.08 | 12.31 | 12.54 |

## A.2 Test System 2 – Piecewise Linear Cost Approximation

| Group | Unit | Pmin (MW) | e1 (MW) | e2 (MW) | Pmax (MW) | nlc ($/MW) | mc1 ($/MWh) | mc2 ($/MWh) | mc3 ($/MWh) |
|---|---|---|---|---|---|---|---|---|---|
| U20 | 1 | 4 | 7 | 13 | 20 | 454.57 | 28.97 | 29.24 | 29.70 |
| | 2 | 4 | 7 | 13 | 20 | 454.56 | 28.96 | 29.23 | 29.69 |
| U76 | 3 | 15 | 25 | 51 | 76 | 263.42 | 18.42 | 19.23 | 20.10 |
| | 4 | 15 | 25 | 51 | 76 | 263.43 | 18.43 | 19.24 | 20.11 |
| U20 | 5 | 4 | 7 | 13 | 20 | 454.55 | 28.95 | 29.22 | 29.68 |
| | 6 | 4 | 7 | 13 | 20 | 454.54 | 28.94 | 29.21 | 29.67 |
| U76 | 7 | 15 | 25 | 51 | 76 | 263.41 | 18.41 | 19.22 | 20.09 |
| | 8 | 15 | 25 | 51 | 76 | 263.40 | 18.40 | 19.21 | 20.08 |
| U100 | 9 | 25 | 33 | 67 | 100 | 306.61 | 17.59 | 18.28 | 18.97 |
| | 10 | 25 | 33 | 67 | 100 | 306.62 | 17.60 | 18.29 | 18.98 |
| | 11 | 25 | 33 | 67 | 100 | 306.60 | 17.58 | 18.27 | 18.96 |
| U197 | 12 | 55 | 66 | 131 | 197 | 482.86 | 17.19 | 17.71 | 18.23 |
| | 13 | 55 | 66 | 131 | 197 | 482.87 | 17.20 | 17.72 | 18.24 |
| | 14 | 55 | 66 | 131 | 197 | 482.88 | 17.21 | 17.73 | 18.25 |
| U12 | 15 | 2 | 4 | 8 | 12 | 365.46 | 29.45 | 30.12 | 30.86 |
| | 16 | 2 | 4 | 8 | 12 | 365.47 | 29.46 | 30.13 | 30.87 |
| | 17 | 2 | 4 | 8 | 12 | 365.48 | 29.47 | 30.14 | 30.88 |
| | 18 | 2 | 4 | 8 | 12 | 365.49 | 29.48 | 30.15 | 30.89 |
| | 19 | 2 | 4 | 8 | 12 | 365.48 | 29.47 | 30.14 | 30.87 |
| U155 | 20 | 54 | 52 | 103 | 155 | 415.54 | 23.81 | 24.52 | 25.24 |
| | 21 | 54 | 52 | 103 | 155 | 415.55 | 23.82 | 24.53 | 25.25 |
| U400 | 22 | 100 | 133 | 267 | 400 | 271.20 | 8.08 | 8.46 | 8.85 |
| | 23 | 100 | 133 | 267 | 400 | 272.91 | 8.09 | 8.48 | 8.87 |
| U50 | 24 | 12 | 17 | 33 | 50 | 626.11 | 28.31 | 29.26 | 30.50 |
| | 25 | 12 | 17 | 33 | 50 | 626.12 | 28.32 | 29.27 | 30.51 |
| | 26 | 12 | 17 | 33 | 50 | 626.10 | 28.30 | 29.25 | 30.49 |
| | 27 | 12 | 17 | 33 | 50 | 626.13 | 28.33 | 29.28 | 30.52 |
| | 28 | 12 | 17 | 33 | 50 | 626.09 | 28.29 | 29.24 | 30.48 |
| | 29 | 12 | 17 | 33 | 50 | 626.11 | 28.31 | 29.26 | 30.50 |
