Evaluation of Grid Level Impacts of Electric Vehicles

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EVALUATION OF GRID LEVEL IMPACTS OF ELECTRIC VEHICLES

A Thesis

Submitted to the Faculty

of

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ABSTRACT

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Currently, most countries are looking to reduce their dependency on imported oil. The added advantage of reducing green house gas emissions and other pollutants has been strong reasons for the growing support for Electric Vehicles. As electric vehicles would be using the power grid to charge their batteries, there are prevalent doubts as to whether the existing power grid will be able to support the increase in load. It is of great interest to the electric utilities to evaluate the capability of the existing grid to withstand high electric vehicle penetration. The fact that there will be higher concentration of electric vehicles in affluent neighborhoods is of great concern. In this thesis, the impact of electric vehicle concentration is studied and the effects evaluated. The electric vehicle flow in the system is first modeled and the corresponding behavior is studied. This model is integrated into an agent-based simulation to model the demand curve of residential customers. Finally, the demand curve is used in a loss-of-life calculation of the transformer to evaluate the impact on the grid.

1. INTRODUCTION

Energy security is one of the biggest concerns in the world political landscape. Instability in oil producing nations has further fueled the need to be less reliant on foreign sources of energy. The U.S. transportation sector, which imports two thirds of its daily consumption, is one sector that is heavily dependent on foreign sources of energy [1]. The ability to move even a part of the sector from petroleum products to electricity is of great interest as it mitigates this risk of crude oil dependence.

In recent times, there have been tremendous developments in electric vehicle (EV) and plug-in hybrid electric vehicle (PHEV) technologies. EVs and PHEVs use electricity stored in batteries as the primary fuel for propulsion. The significant difference between the two technologies is that PHEVs can utilize a secondary fuel source for propulsion when the battery is depleted. Current examples of EVs include Nissan Leaf, Think City and Tesla Roadster. The dominant model for PHEVs is the Chevrolet Volt. In this study, there is no distinction between PHEVs and EVs as the impact on the grid would be the same. Henceforth, the term EVs is used to describe vehicles that use the grid to charge the batteries. When compared to other alternative fuel vehicle technologies, these vehicles have an advantage because of the readily available power grid infrastructure. However, this shifting of the energy requirement from the transportation sector to the power grid might increase the strain on the grid. Battery charging during peak hours might increase the peak load and would require relatively expensive energy from peaking power plants. On the other hand, off-peak charging could potentially be very beneficial to the electricity industry due to load-leveling. Load-leveling could reduce utility system average costs of power [2].

Electric distribution systems are designed for a particular expected demand based on a regular demand pattern. High penetration of electric vehicles (EVs) would cause a considerable change in the regular consumption pattern [2]. Though only a small percent of vehicles will be electric in the coming years, the fact that there would higher penetration of EVs in affluent neighborhoods would cause localized effects, and is a major concern to electric utilities. It is possible that the electric power system may be adequate to handle the new patterns and levels of demand, or the system may be overloaded for prolonged time periods. Both circuits and transformers are vulnerable to these overloads with the transformer being more susceptible. The objective of this thesis is to evaluate the impacts of electric vehicle on the distribution transformers.

1.1 Related Work

Some of the recent studies [3–9] have tried to model the electric demand from uncontrolled charging of EVs. In these studies, the time of charging is usually assumed or based on vehicle arrival data from national household surveys. The quantity of charge required is dependent on the distance traveled by the vehicles. Some of the work assume that the charge in the batteries are completed depleted every day. Others use either empirical data or vehicle miles traveled (VMT) from transportation authorities to obtain the distance traveled by the vehicles in the system.

Bri et al. [9] proposed a multi-paradigm modeling methodology to analyze the effects of PHEV adoption on electricity demand. The traffic system and the electricity demand were modeled separately. TRANSIMS (an open-source transportation software) was used in traffic system modeling. The model is a very detailed agent-based simulation model. The velocity of the vehicles is used in charge depletion. Detailed and large amount of transportation data is required for such a model. The electricity demand is modeled using a bottom-up engineering approach. The data from the transportation simulation is incorporated into the demand model to obtain the electricity demand with EVs in the system.

Meliopolous et al. [10,11] proposed a methodology for computing loss of life of distribution transformers for given power profiles. A random load schedule was assumed.

The method is split into three parts. First, a distribution transformer was simulated to obtain the current flows through a transformer for a given load profile. Then, an electro-thermal model of the transformer is used to obtain the hot-spot temperature inside a transformer. Finally, the hot-spot temperature is used to calculate the loss of life of a transformer.

J. Taylor et al. [8] used conditional miles driven and arrival time probabilities to simulate the charging of EVs. The system VMT and arrival data is used in their study. The system-wide impact analysis was also performed. However, the importance of evaluating localized effects of EV penetration was recognized and proposed as future work.

1.2 Proposed Methodology

A multi-paradigm modeling approach (Figure 1.1) is used to examine the effects of the introduction of EVs on the electricity grid. The multi-paradigm approach enables different sub-systems to be simulated with the most representative modeling approaches, levels of data, and model granularity that reflect the subsystems most accurately. This paper considers three subsystems of the electricity system: an electrified personal transportation system, residential electricity demand model and a transformer model. The analysis is performed for the city of Indianapolis, Indiana. The proposed modeling methodology is a combination of the most accurate and feasible aspects of the mentioned works. As mentioned in Taylor et al. [8], the spatial diversity in EV penetration is important because of the higher penetration of EVs in affluent neighborhoods. The proposed model identifies the high penetration locations in Indianapolis, Indiana, and EV impact analysis is performed for those zones. Location specific vehicle miles traveled is used in the simulation.

A four step transportation model is adapted to model the behavior of vehicles in the system using TransCAD (transportation planning software). As many transportation planning organizations use TransCAD, we use the software to obtain zonal vehicle miles traveled and for related analyses. Then, we use a residential demand model that simulates the consumption pattern of all electric appliances in the system. The EV data model is then integrated into this model as an appliance. After integration, we can obtain the modified load consumption pattern. To quantify the impact that the EV charging could have on distribution transformers, a loss of life calculation from Meliopolous et al. [10] is utilized.

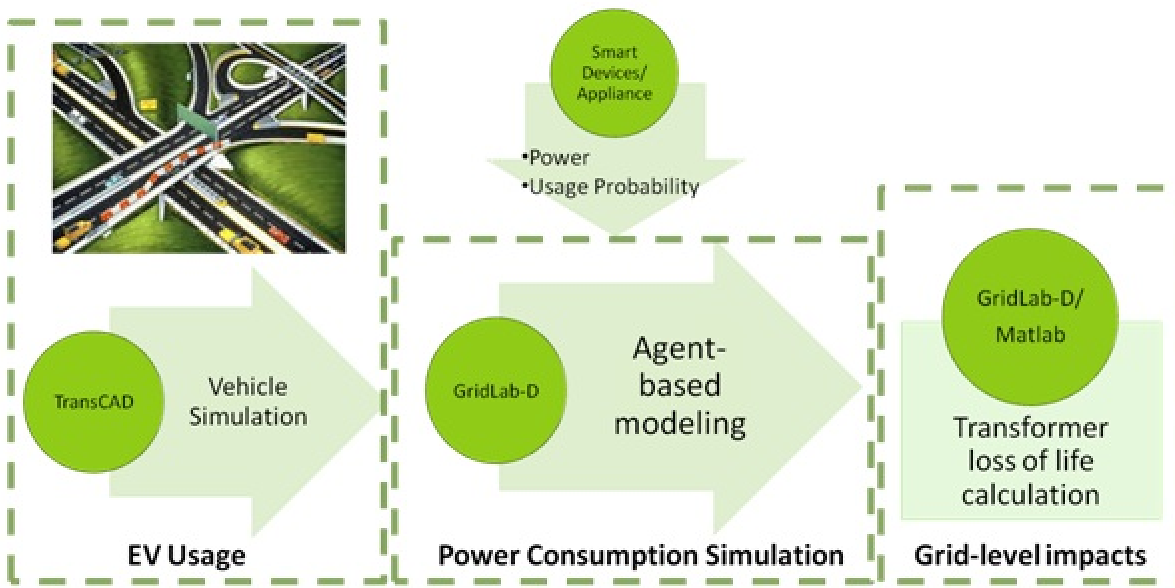

Figure 1.1.: The multi-paradigm modeling framework

This thesis covers numerous aspects of the modeling process. The remainder of the thesis is organized as follows:

- Chapter 2 discusses the electric vehicle modeling methodology. Along with the description of methodology, an application of the traffic simulation is also discussed.
- Chapter 3 discusses the residential demand model along with various electricity demand prediction techniques in practice.
- Chapter 4 describes the methods used to obtain the transformer loss of life.