| U155 | 30 | 54 | 52 | 103 | 155 | 415.53 | 23.80 | 24.51 | 25.23 |
| | 31 | 54 | 52 | 103 | 155 | 415.56 | 23.83 | 24.54 | 25.26 |
| U350 | 32 | 70 | 117 | 233 | 350 | 303.78 | 15.73 | 16.02 | 16.32 |
| U20 | 33 | 4 | 7 | 13 | 20 | 454.58 | 29.07 | 29.34 | 29.80 |
| | 34 | 4 | 7 | 13 | 20 | 454.57 | 29.06 | 29.33 | 29.79 |
| U76 | 35 | 15 | 25 | 51 | 76 | 263.42 | 18.52 | 19.33 | 20.20 |
| | 36 | 15 | 25 | 51 | 76 | 263.43 | 18.53 | 19.34 | 20.21 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| U20 | 37 | 4 | 7 | 13 | 20 | 454.56 | 29.05 | 29.32 | 29.78 |
| | 38 | 4 | 7 | 13 | 20 | 454.55 | 29.04 | 29.31 | 29.77 |
| U76 | 39 | 15 | 25 | 51 | 76 | 263.41 | 18.51 | 19.32 | 20.19 |
| | 40 | 15 | 25 | 51 | 76 | 263.40 | 18.50 | 19.31 | 20.18 |
| U100 | 41 | 25 | 33 | 67 | 100 | 306.62 | 17.69 | 18.38 | 19.07 |
| | 42 | 25 | 33 | 67 | 100 | 306.63 | 17.70 | 18.39 | 19.08 |
| | 43 | 25 | 33 | 67 | 100 | 306.61 | 17.68 | 18.37 | 19.06 |
| U197 | 44 | 55 | 66 | 131 | 197 | 482.87 | 17.29 | 17.81 | 18.33 |
| | 45 | 55 | 66 | 131 | 197 | 482.88 | 17.30 | 17.82 | 18.34 |
| | 46 | 55 | 66 | 131 | 197 | 482.89 | 17.31 | 17.83 | 18.35 |
| U12 | 47 | 2 | 4 | 8 | 12 | 365.47 | 29.55 | 30.22 | 30.96 |
| | 48 | 2 | 4 | 8 | 12 | 365.48 | 29.56 | 30.23 | 30.97 |
| | 49 | 2 | 4 | 8 | 12 | 365.49 | 29.57 | 30.24 | 30.98 |
| | 50 | 2 | 4 | 8 | 12 | 365.50 | 29.58 | 30.25 | 30.99 |
| | 51 | 2 | 4 | 8 | 12 | 365.48 | 29.57 | 30.24 | 30.97 |
| U155 | 52 | 54 | 52 | 103 | 155 | 415.55 | 23.91 | 24.62 | 25.34 |
| | 53 | 54 | 52 | 103 | 155 | 415.56 | 23.92 | 24.63 | 25.35 |
| U400 | 54 | 100 | 133 | 267 | 400 | 279.34 | 8.32 | 8.72 | 9.12 |
| | 55 | 100 | 133 | 267 | 400 | 281.10 | 8.33 | 8.73 | 9.13 |
| U50 | 56 | 12 | 17 | 33 | 50 | 626.11 | 28.41 | 29.36 | 30.60 |
| | 57 | 12 | 17 | 33 | 50 | 626.12 | 28.42 | 29.37 | 30.61 |
| | 58 | 12 | 17 | 33 | 50 | 626.10 | 28.40 | 29.35 | 30.59 |
| | 59 | 12 | 17 | 33 | 50 | 626.13 | 28.43 | 29.38 | 30.62 |
| | 60 | 12 | 17 | 33 | 50 | 626.09 | 28.39 | 29.34 | 30.58 |
| | 61 | 12 | 17 | 33 | 50 | 626.11 | 28.41 | 29.36 | 30.60 |