- Chapter 5 elaborates on the obtained results and its implications to electricity distribution networks. The chapter also discusses the future work in this area.

2. ELECTRIC VEHICLE MODELLING

At present, 27% [1] of the total energy consumption in the U.S. is used for transportation. Gasoline and diesel fuel, the primary sources of energy used in the transportation sector, constitute 69% [12] of the total U.S. petroleum products consumption. In 2009, the petroleum products consumption in the U.S. was 18.8 million barrels per day [12], and 51% [13] of it is attributed to foreign import of crude oil and petroleum products. Such high dependence on foreign imports creates a major concern about energy security, mainly because a considerable amount of the foreign imports are from national oil companies that reflect their respective government's motive either financially or strategically [14]. As energy plays a vital role in the health of any economy, it is essential for oil importing countries to move towards alternative energy sources. There have been several recent developments in automobile technology that use alternative energy sources instead of petroleum products. The two major technologies that are widely researched and developed are electric vehicles and hydrogen fuel-cell vehicles. The functioning of a hydrogen fuel-cell vehicle closely resembles a conventional vehicle in terms of driving range (distance) and refueling time. But the need to set up a hydrogen fuel pump infrastructure is daunting. All efforts to establish a "technology readiness" for fuel cell vehicles will take several years [15]. On the other hand, electric vehicles have considerably less driving range per full charge and the batteries require long periods to attain full charge. In spite of these disadvantages, the fact that the average distance traveled per day is 40 miles [16] and the ready availability of charging facilities make electric vehicle usage immediately viable. Furthermore, continuous development in the field of battery technology will bring down the cost as well as increasing battery capacity, thereby, increasing driving range. Hence, this study is based on electric vehicles and plug-in hybrid electric vehicles instead of fuel-cell vehicles. In this chapter, the methodology to model vehicle flows and vehicle miles traveled per zone is described. These two parameters are used to model the power consumption pattern of electric vehicles. The fact that there are range anxiety problems attached to electric vehicle usage is recognized in this study. A Shukla et al. [17] had developed an optimization framework for choosing alternative fuel charging station locations. But, the optimization was done for fast-charging (Level 3: 15 minutes charging time). But, Level 3 chargers are not expected to be available in the near future. As a holistic solution to facilitate electric vehicle usage, a method is devised to rank a given set of proposed Level 1/Level 2 charging station locations also. The proposed locations are public places where people tend to spend a considerable amount of time. Details of the charging levels are described in the following chapters.

2.1 Background: Electric Vehicles

Conventional internal combustion engine vehicles use gasoline or diesel powered engines to provide power to the power train for propulsion. The IC (internal combustion) engines have poor energy conversion efficiencies; a typical IC engine operates at 20% [18]. These engines are also blamed for their negative effect on the environment. Alternative technologies have used electric motors to replace or supplement IC engines in automobiles. Automobiles that require electricity drawn from the power grid are broadly categorized into battery electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs). The equipment configuration used in battery electrical vehicles is comparatively simple. It consists of a battery pack(s) that can be charged using an electric outlet. The battery feeds electrical energy to the electric motor that is used to propel the vehicle. Vehicles of this type currently available in the market are Nissan Leaf, Think City and Tesla Roadster. There are several configurations of plug-in hybrid electric vehicles that are more complicated than battery electric vehicles. The three major configurations are parallel hybrid systems, series hybrid systems and series-parallel hybrid systems. In the parallel architecture, both the engine and electric motor is connected to the power-train. Depending on the on-board computer logic, the engine and electric motor is variably used to propel the vehicle and achieve efficient operation. On the other hand, in series architecture, only the electric motor is connected to the power-train. The engine is connected to a generator that either powers the electric motor or charges the battery pack. This configuration is seen in the GM Chevy Volt. The third is the series-parallel architecture, in this arrangement the engine is connected to the power-train and a generator. It is a hybrid of the series and parallel architecture [10].The current and future vehicles will be of the above configurations.

All of the above mentioned vehicle systems require electrical energy from the power grid to charge the on-board batteries. The charging scheme can be classified into different levels: level 1, level 2 and level 3 [19, 20]. Table 2.1 describes each of the type.

Table 2.1: Different charging levels

Charging Level	**Voltage/Current Requirement**
Level 1	120 V / 16 A
Level 2	208-240 V / 12 A to 80 A
Level 3	No specific limits; very high voltages (300-600 V DC), very high currents

Though the power requirement of Level 1 charging is only about 1.44 kW (12 A) or 1.92 kW (16 A), a dedicated circuit is recommended as existing circuits will have multiple outlets and a shared circuit breaker. A shared circuit breaker would cause frequent tripping when other appliances are used simultaneously with EV charging. Level 2 and Level 3 chargers would require special equipment because of the high voltage and high current requirement. Level 3 charging requires high voltage setup and exorbitantly expensive infrastructure. Level 2 is the preferred and recommended scheme for residential charging because Level 1 charging can take a very long time to attain full charge (typically 8 hours or more) and could pose as a deterrent to electric vehicle acceptance. Since utility companies are responsible for providing required electrical energy for charging, the infrastructure setup becomes a big challenge as the present distribution systems may not handle the heavy loads from EVs. The time of charging and the vehicle miles traveled are good indicators of charging patterns. The latter (vehicle miles traveled) is an important information for utilities as it is an indication of the amount of energy that would be drawn from the grid. This chapter elaborates on the method that would be used to calculate these parameters. The method is based on a widely used and accepted transportation planning methodology known as the four-step process.

2.2 Transportation Planning Methodology

The most widely used and accepted transportation planning and forecasting method is the conventional four-step model [21–23]. The steps involved in the modeling are as shown in Figure 2.1. The internal Activity System (A) is typically represented by socio-economic, demographic, and land use data defined for TAZs (traffic analysis zones) or other convenient spatial units. The Transportation System T (T) is typically represented via network graphs defined by links (one-way homogeneous sections of transportation infrastructure or service) and nodes (link endpoints, typically intersections or points representing changes in link attributes). Both links and nodes have associated attributes (for example, length, speed, and capacity for links and turn prohibitions and penalties for nodes).

The geographical area being considered is split into zones known as transportation/traffic analysis zones (TAZs). A traffic analysis zone is the unit of geography most commonly used in conventional transportation planning models such as the four step model. The spatial extent of zones typically varies in models, ranging from very large areas in the exurb to as small as city blocks or buildings in central business districts. There is no technical reason why zones cannot be as small as single buildings. However, additional zones add to the computational burden [24].

Zones are constructed by census block information. These blocks are used in the transportation model by providing socio-economic data. States differ in the socio-economic data that they attribute to the zones. Most often the critical information is the number of automobiles per household, household income, and employment within these zones. This information helps to further the understanding of trips that are produced (departure) and attracted (arrival) by the zone. The trips produced and attracted are converted to origin-destination (OD) matrices, where each element of the matrix represents the number of travelers moving from the origin to the destination. The OD matrix is used with the road network information (transportation system) in the four-step model to calculate the flow on each road/link. The modeling of vehicle flow in each road/link involves an iterative procedure to achieve an equilibrium (a state in which the traffic flow in each link does not violate any constraint). Metropolitan planning agencies use the vehicle flow information for congestion management and road network planning. A detailed description of the four-step model is presented in the following sections. The steps in the model are described in the subsequent sections.

2.2.1 Trip Generation

In this study, we use the term "trip" to denote the movement of a vehicle from one location to another. The trip generation step is used to determine the number of trips produced and attracted by each travel analysis zone (TAZ).