| U155 | 62 | 54 | 52 | 103 | 155 | 415.54 | 23.90 | 24.61 | 25.33 |
| | 63 | 54 | 52 | 103 | 155 | 415.57 | 23.93 | 24.64 | 25.36 |
| U350 | 64 | 70 | 117 | 233 | 350 | 303.79 | 15.79 | 16.08 | 16.38 |
| U20 | 65 | 4 | 7 | 13 | 20 | 454.52 | 29.17 | 29.44 | 29.90 |
| | 66 | 4 | 7 | 13 | 20 | 454.53 | 29.16 | 29.43 | 29.89 |
| U76 | 67 | 15 | 25 | 51 | 76 | 263.42 | 18.62 | 19.43 | 20.30 |
| | 68 | 15 | 25 | 51 | 76 | 263.43 | 18.63 | 19.44 | 20.31 |
| U20 | 69 | 4 | 7 | 13 | 20 | 454.53 | 29.15 | 29.42 | 29.88 |
| | 70 | 4 | 7 | 13 | 20 | 454.53 | 29.14 | 29.41 | 29.87 |
| U76 | 71 | 15 | 25 | 51 | 76 | 263.43 | 18.61 | 19.42 | 20.29 |
| | 72 | 15 | 25 | 51 | 76 | 263.43 | 18.60 | 19.41 | 20.28 |
| U100 | 73 | 25 | 33 | 67 | 100 | 306.62 | 17.79 | 18.48 | 19.17 |
| | 74 | 25 | 33 | 67 | 100 | 306.63 | 17.80 | 18.49 | 19.18 |
| | 75 | 25 | 33 | 67 | 100 | 306.62 | 17.78 | 18.47 | 19.16 |
| U197 | 76 | 55 | 66 | 131 | 197 | 482.82 | 17.39 | 17.91 | 18.43 |
| | 77 | 55 | 66 | 131 | 197 | 482.83 | 17.40 | 17.92 | 18.44 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 78 | 55 | 66 | 131 | 197 | 482.83 | 17.41 | 17.93 | 18.45 |
| U12 | 79 | 2 | 4 | 8 | 12 | 365.42 | 29.65 | 30.32 | 31.06 |
| | 80 | 2 | 4 | 8 | 12 | 365.42 | 29.66 | 30.33 | 31.07 |
| | 81 | 2 | 4 | 8 | 12 | 365.43 | 29.67 | 30.34 | 31.08 |
| | 82 | 2 | 4 | 8 | 12 | 365.43 | 29.68 | 30.35 | 31.09 |
| | 83 | 2 | 4 | 8 | 12 | 365.43 | 29.67 | 30.34 | 31.07 |
| U155 | 84 | 54 | 52 | 103 | 155 | 415.53 | 24.01 | 24.72 | 25.44 |
| | 85 | 54 | 52 | 103 | 155 | 415.53 | 24.02 | 24.73 | 25.45 |
| U400 | 86 | 100 | 133 | 267 | 400 | 287.47 | 8.56 | 8.97 | 9.38 |
| | 87 | 100 | 133 | 267 | 400 | 289.28 | 8.57 | 8.99 | 9.40 |
| U50 | 88 | 12 | 17 | 33 | 50 | 626.12 | 28.51 | 29.46 | 30.70 |
| | 89 | 12 | 17 | 33 | 50 | 626.13 | 28.52 | 29.47 | 30.71 |
| | 90 | 12 | 17 | 33 | 50 | 626.12 | 28.50 | 29.45 | 30.69 |
| | 91 | 12 | 17 | 33 | 50 | 626.12 | 28.53 | 29.48 | 30.72 |
| | 92 | 12 | 17 | 33 | 50 | 626.13 | 28.49 | 29.44 | 30.68 |
| | 93 | 12 | 17 | 33 | 50 | 626.13 | 28.51 | 29.46 | 30.70 |