The trips are classified into three categories. First, the home-based work (HBW) trips. These trips start from home and end in a work place. Second, the home-based other (HBO) trips. These trips originate at home and are undertaken for purposes other than work, for example: trips to a shopping mall from home, trips to a grocery

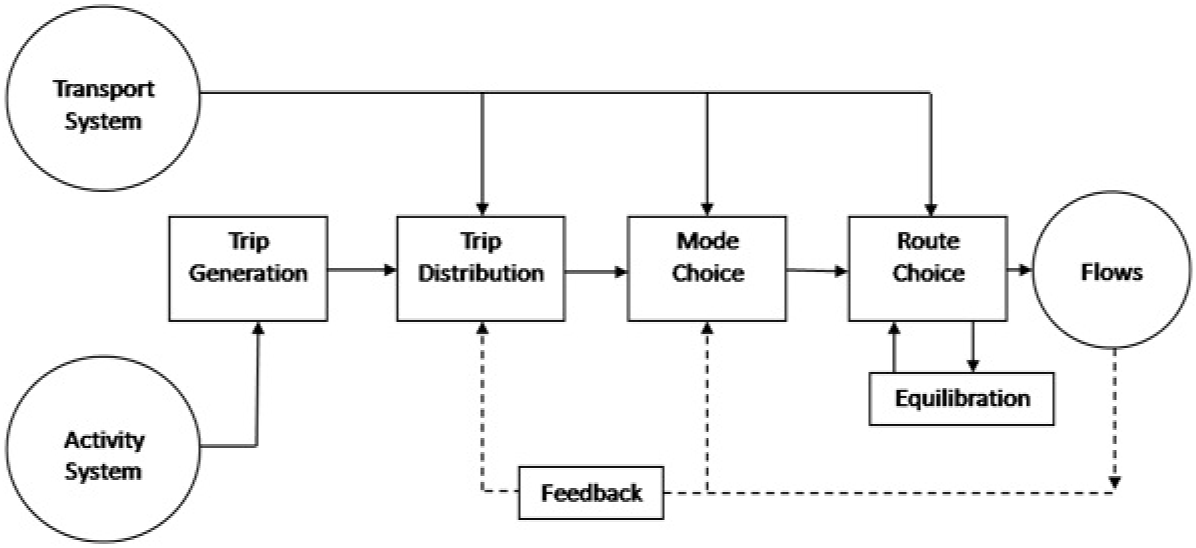

Figure 2.1.: The four step model [22]

store from home etc. Third, the non-home-based (NHB) trips. These trips do not originate from home, for example: trips from an office to a restaurant, etc.

The procedure makes use of certain available information about a zone to estimate the number of trips that would originate from or end in the zone. The socio-economic and geographical data of each zone contain valuable indicators that could be used to estimate the trips. For instance, a zone closer to the downtown area, with lots of shopping activities, will make shorter trips than a zone in the outer suburbs.

In the trip generation step, each trip is composed of an origin end and a destination end. The trip ends are denoted as “production” or “attraction” based on the trip type. For home-based trips (HBW or HBO), the home-end of the trip is always the production and the non-home end is the attraction. For a non-home-based trip, origin of the trip is the production and destination of the trip is the attraction.

Socio-economic data of the zone such as population, number of households and employment information are used to estimate the trips between zones. Household data gives an indication of the number of people residing in the zone and are used for estimating the home-based trip productions. The employment in the zone relates to the work trip attraction. The other interesting data is the retail employment that are used for calculating shopping based trips.

2.2.2 Trip Distribution

This step is used to match the trip production and attraction of each zone based on geographical factors to form complete trips. For example, the trips that are produced in a zone in Carmel, IN will be distributed to other zones in Indianapolis downtown, shopping districts, etc. based on their geographical proximity and thereby forming complete trips (with an origin and a destination). The process is repeated for every zone in the system.

The equation for calculating the trip distribution is based on the general assumption that the farther the distance of the destination, the lesser trip attractions [22]. The effect of travel time varies depending on the trip type. Travel time has a pronounced effect on non-home-based trips as it is discouraging to travel very long distances for personal chores. On the other hand, travel time has very little effect on work-based trips as the travel destination cannot be substituted.

For the model, the most widely used procedure in trip distribution known as the "gravity model" is used. The trip length or travel time between zones are represented by using the "friction factors". As a result of this procedure, the number of complete trips from one zone to another is estimated. The Gravity Model formulation [25] is expressed as follows:

$$T_{ij} = P_i * \frac{A_j F_{ij} K_{ij}}{\sum_{j=1}^{n}(A_j F_{ij} K_{ij})}, \tag{2.1}$$

where,

T_{ij} : number of trips from zone i to zone j,

P_i : number of trip productions in zone i,

A_j : number of trip attractions in zone j,

F_{ij} : the friction factor between zones i and j (travel time between i and j),

K_{ij} : optional adjustment factor.

Friction Factors Table ($\mathbf{F}_{ij}$)

Friction factors [25] are used to account for the impedance or separation between two zones. Factors like distance or travel time are used as a measure of impedance. Friction factors are inversely proportional to the impedance factors. It attempts to include the willingness to travel. The friction factors are different for each of the trip types. For our model, friction factors are developed using a gamma function. The gamma functions [25] used to develop these functions used the following equation:

$$F_{ij} = \alpha * I_{ij}^{\beta} * e^{I_{ij} * \gamma}, \tag{2.2}$$

where,

F_{ij}	:	the friction factor between zones i and j,
α, β and γ	:	model coefficients; β and γ should be negative; α is the scaling factor,
I_{ij}	:	the impedance factor(travel time) between zones i and j, and
e	:	the base of natural logarithm.

$\boldsymbol{I}$ is the impedance matrix. The trip length (in minutes) is used as impedance in our study. $\boldsymbol{I}$ is represented as a matrix and each cell I_{ij} represents the time it takes to travel from zone i to zone j without traffic. The $\boldsymbol{I}$ matrix is obtained by processing the road network GIS (Geographic Information System) of Indianapolis. The GIS road network of Indianapolis is as shown in Figure 2.2.

The aim is to select an impedance function and its corresponding parameters such that the gravity model reproduces the trip length distribution of the study area. There are several ways to arrive at the parameters. We have used parameters suggested by *NCHRP Report 365 - Travel Estimation Techniques for Urban Planning* [25]. The report used several calibrated models from urban areas and found the relation between the number of trips and travel to fit a gamma distribution function. From the results, the work suggests that the gamma function be used with the parameters presented in Table 2.2.

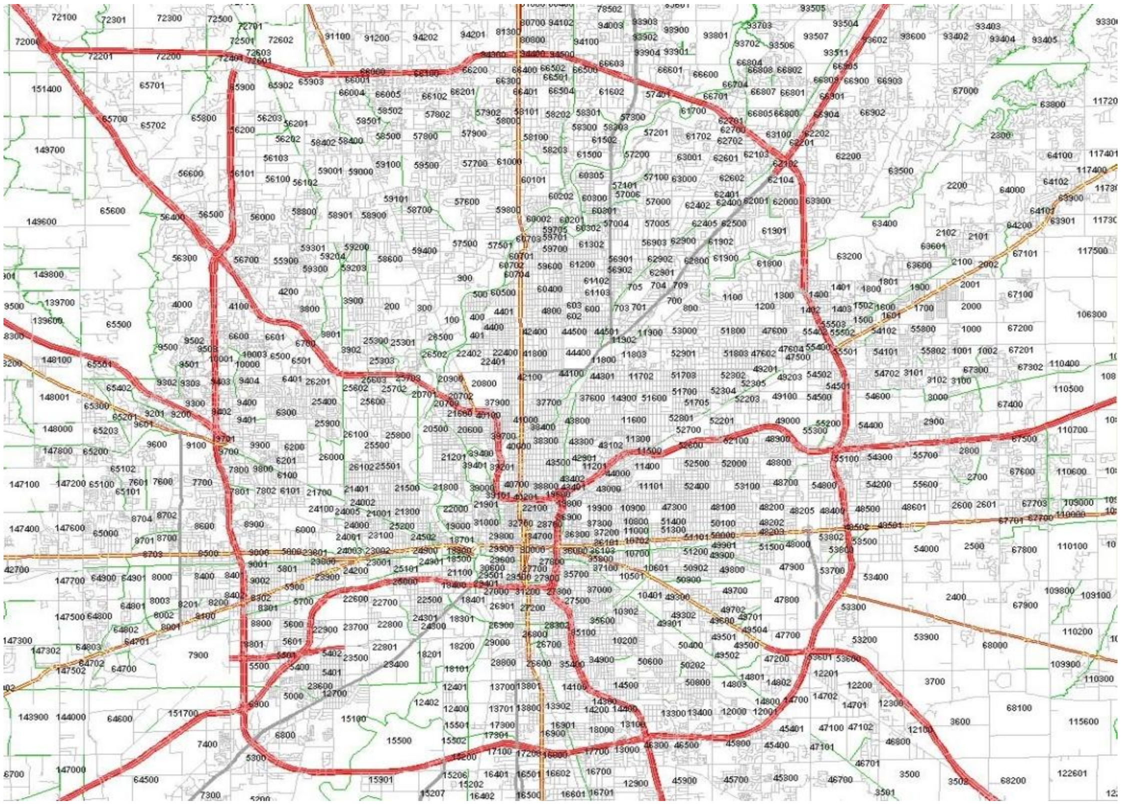

Figure 2.2.: Indianapolis GIS road network

Table 2.2: Gamma function parameters

Trip Purpose	α	β	γ
HBW	28,507	-0.02	-0.123
HBO	139,173	-1.285	-0.094
NHB	219,113	-1.332	-0.01

2.2.3 Mode Choice

The next step in the modeling process is the mode choice. The travelers will be assigned to different modes of transportation based on several factors. The choices are based on relative availability and attractiveness of the mode. The attractiveness of the mode is dependent on mass transit accessibility, time spent on travel, cost of travel, automobile ownership and facilities such as carpool lanes.

The cost of travel could be mass transit fares, the price of gasoline, parking, and a mileage rate for driving. Time spent on travel will comprise time spent waiting for transit, time transferring between routes, or time spent to drive and park the car and reach the final destination. All these parameters are factored into the mode choice selection procedure. Some other factors such as parking costs and the time it takes to walk from garage or parking spot to the destination are also accounted. The downtown parking costs are generally high and when accounted for would discourage automobile use. This data is very difficult to collect and hence is ususally omitted in the modeling. But inclusion of these factors would make the modeling more accurate.

Further assumptions can be made for mass transit riders. For example, the traveler would use mass transit only if the facility is accessible within a predetermined distance from home. Otherwise, they would have to travel by car or other means to use the mass transit.

2.2.4 Trip Assignment

The final step of the modeling is the trip assignment process. This step is used to estimate vehicle flows on each of the road segments, also called as links. In this process, the model initially uses the GIS information to choose the shortest route between two zones. It then iterates based on the congestion pattern to achieve equilibrium on the flow. This step is used in analyzing the congestion in road networks. Since the focus of this study is not concerned with road network congestions, we do not use this step. The result of this step is used by planning organizations to manage congestion and in road network planning.

2.3 Electric Vehicle Behavior Modeling

For our analysis, the hourly vehicle departure and arrival data for each zone would be required to estimate the residential time of charging. The daily vehicle miles traveled would be required to estimate the electrical energy used from the grid to recharge the batteries. Using these two parameters for each zone, the electrical vehicle charging behavior would be easily estimated since the time of charging and the quantity of charging is known. For commercial locations, the hourly vehicle flow data would be used to estimate the number of vehicle that would be influenced by the charging facility. The hourly vehicle flow would be calculated using the production-attraction matrix and origin-destination matrix from the trip distribution step.

2.4 Facts and Assumptions

Recent studies reveal that most cars travel with only one or two people in a car, an average of 1.58 passengers per car [26] dropping to under 1.2 per vehicle for travelling to work. We use the average car occupancy of 1.58 to convert person trips to vehicle trips in the OD matrix.

According to the national household survey conducted by the *U.S. Bureau of Transportation statistics* [16], 87 percent of daily trips take place in personal vehicles and 91 percent of people commuting to work use personal vehicles. Furthermore, the public transit system functions mostly in urban Indianapolis with limited or no service to suburban areas. Due to these facts, less emphasis is given to mass transit and the mode choice step is not used extensively. The analysis is more focused on personal vehicles and the related trips.

While converting the productions-attractions to an origin-destination matrix, we use an hourly distribution table [27] for the time-of-day analysis. We split the given trips based on the hourly distribution table. This data is essential in analyzing the number of trips for each hour of the day. Different distributions are used for each trip type. Table 2.3 [27] shows the trip distribution used. The departure/arrival distributions specify the pattern of vehicle departures/arrivals in a given zone. As for the analysis, we will be concerned with the arrival distribution as it reflects the number of people likely to use the service.

Table 2.3: Hourly distribution table [27]

HOUR	DEPARTURE_HBW	RETURN_HBW	DEPARTURE_HBO	RETURN_HBO	DEPARTURE_NHB	RETURN_NHB
0	0.4	0	0.35	0.35	0.3	0.3
1	0.2	0	0.15	0.15	0.1	0.1
2	0	0	0	0	0	0
3	0.2	0	0.05	0.05	0	0
4	0.4	0	0	0	0.05	0.05
5	2.7	0	0.25	0.25	0.2	0.2
6	7.9	0	1	1	0.75	0.75
7	19.2	0	2.9	2.9	3.3	3.3
8	9.2	0	1.7	1.7	2	2
9	3	0	1.5	1.5	1.8	1.8
10	0.7	0	2.2	2.2	2.8	2.8
11	0.6	0	2.2	2.2	3.15	3.15
12	0.7	1.4	2	2	5.1	5.1
13	0.6	1.4	2.4	2.4	3.6	3.6
14	0.6	3.2	2.1	2.1	3.45	3.45
15	0.6	5.7	3.1	3.1	4	4
16	0.6	13.1	4.05	4.05	4	4
17	0.6	11.8	4	4	3.1	3.1
18	0.6	3.1	4.25	4.25	2.35	2.35
19	0.6	1.7	5.6	5.6	3.15	3.15
20	0.6	1	3.95	3.95	2.9	2.9
21	0	2.9	3	3	1.95	1.95
22	0	2.8	1.95	1.95	1.2	1.2

2.5 Methodology

The transportation planning software TransCAD [28] is used for the modeling purpose. TransCAD is a widely used transportation planning software. It uses GIS (Geographical Infomation Systems) and transportation modeling capabilities (four-step model) to analyze the road network and traffic systems. The zone level socio-economic data and the road network information were obtained from the Indianapolis Metropolitan Planning Organization (IndyMPO). The data is for the nine counties in Indianapolis. They are Boone, Hamilton, Hancock, Hendricks, Johnson, Madison, Marion, Morgan and Shelby. For each of the zones in these counties, we have information on population, number of households, number of automobiles per household, number of people employed in each sector, average income and income level classification among other data. TransCAD uses the four-step model mentioned above to process the data. The GIS capability of TransCAD is used to identify the affluent neighborhoods. The TAZs with an average income greater than \$91336 and where more than 70% of the people have more than one vehicle are chosen. These locations represent the zones that are expected to have high EV penetration. The selected zones in Indianapolis are as shown in bright red in Figure 2.3.

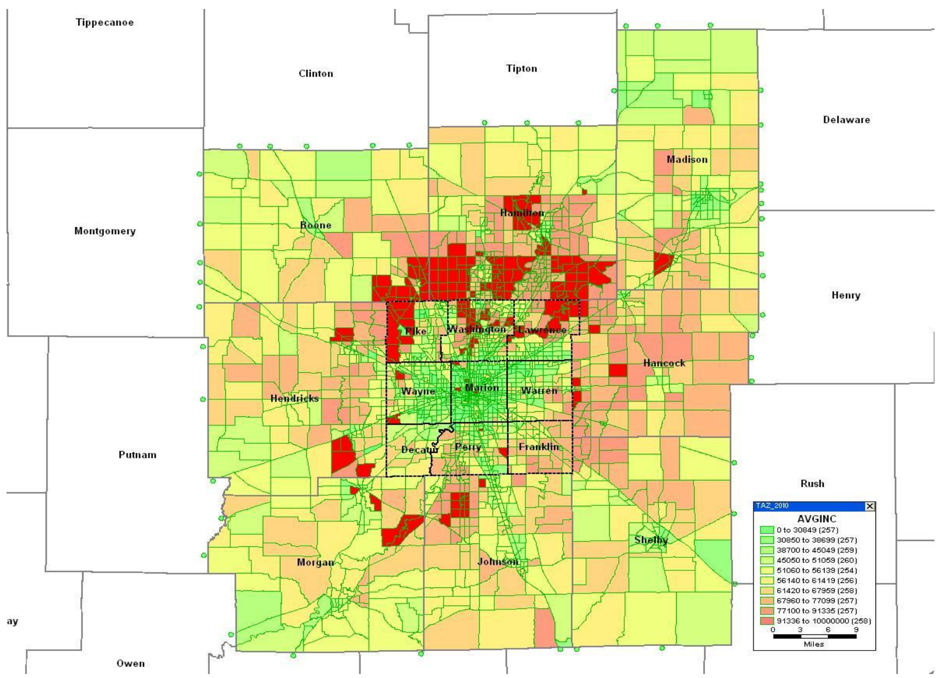

Figure 2.3.: Selected zones in Indianapolis

2.5.1 Hourly Vehicle Flow Modeling

The socio-economic data is used in the trip generation process to generate the trip productions and attractions per zone for each trip type. These trips are then made into complete trips by matching trip productions from one zone to trip attractions in another zone in the trip distribution step. The final result of this step is a production-attraction (PA) matrix whose rows and columns are made up of all the zones in the system. The average car occupancy of 1.58 is used to convert the person trips to vehicle trips. Each row in the matrix represents the vehicle trip productions of a zone and the column represents the vehicle trip attractions of the zone. The production-attraction (PA) matrix is then converted to an origin-destination (OD) matrix. For home-based trips, the production-attraction matrix follows the convention that the home-end of a trip is always the production end. For example, even if the trip originates at work and ends at home, the home end would be the production end. On the other hand, the origin-destination matrix does not follow this convention. For home-based trips, if the trip originates at work and ends at home, the work-end is the origin and the home-end is the destination. For example, consider the HBW trip matrix shown in Figure 2.4. If the matrix is a PA matrix, there would be 280 trips that could either start or end at Zone-380 (home). Essentially, there are 140 people who live in Zone-380 and work in Zone-440. If the matrix is an OD matrix, there would be 280 trips that start at Zone-380 and end at Zone-440. Essentially, there are 280 people who live in Zone-380 and work in Zone-440.