| U155 | 94 | 54 | 52 | 103 | 155 | 415.52 | 24.00 | 24.72 | 24.73 |
| | 95 | 54 | 52 | 103 | 155 | 415.53 | 24.73 | 24.74 | 24.74 |
| U350 | 96 | 70 | 117 | 233 | 350 | 303.72 | 14.85 | 14.85 | 14.85 |

# APPENDIX B

## B.1 TEST SYSTEM 1 – GENERATOR SPECIFICATIONS & INITIAL CONDITIONS

| Group | Unit | Capacity (MW) | Start up Cost ($) | Ramp up Limit (MW/hr) | Ramp Down Limit (MW/hr) | Initial On (hr) | Initial Off (hr) | Min Up (hr) | Min Down (hr) |
|---|---|---|---|---|---|---|---|---|---|
| U20 | 1 | 20 | 5 | 31 | 70 | 1 | 0 | 1 | 1 |
| | 2 | 20 | 5 | 31 | 70 | 400 | 0 | 1 | 1 |
| U76 | 3 | 76 | 656 | 39 | 80 | 220 | 0 | 3 | 2 |
| | 4 | 76 | 656 | 39 | 80 | 0 | 1 | 3 | 2 |
| U20 | 5 | 20 | 5 | 31 | 70 | 0 | 17 | 1 | 1 |
| | 6 | 20 | 5 | 31 | 70 | 0 | 4 | 1 | 1 |
| U76 | 7 | 76 | 656 | 39 | 80 | 0 | 66 | 3 | 2 |
| | 8 | 76 | 656 | 39 | 80 | 0 | 33 | 3 | 2 |
| U100 | 9 | 100 | 566 | 51 | 74 | 11 | 0 | 4 | 2 |
| | 10 | 100 | 566 | 51 | 74 | 2 | 0 | 4 | 2 |
| | 11 | 100 | 566 | 51 | 74 | 2 | 0 | 4 | 2 |
| U197 | 12 | 197 | 775 | 55 | 99 | 2 | 0 | 5 | 4 |
| | 13 | 197 | 775 | 55 | 99 | 2 | 0 | 5 | 4 |
| | 14 | 197 | 775 | 55 | 99 | 0 | 2 | 5 | 4 |
| U12 | 15 | 12 | 68 | 48 | 60 | 6 | 0 | 1 | 1 |
| | 16 | 12 | 68 | 48 | 60 | 7 | 0 | 1 | 1 |
| | 17 | 12 | 68 | 48 | 60 | 8 | 0 | 1 | 1 |
| | 18 | 12 | 68 | 48 | 60 | 0 | 9 | 1 | 1 |
| | 19 | 12 | 68 | 48 | 60 | 0 | 5 | 1 | 1 |
| U155 | 20 | 155 | 1048 | 55 | 78 | 8 | 0 | 5 | 3 |
| | 21 | 155 | 1048 | 55 | 78 | 8 | 0 | 5 | 3 |
| U400 | 22 | 400 | 40000 | 100 | 100 | 0 | 8 | 8 | 5 |
| | 23 | 400 | 40000 | 100 | 100 | 8 | 0 | 8 | 5 |
| U50 | 24 | 50 | 60 | 39 | 80 | 8 | 0 | 2 | 1 |
| | 25 | 50 | 60 | 39 | 80 | 8 | 0 | 2 | 1 |
| | 26 | 50 | 60 | 39 | 80 | 0 | 8 | 2 | 1 |
| | 27 | 50 | 60 | 39 | 80 | 0 | 8 | 2 | 1 |
| | 28 | 50 | 60 | 39 | 80 | 8 | 0 | 2 | 1 |
| | 29 | 50 | 60 | 39 | 80 | 8 | 0 | 2 | 1 |
| U155 | 30 | 155 | 1048 | 55 | 78 | 8 | 0 | 5 | 3 |
| | 31 | 155 | 1048 | 55 | 78 | 0 | 8 | 5 | 3 |
| U350 | 32 | 350 | 4468 | 70 | 120 | 0 | 8 | 8 | 5 |
| U20 | 33 | 20 | 5 | 31 | 70 | 8 | 0 | 1 | 1 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 34 | 20 | 5 | 31 | 70 | 89 | 0 | 1 | 1 |