	Zone 440	Zone 441
Zone 380	280	109
Zone 381	34	59
Zone 382	420	190

Figure 2.4.: HBW matrix

While converting the PA matrix, we make use of the hourly distribution matrix [27] to obtain hourly OD matrices. The summations of the elements of each row of the hourly OD matrices are the hourly vehicle flow for each zone. For example, in Figure 2.4, consider Zone-382 , the summation of the elements of the row corresponding to Zone-382 in the 1st hour OD matrix reflects the number of vehicle that depart from Zone-382 at hour 1. In the given matrix, 610 people are leaving Zone-382 at the particular time. By repeating the procedure for each of the 24 hourly OD matrices, we could obtain the hourly flow for each zone. The hourly vehicle flow for a zone with high EV penetration is as shown in Figure 2.5.

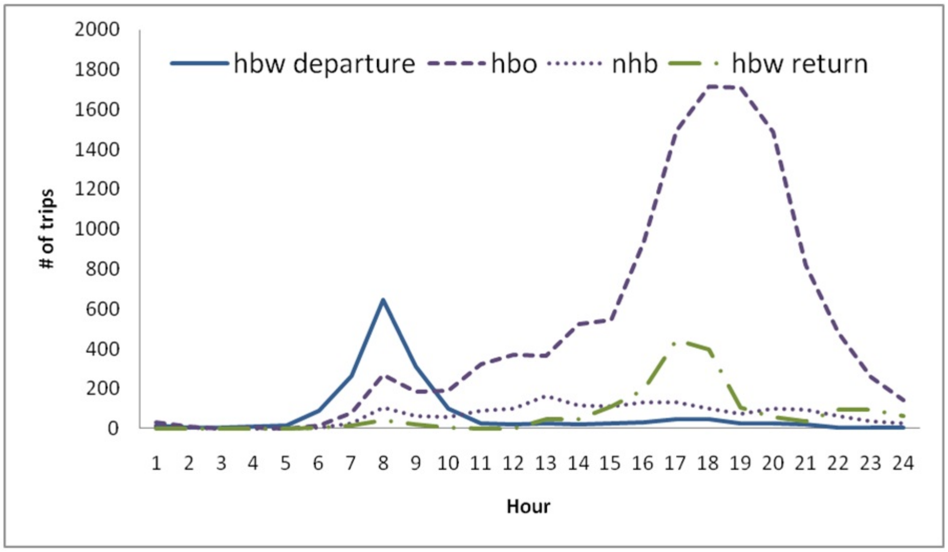

Figure 2.5.: Hourly vehicle flow for a zone with high EV penetration

2.5.2 Vehicle Miles Traveled

The vehicle miles traveled distribution data for each zone is very essential in modeling the energy consumption of the electric vehicles. The production-attraction matrix and distance matrix is used to estimate the vehicle miles traveled distribution data. Each element of the distribution matrix represents the distance between the row zone and column zone. As the PA matrix gives the number of trips between the zones, and the distance matrix gives the distance between the zones, we arrive at a distance frequency table by matching the rows of the PA matrix and distance matrix. This data will be used in the power system simulation as a distribution to account for variability in the energy consumption of electric vehicles. The vehicle distance traveled distribution is as shown in Figure 2.6. In the simulation, this distribution would be used to generate the quantity of charge. The procedure will be described in Section 4.2.1.

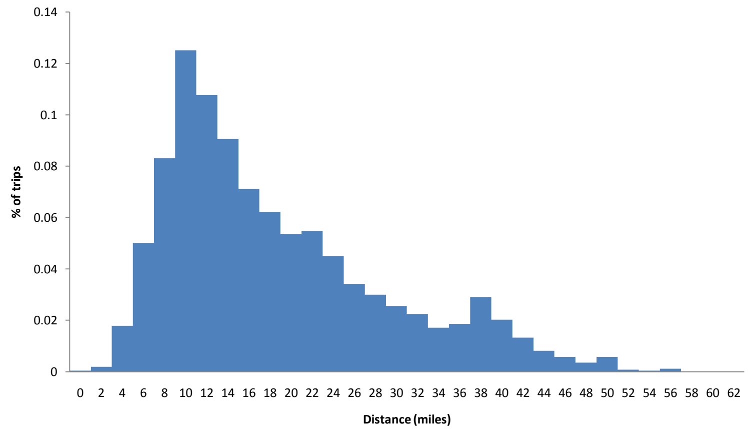

Figure 2.6.: Hourly vehicle flow for a zone with high EV penetration

2.5.3 Commercial Charging Station Ranking

One of the major hindrances to EV adoption is the range anxiety problem. Many people worry about the EVs running out of charge. Since EVs take hours to charge, there is a prevalent anxiety about the vehicle range among EV users. To mitigate this and increase public confidence, the utility company in Indianapolis had proposed to build charging stations in chosen locations. This study benefits them by evaluating each of the locations. The evaluation gives an indication to the number of vehicles that could benefit from the charging station at a location. The proposed charging station locations are as follows: (1) IPL at 1230 W Morris Street, (2) IPL at 3600 N Arlington Avenue, (3) Denison Merchants Garage at 31 S Meridian Street, (4) Simon Mall Garage at 50 W Georgia Street, (5) Simon Mall Garage at 129 W Maryland Street, (6) IMA at 4000 Michigan Road, (7) Indy airport at 7801 Col H Weir Cook Memorial Drive, (8) JW Marriot at 10 S W Street, (9) State of Indiana at 100 N Senate Avenue, (10) Convention and Visitors bureau at 100 S Capitol Avenue, (11) IUPUI at 1040 W Michigan Street, and (12) Enerdel at 8740 Hague Road

The task was to rank the charging stations based on the number of vehicles that could be influenced. We map the proposed charging station locations in TransCAD

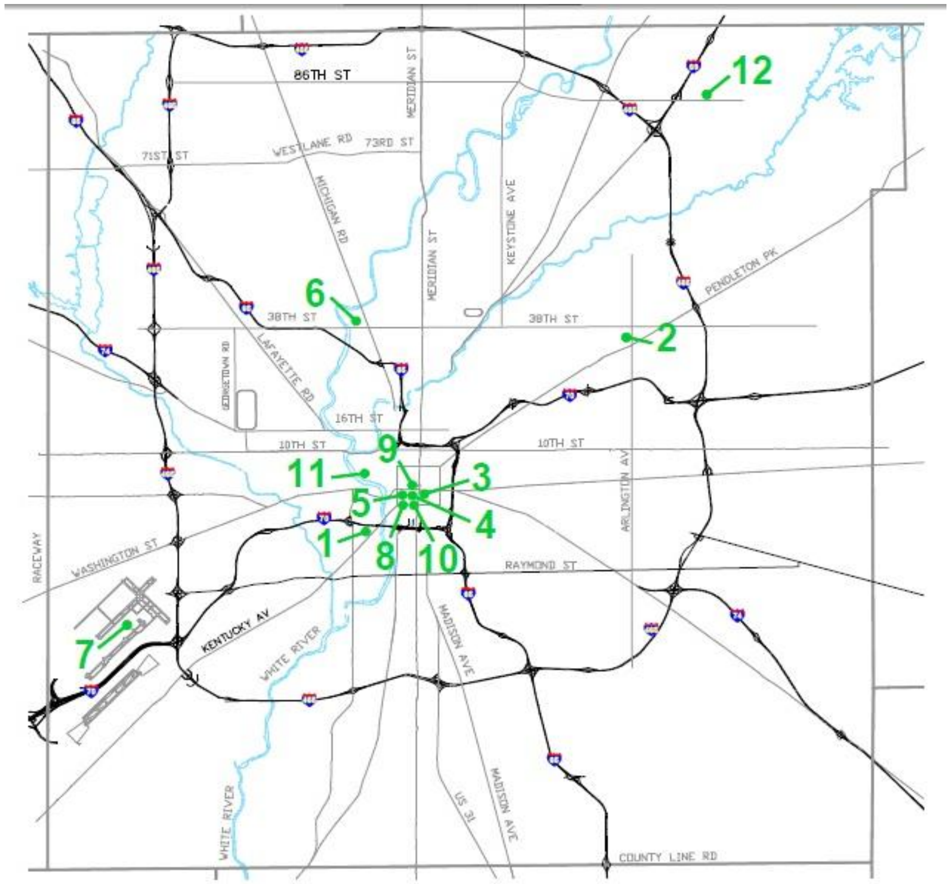

Figure 2.7.: Proposed charging station locations

and identify the corresponding zone. Charging stations will attract not only the visitors to a particular zone but also the visitors to the neighboring zones. Based on this idea, the analysis is performed for all the zones covered by a 0.25 mile as well as a 0.5 mile radius. Figure 2.8 shows the zones being covered by the charging station at Denison Merchants garage. The green circle represents the 0.25 mile radius area of influence and the red circle represents the 0.5 mile radius area of influence.