| U76 | 35 | 76 | 656 | 39 | 80 | 66 | 0 | 3 | 2 |
| | 36 | 76 | 656 | 39 | 80 | 0 | 66 | 3 | 2 |
| U20 | 37 | 20 | 5 | 31 | 70 | 0 | 66 | 1 | 1 |
| | 38 | 20 | 5 | 31 | 70 | 0 | 66 | 1 | 1 |
| U76 | 39 | 76 | 656 | 39 | 80 | 0 | 66 | 3 | 2 |
| | 40 | 76 | 656 | 39 | 80 | 0 | 1 | 3 | 2 |
| U100 | 41 | 100 | 566 | 51 | 74 | 1 | 0 | 4 | 2 |
| | 42 | 100 | 566 | 51 | 74 | 56 | 0 | 4 | 2 |
| | 43 | 100 | 566 | 51 | 74 | 56 | 0 | 4 | 2 |
| U197 | 44 | 197 | 775 | 55 | 99 | 56 | 0 | 5 | 4 |
| | 45 | 197 | 775 | 55 | 99 | 56 | 0 | 5 | 4 |
| | 46 | 197 | 775 | 55 | 99 | 0 | 56 | 5 | 4 |
| U12 | 47 | 12 | 68 | 48 | 60 | 56 | 0 | 1 | 1 |
| | 48 | 12 | 68 | 48 | 60 | 56 | 0 | 1 | 1 |
| | 49 | 12 | 68 | 48 | 60 | 98 | 0 | 1 | 1 |
| | 50 | 12 | 68 | 48 | 60 | 0 | 124 | 1 | 1 |
| | 51 | 12 | 68 | 48 | 60 | 0 | 1000 | 1 | 1 |
| U155 | 52 | 155 | 1048 | 55 | 78 | 1000 | 0 | 5 | 3 |
| | 53 | 155 | 1048 | 55 | 78 | 1000 | 0 | 5 | 3 |
| U400 | 54 | 400 | 40000 | 100 | 100 | 0 | 50 | 8 | 5 |
| | 55 | 400 | 40000 | 100 | 100 | 50 | 0 | 8 | 5 |
| U50 | 56 | 50 | 60 | 39 | 80 | 90 | 0 | 2 | 1 |
| | 57 | 50 | 60 | 39 | 80 | 900 | 0 | 2 | 1 |
| | 58 | 50 | 60 | 39 | 80 | 0 | 900 | 2 | 1 |
| | 59 | 50 | 60 | 39 | 80 | 0 | 900 | 2 | 1 |
| | 60 | 50 | 60 | 39 | 80 | 900 | 0 | 2 | 1 |
| | 61 | 50 | 60 | 39 | 80 | 900 | 0 | 2 | 1 |
| U155 | 62 | 155 | 1048 | 55 | 78 | 900 | 0 | 5 | 3 |
| | 63 | 155 | 1048 | 55 | 78 | 0 | 900 | 5 | 3 |
| U350 | 64 | 350 | 4468 | 70 | 120 | 0 | 900 | 8 | 5 |
| U20 | 65 | 20 | 5 | 31 | 70 | 900 | 0 | 1 | 1 |
| | 66 | 20 | 5 | 31 | 70 | 90 | 0 | 1 | 1 |
| U76 | 67 | 76 | 656 | 39 | 80 | 789 | 0 | 3 | 2 |
| | 68 | 76 | 656 | 39 | 80 | 0 | 456 | 3 | 2 |
| U20 | 69 | 20 | 5 | 31 | 70 | 0 | 375 | 1 | 1 |
| | 70 | 20 | 5 | 31 | 70 | 0 | 375 | 1 | 1 |
| U76 | 71 | 76 | 656 | 39 | 80 | 0 | 170 | 3 | 2 |
| | 72 | 76 | 656 | 39 | 80 | 0 | 170 | 3 | 2 |
| U100 | 73 | 100 | 566 | 51 | 74 | 170 | 0 | 4 | 2 |
| | 74 | 100 | 566 | 51 | 74 | 800 | 0 | 4 | 2 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 75 | 100 | 566 | 51 | 74 | 2500 | 0 | 4 | 2 |