The zones covered by the area of influence are manually counted from the map. The previously mentioned vehicle flow modeling procedure is performed for all the

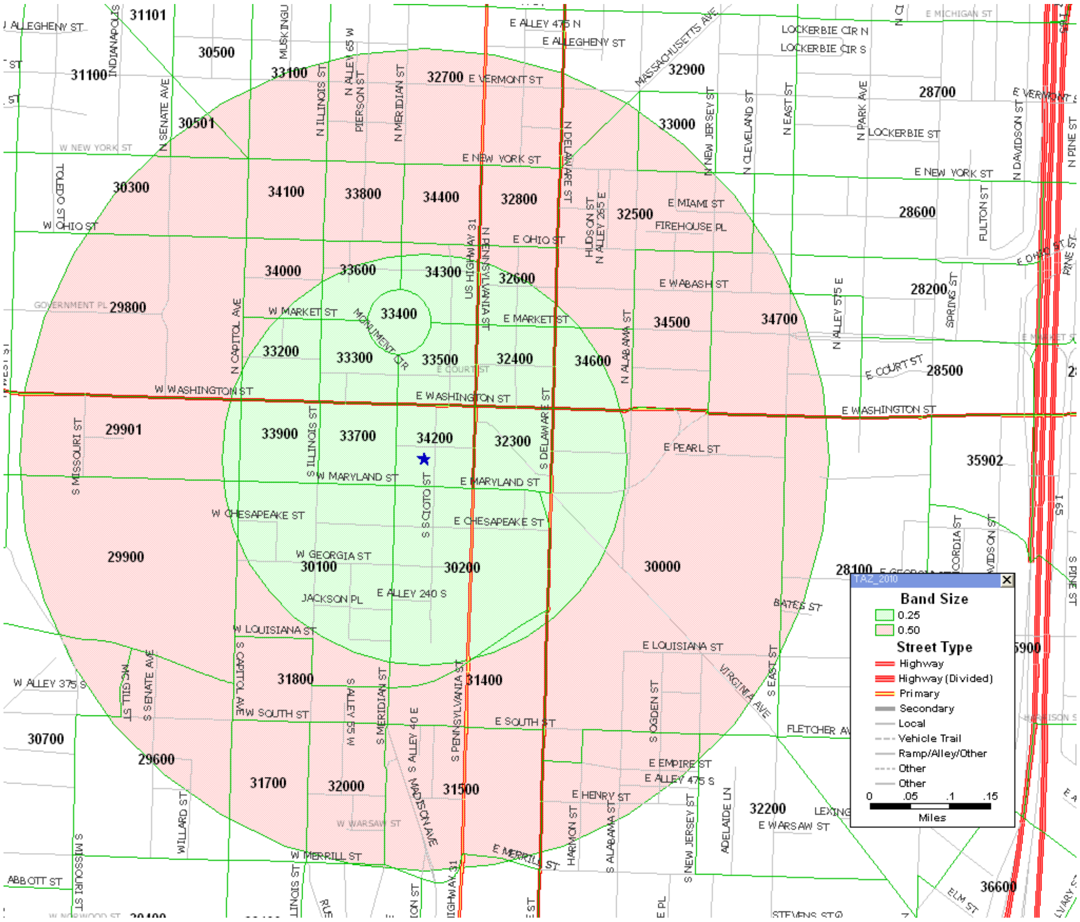

Figure 2.8.: Area of influence of Denison Merchants garage

zones. The summation of the results represents the number of vehicles that would be influenced by the charging station. Figures 2.9 and 2.10 show the hourly vehicle flow through each of the proposed locations. The proposed locations are split into commercial and fleet locations. Commercial locations are those with heavy public access, while, fleet locations are owned by a certain organization with a fleet of EVs. From the vehicle flow modeling, the total vehicle flow through each of the locations is obtained (Figures 2.11 and 2.12).