| U197 | 76 | 197 | 775 | 55 | 99 | 2500 | 0 | 5 | 4 |
| | 77 | 197 | 775 | 55 | 99 | 2500 | 0 | 5 | 4 |
| | 78 | 197 | 775 | 55 | 99 | 0 | 2500 | 5 | 4 |
| U12 | 79 | 12 | 68 | 48 | 60 | 1000 | 0 | 1 | 1 |
| | 80 | 12 | 68 | 48 | 60 | 203 | 0 | 1 | 1 |
| | 81 | 12 | 68 | 48 | 60 | 600 | 0 | 1 | 1 |
| | 82 | 12 | 68 | 48 | 60 | 0 | 46 | 1 | 1 |
| | 83 | 12 | 68 | 48 | 60 | 0 | 236 | 1 | 1 |
| U155 | 84 | 155 | 1048 | 55 | 78 | 236 | 0 | 5 | 3 |
| | 85 | 155 | 1048 | 55 | 78 | 64 | 0 | 5 | 3 |
| U400 | 86 | 400 | 40000 | 100 | 100 | 0 | 6 | 8 | 5 |
| | 87 | 400 | 40000 | 100 | 100 | 8 | 0 | 8 | 5 |
| U50 | 88 | 50 | 60 | 39 | 80 | 90 | 0 | 2 | 1 |
| | 89 | 50 | 60 | 39 | 80 | 5 | 0 | 2 | 1 |
| | 90 | 50 | 60 | 39 | 80 | 0 | 6 | 2 | 1 |
| | 91 | 50 | 60 | 39 | 80 | 0 | 7 | 2 | 1 |
| | 92 | 50 | 60 | 39 | 80 | 8 | 0 | 2 | 1 |
| | 93 | 50 | 60 | 39 | 80 | 9 | 0 | 2 | 1 |
| U155 | 94 | 155 | 1048 | 55 | 78 | 7 | 0 | 5 | 3 |
| | 95 | 155 | 1048 | 55 | 78 | 0 | 66 | 5 | 3 |
| U350 | 96 | 350 | 4468 | 70 | 120 | 0 | 55 | 8 | 5 |

## B.2 Test System 2 – Generator Specifications & Initial Conditions

| Group | Unit | Capacity (MW) | Start up Cost ($) | Ramp up Limit (MW/hr) | Ramp Down Limit (MW/hr) | Initial On (hr) | Initial Off (hr) | Min Up (hr) | Min Down (hr) |
|---|---|---|---|---|---|---|---|---|---|
| U20 | 1 | 20 | 46 | 90 | 100 | 1 | 0 | 1 | 1 |
| | 2 | 20 | 46 | 90 | 100 | 400 | 0 | 1 | 1 |
| U76 | 3 | 76 | 92 | 120 | 120 | 220 | 0 | 3 | 2 |
| | 4 | 76 | 92 | 120 | 120 | 0 | 1 | 3 | 2 |
| U20 | 5 | 20 | 46 | 90 | 100 | 0 | 17 | 1 | 1 |
| | 6 | 20 | 46 | 90 | 100 | 0 | 4 | 1 | 1 |
| U76 | 7 | 76 | 92 | 120 | 120 | 0 | 66 | 3 | 2 |
| | 8 | 76 | 92 | 120 | 120 | 0 | 33 | 3 | 2 |
| U100 | 9 | 100 | 120 | 420 | 420 | 11 | 0 | 4 | 2 |
| | 10 | 100 | 120 | 420 | 420 | 2 | 0 | 4 | 2 |
| | 11 | 100 | 120 | 420 | 420 | 2 | 0 | 4 | 2 |
| U197 | 12 | 197 | 230 | 310 | 310 | 2 | 0 | 5 | 4 |
| | 13 | 197 | 230 | 310 | 310 | 2 | 0 | 5 | 4 |
| | 14 | 197 | 230 | 310 | 310 | 0 | 2 | 5 | 4 |
| U12 | 15 | 12 | 40 | 60 | 70 | 6 | 0 | 1 | 1 |
| | 16 | 12 | 40 | 60 | 70 | 7 | 0 | 1 | 1 |
| | 17 | 12 | 40 | 60 | 70 | 8 | 0 | 1 | 1 |
| | 18 | 12 | 40 | 60 | 70 | 0 | 9 | 1 | 1 |
| | 19 | 12 | 40 | 60 | 70 | 0 | 5 | 1 | 1 |
| U155 | 20 | 155 | 2058 | 70 | 80 | 8 | 0 | 5 | 3 |
| | 21 | 155 | 2058 | 70 | 80 | 8 | 0 | 5 | 3 |
| U400 | 22 | 400 | 40000 | 100 | 100 | 0 | 8 | 8 | 5 |
| | 23 | 400 | 40000 | 100 | 100 | 8 | 0 | 8 | 5 |
| U50 | 24 | 50 | 60 | 120 | 120 | 8 | 0 | 2 | 1 |
| | 25 | 50 | 60 | 120 | 120 | 8 | 0 | 2 | 1 |
| | 26 | 50 | 60 | 120 | 120 | 0 | 8 | 2 | 1 |
| | 27 | 50 | 60 | 120 | 120 | 0 | 8 | 2 | 1 |
| | 28 | 50 | 60 | 120 | 120 | 8 | 0 | 2 | 1 |
| | 29 | 50 | 60 | 120 | 120 | 8 | 0 | 2 | 1 |
| U155 | 30 | 155 | 2058 | 70 | 80 | 8 | 0 | 5 | 3 |
| | 31 | 155 | 2058 | 70 | 80 | 0 | 8 | 5 | 3 |
| U350 | 32 | 350 | 12064 | 140 | 140 | 0 | 8 | 8 | 5 |
| U20 | 33 | 20 | 46 | 90 | 100 | 8 | 0 | 1 | 1 |
| | 34 | 20 | 46 | 90 | 100 | 89 | 0 | 1 | 1 |
| U76 | 35 | 76 | 92 | 120 | 120 | 66 | 0 | 3 | 2 |
| | 36 | 76 | 92 | 120 | 120 | 0 | 66 | 3 | 2 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| U20 | 37 | 20 | 46 | 90 | 100 | 0 | 66 | 1 | 1 |
| | 38 | 20 | 46 | 90 | 100 | 0 | 66 | 1 | 1 |
| U76 | 39 | 76 | 92 | 120 | 120 | 0 | 66 | 3 | 2 |
| | 40 | 76 | 92 | 120 | 120 | 0 | 1 | 3 | 2 |
| U100 | 41 | 100 | 120 | 420 | 420 | 1 | 0 | 4 | 2 |
| | 42 | 100 | 120 | 420 | 420 | 56 | 0 | 4 | 2 |
| | 43 | 100 | 120 | 420 | 420 | 56 | 0 | 4 | 2 |
| U197 | 44 | 197 | 230 | 310 | 310 | 56 | 0 | 5 | 4 |
| | 45 | 197 | 230 | 310 | 310 | 56 | 0 | 5 | 4 |
| | 46 | 197 | 230 | 310 | 310 | 0 | 56 | 5 | 4 |
| U12 | 47 | 12 | 40 | 60 | 70 | 56 | 0 | 1 | 1 |
| | 48 | 12 | 40 | 60 | 70 | 56 | 0 | 1 | 1 |
| | 49 | 12 | 40 | 60 | 70 | 98 | 0 | 1 | 1 |
| | 50 | 12 | 40 | 60 | 70 | 0 | 124 | 1 | 1 |
| | 51 | 12 | 40 | 60 | 70 | 0 | 1000 | 1 | 1 |
| U155 | 52 | 155 | 2058 | 70 | 80 | 1000 | 0 | 5 | 3 |
| | 53 | 155 | 2058 | 70 | 80 | 1000 | 0 | 5 | 3 |
| U400 | 54 | 400 | 40000 | 100 | 100 | 0 | 50 | 8 | 5 |
| | 55 | 400 | 40000 | 100 | 100 | 50 | 0 | 8 | 5 |
| U50 | 56 | 50 | 60 | 120 | 120 | 90 | 0 | 2 | 1 |