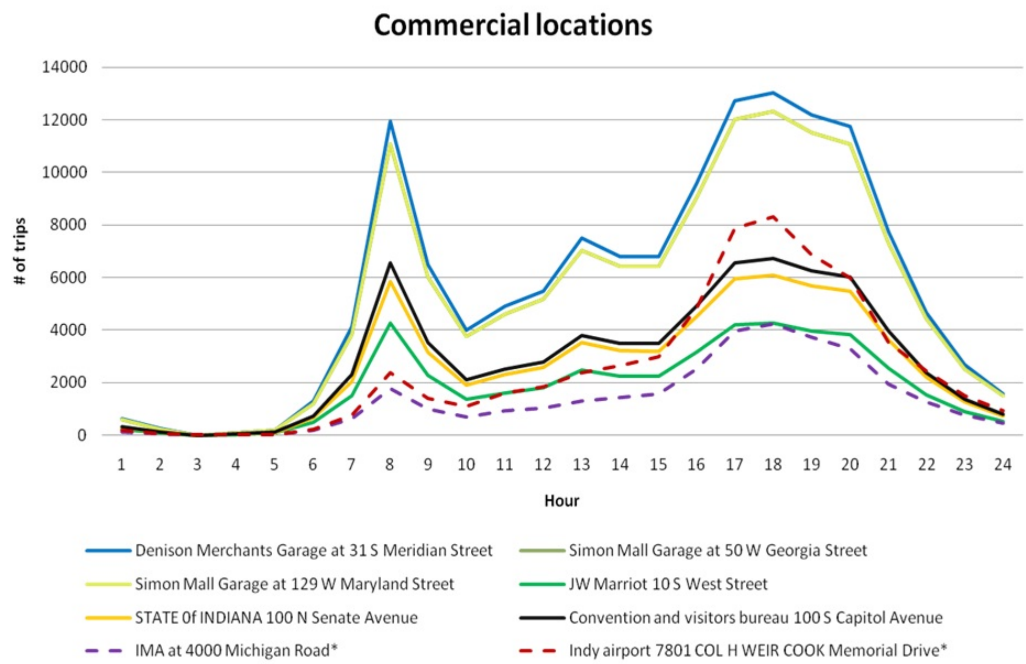

Figure 2.9.: Hourly vehicle flow in commercial locations

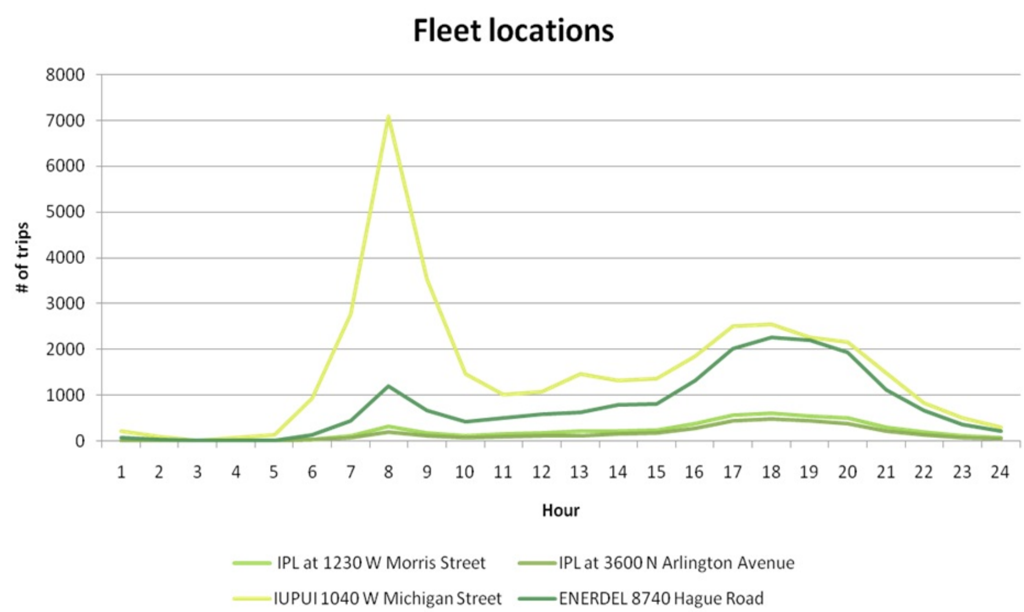

Figure 2.10.: Hourly vehicle flow in fleet locations

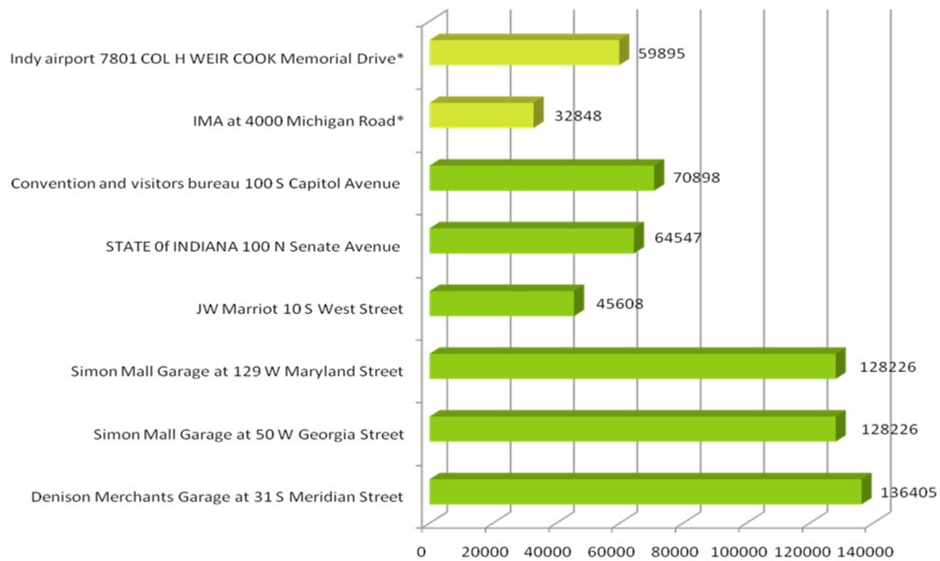

Figure 2.11.: Total vehicle flow through commercial locations

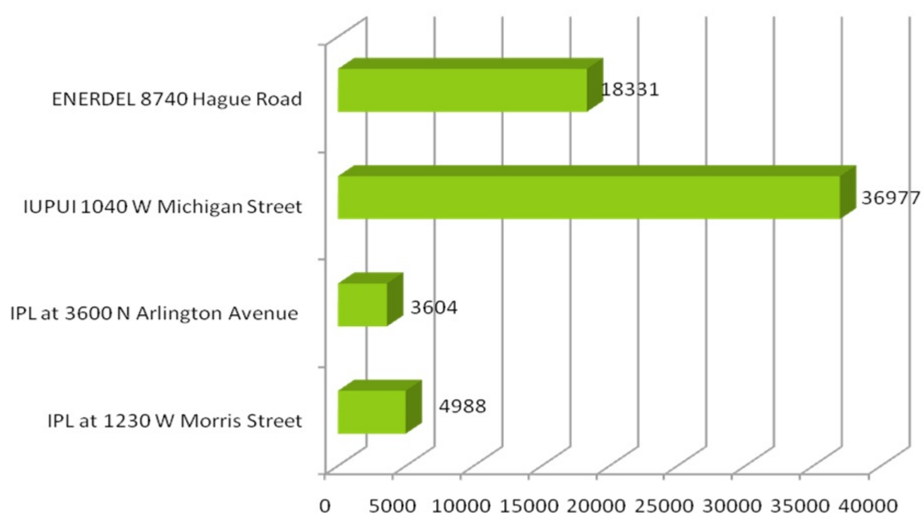

Figure 2.12.: Total vehicle flow through fleet locations

3. RESIDENTIAL DEMAND MODELLING

Accurate electricity demand prediction is essential for the efficient operation of power systems. Independent System Operators (ISOs), balancing authorities and utility companies use predicted demand for procuring and managing the available sources of power. The decision makers are faced with a multitude of operational difficulties on different time-horizons and at different hierarchies of the power grid. For instance, the grid operators must forecast the day-to-day energy demand of the system for the unit commitment and economic dispatch procedures. Also, yearly energy predictions are used for capacity planning and investment decisions. Accurate demand prediction is essential for participating in deregulated electricity markets. An electricity market participant should have an accurate estimate of the hourly load to procure energy in advance. An underestimation would lead to paying high real-time prices for over consumption. Overestimation would result in wastage of resources. Furthermore, the electricity market price is set based on electricity demand prediction. Load forecasting is therefore at the core of electricity markets [29].

Energy demand prediction models have been used for a variety of reasons. Commonly, energy demand prediction is used on a macro-level to measure the system electricity load for optimal generator scheduling. The same analysis done on a longer time-horizon is useful for guiding important policy decisions. For this kind of modeling, more attention is paid to macro-level factors such as temperature, weather, etc. Time-series predictions seem to be the most common technique for this application. These techniques are good at using historical data to predict cyclical patterns and thus are a good choice. At a macro-level, the effect of switching ON/OFF of a single device does not affect the system and hence is not of much interest. However, for building-level analysis of the effect of electric vehicles, the ON/OFF switching of a single high-power consuming device is of great importance. More detailed modeling techniques are required to represent the complex interactions of the end-use applications in a building. The level of detail of input parameters is a function of data availability, model focus and purpose, and assumptions. Increased detail allows for a more comprehensive investigation of consumption patterns, although accurate assumptions may significantly ease the modeling process and provide suitable results. Since the modeling is done for only a few buildings at a time, computationally intensive calculations are both feasible and economical.

Emphasis of this chapter is placed on models that are applicable to utility level energy prediction through building energy modeling. The total energy consumption of a building comprises of the energy required by all the end-use appliances, inclusive of the losses and the system inefficiencies. The end-uses may have complex interrelated effects with regards to energy consumption. Energy consumption modeling of buildings seeks to quantify the energy requirements as a function of certain measurable parameters.

3.1 Time-horizons of Demand Prediction

Demand forecasting is done for various purposes. The choice of the time period of a forecast depends on its purpose. Forecasts can therefore be classified based on the time-horizons: short-term load forecasts aim to predict the demand for an hour into the future and up to several days, medium-term load forecasts are from one-week to a year, and long-term load forecasts are for several years. Usually, the short-term load forecast is used for a time-horizon of less than 24 hours. Until recently, the main focus of demand prediction has been short-term load forecasts as most day-to-day power system operations depend on it. Electricity deregulation has increased interests in medium-term load forecasts. Medium-term load forecast enables companies to estimate the load demand for a longer time interval which helps them, for example, in the negotiation of contracts with other companies. Long- term forecasts are primarily used in capacity planning and investments decisions. Each of these forecasts would require different sets of input variables depending on the application.

Electricity demand is influenced by several factors - ranging from socio-economic factors to seasonal and weather effects. Depending on the region and climatic conditions, some factors may have a greater impact than others. The prediction has to be constructed depending on the task and data at hand. Therefore, it is essential to determine the factors that have a significant effect on electricity demand. Univariate models are used when extensive data is not available. Univariate models use only one variable (past demand) to predict future demand. They are standard and effective for very short term load forecasts for up to six hours ahead [29–31].

3.2 Demand Prediction Techniques

Techniques used for demand prediction can be broadly classified into two categories: top-down and bottom-up. The terminology is with respect to the hierarchical position on input data as compared to the housing sector [32].

One method traditionally used in estimating demand is by performing statistical analysis on historic data to project observed trends in consumption into the future. A number of statistical methods, such as regressions and exponential smoothing, as well as classification methods, such as neural networks and fuzzy logic, have been used to predict future demand loads based on past data. In this study, we use an agent-based model which is a combination of statistical and engineering models.