| | 57 | 50 | 60 | 120 | 120 | 900 | 0 | 2 | 1 |
| | 58 | 50 | 60 | 120 | 120 | 0 | 900 | 2 | 1 |
| | 59 | 50 | 60 | 120 | 120 | 0 | 900 | 2 | 1 |
| | 60 | 50 | 60 | 120 | 120 | 900 | 0 | 2 | 1 |
| | 61 | 50 | 60 | 120 | 120 | 900 | 0 | 2 | 1 |
| U155 | 62 | 155 | 2058 | 70 | 80 | 900 | 0 | 5 | 3 |
| | 63 | 155 | 2058 | 70 | 80 | 0 | 900 | 5 | 3 |
| U350 | 64 | 350 | 12064 | 140 | 140 | 0 | 900 | 8 | 5 |
| U20 | 65 | 20 | 46 | 90 | 100 | 900 | 0 | 1 | 1 |
| | 66 | 20 | 46 | 90 | 100 | 90 | 0 | 1 | 1 |
| U76 | 67 | 76 | 92 | 120 | 120 | 789 | 0 | 3 | 2 |
| | 68 | 76 | 92 | 120 | 120 | 0 | 456 | 3 | 2 |
| U20 | 69 | 20 | 46 | 90 | 100 | 0 | 375 | 1 | 1 |
| | 70 | 20 | 46 | 90 | 100 | 0 | 375 | 1 | 1 |
| U76 | 71 | 76 | 92 | 120 | 120 | 0 | 170 | 3 | 2 |
| | 72 | 76 | 92 | 120 | 120 | 0 | 170 | 3 | 2 |
| U100 | 73 | 100 | 120 | 420 | 420 | 170 | 0 | 4 | 2 |
| | 74 | 100 | 120 | 420 | 420 | 800 | 0 | 4 | 2 |
| | 75 | 100 | 120 | 420 | 420 | 2500 | 0 | 4 | 2 |
| U197 | 76 | 197 | 230 | 310 | 310 | 2500 | 0 | 5 | 4 |
| | 77 | 197 | 230 | 310 | 310 | 2500 | 0 | 5 | 4 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 78 | 197 | 230 | 310 | 310 | 0 | 2500 | 5 | 4 |
| U12 | 79 | 12 | 40 | 60 | 70 | 1000 | 0 | 1 | 1 |
| | 80 | 12 | 40 | 60 | 70 | 203 | 0 | 1 | 1 |
| | 81 | 12 | 40 | 60 | 70 | 600 | 0 | 1 | 1 |
| | 82 | 12 | 40 | 60 | 70 | 0 | 46 | 1 | 1 |
| | 83 | 12 | 40 | 60 | 70 | 0 | 236 | 1 | 1 |
| U155 | 84 | 155 | 2058 | 70 | 80 | 236 | 0 | 5 | 3 |
| | 85 | 155 | 2058 | 70 | 80 | 64 | 0 | 5 | 3 |
| U400 | 86 | 400 | 40000 | 100 | 100 | 0 | 6 | 8 | 5 |
| | 87 | 400 | 40000 | 100 | 100 | 8 | 0 | 8 | 5 |
| U50 | 88 | 50 | 60 | 120 | 120 | 90 | 0 | 2 | 1 |
| | 89 | 50 | 60 | 120 | 120 | 5 | 0 | 2 | 1 |
| | 90 | 50 | 60 | 120 | 120 | 0 | 6 | 2 | 1 |
| | 91 | 50 | 60 | 120 | 120 | 0 | 7 | 2 | 1 |
| | 92 | 50 | 60 | 120 | 120 | 8 | 0 | 2 | 1 |
| | 93 | 50 | 60 | 120 | 120 | 9 | 0 | 2 | 1 |
| U155 | 94 | 155 | 2058 | 70 | 80 | 7 | 0 | 5 | 3 |
| | 95 | 155 | 2058 | 70 | 80 | 0 | 66 | 5 | 3 |
| U350 | 96 | 350 | 12064 | 140 | 140 | 0 | 55 | 8 | 5 |