3.2.1 Top-down Models

Top-down models predict the energy consumption using macro-level factors; variables which are commonly used by top-down models include macroeconomic indicators (gross domestic product (GDP), employment rates, and price indices), climatic conditions, housing construction/demolition rates, and estimates of appliance own-

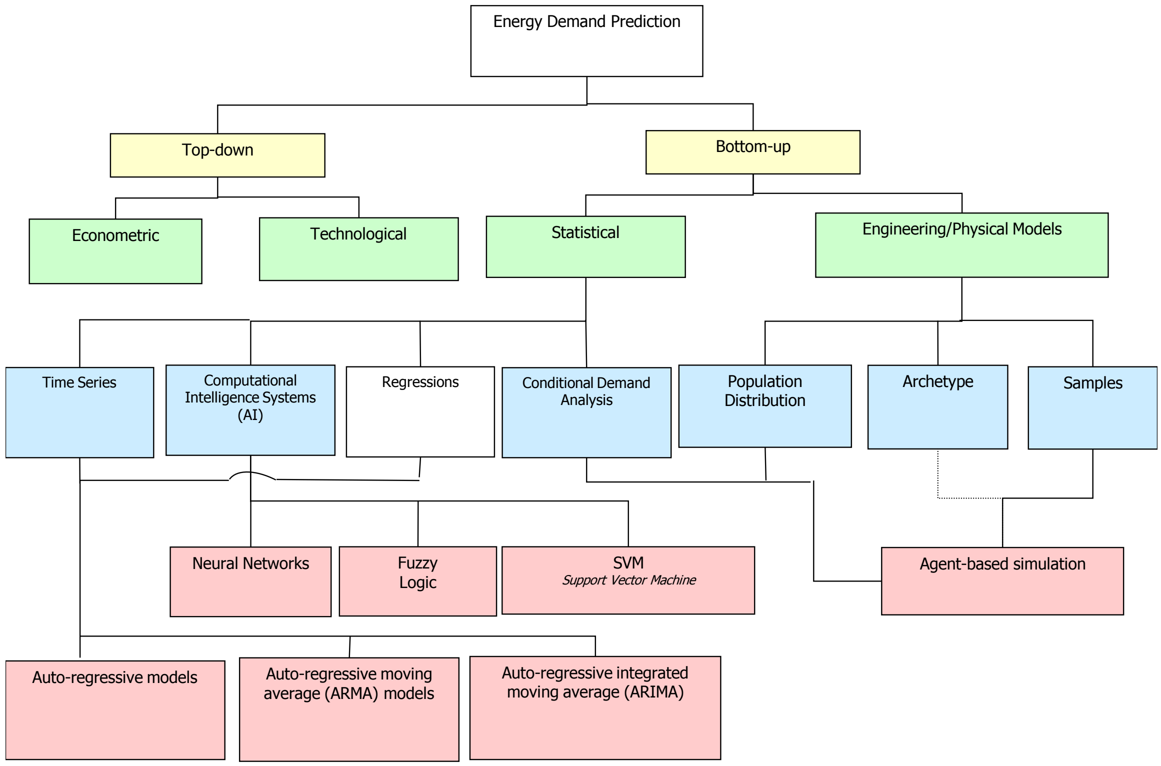

Figure 3.1.: Demand prediction techniques in practice

ership and number of units in the residential sector. The two types of top-down approaches identified by [32] are:

Econometric models: These models are based on price (of, for example, appliances) and income. The model develops relations between the income factor and affordability of appliance. Based on the different income groups, energy consumption is predicted.

Technological models: Technological models attribute energy consumption to broad characteristics of the entire housing stock such as appliance ownership trends.

3.2.2 Bottom-up Models

The bottom-up approach uses end-use or appliance level input data for demand prediction. Usually, models account for consumption of individual end-uses, individual houses or group of houses. These models are then extrapolated or scaled-up to represent the whole system. The bottom-up models are classified into two types based on the methodology: statistical methods and engineering methods. Most statistical models are based on the idea of regression analysis; the methods attribute housing energy consumption to particular end-use or end-use parameters. Engineering methods (EM) explicitly account for the energy consumption of end-uses based on power ratings and use of equipment and systems and/or heat transfer and thermodynamic relationships.

Statistical Techniques

The vast quantity of customer energy billing information stored at the major energy suppliers worldwide is a very valuable data source for energy modeling. Customer energy billing information is one of the most valuable sources of data for energy prediction. Historically, various statistical techniques have been used to utilize this and other source of data to regress the energy consumption as a function of end-use appliances and house characteristics. Occupant's behavior seems to have a far greater impact than any other parameter. The statistical techniques have the ability to incorporate occupant behavior into the model. This is of great benefit to the residential building models. The following is a brief description of each of the mentioned models:

Regression [29, 32] - The regression technique uses regression analysis to determine the coefficient of the model corresponding to the input parameter. The coefficient signifies the amount of change in the energy consumption per unit change in input parameters. The input parameters are those factors that affect or are likely to affect the energy consumption. So, these models regress to find a relation between aggregate energy consumption of the dwelling to certain factors. Those relations that are determined to have a negligible effect are removed for simplicity. Based on the combinations of inputs, the model's coefficients may or may not have physical significance.

Conditional Demand Analysis (CDA) [33] - This method makes use of end-use appliance penetration levels in regression. The appliance ownership is indicated as a binary variable. The coefficients attached to the appliance parameter can denote the usage or rating. This method reflects the differences in ownership of each household appliance in the regression model.

Artificial Intelligence/Computational Intelligence systems [29,32] - These methods are relatively new compared to the other statistical methods. They are basically an extension of the idea of building a mathematical model to represent the system. But, the system model and data fitting are derived from the principles of computer science.

Engineering Techniques

The engineering techniques model the physical characteristics and interactions of the appliances in a system. They are the only method that does not rely on historical data. The engineering model could be as detailed as possible. There are several models that reflect the exact thermodynamic characteristics of the system. The engineering models could also use a simple representation for appliance that do not have complicated operation or interactions. The engineering techniques have the greatest flexibility when modeling new technologies that do not have any historical information. The prevalent engineering techniques [32] are as follows:

Distributions - This technique makes use of appliance ownership and usage characteristics to model the energy consumption. The method does not consider the interactions of the end-use appliances.

Archetypes - This technique classifies the housing stock broadly into certain categories. One house of each category is modeled and then expanded to represent the system under consideration.

Sample - This technique uses input information from an actual sample house. This model has the capability to represent the intricate interactions between end-uses. As the type of houses varies widely, a large number of houses have to be modeled to represent the entire power system.

3.2.3 Critical Analysis of Prediction Techniques [32]

Table 3.1: Comparison of different prediction techniques

	Top-down	**Bottom-up statistical**	**Bottom-up Engineering**
Positive attirbutes	- Long term forecasting in the absence of any discontinuity - Inclusion of macroeconomic and socioeconomic effects - Simple input information - Encompasses trends	- Encompasses occupant behavior - Determination of typical end-use energy contribution - Inclusion of macroeconomic and socioeconomic effects - Uses billing data and simple survey information	- Model new technologies - "Ground-up" energy estimation - Determination of each end-use energy consumption by type, rating, etc - Determination of end-use qualities based on simulation
Negative attirbutes	- Reliance on historical consumption information - No explicit representation of end-uses - Coarse analysis	- Multi-collinearity - Reliance on historical consumption information - Large survey sample to exploit variety	- Assumption of occupant behavior and unspecified end-uses - Detailed input information - Computationally intensive - No economic factors

Each approach meets a specific need for energy modeling which corresponds to its strongest attribute:

- Top-down approaches are used for supply analysis based on long-term projections of energy demand by accounting for historic response.

- Bottom-up statistical techniques are used to determine the energy demand contribution of end-uses inclusive of behavioral aspects based on data obtained from energy bills and simple surveys.
- Bottom-up engineering techniques are used to explicitly calculate energy consumption of end-uses based on detailed descriptions of a representative set of houses, and these techniques have the capability of determining the impact of new technologies.

3.3 Demand Prediction using Agent-based Simulation

Most of the prevalent top-down/classical demand prediction models use historical usage patterns to predict future demand. However, in the future, there could be devices like EVs that has not been used in the past. Due to the lack of information for these kinds of devices, many of the classical methods often fail. For this reason an agent-based simulation technique is used in this work for forecasting the residential electricity demand with EVs.

A bottom-up approach has been used to forecast electricity usage at the household level using an engineering model that decomposes usage to the appliance level. Each appliance in the agent-based model is modeled independently with varying degrees of complexity. Some of the devices such as lights have only two states (ON and OFF), while other devices such as air-conditioners have several states of operation. Appliances such as air-conditioners and refrigerators consume more electricity during periods of high temperature, and the usage of other devices such as water-heaters has a negative correlation with the temperature. These complexities are well defined in the agent-based model. The bottom-up approach also enables the addition of new devices such as EVs. It is comparatively easy to add the effects of these devices to the system. An EV is added as another device to the system and modeled independently.

Appliances are assigned to the household based upon local appliance saturation levels, in our case for the city of Indianapolis. Every appliance has an hourly starting probability, as well as a consumption cycle that dictates its electricity usage when turned ON. Starting probabilities differ for weekdays and weekends while appliances that consume electricity during standby periods are also given a standby load. The household's electricity usage is then determined at the minute time scale through the simulation of whether every appliance available in the representative household is currently ON or OFF, and if ON, the level of electricity being drawn is measured. The daily household usage amount can then be calculated through a summation of the usage levels at every minute during the day. The daily profile results of a number of representative households can be combined to form an average household usage profile.

The framework for the model is built on two major components: a dataset and a simulation engine. The first component includes a list of the appliances that may appear in a household, appliance saturation levels, daily frequency at which a particular appliance is used, usage profile of an individual appliance, standby power needed by a particular appliance and the consumption cycle of an appliance. The second component includes a set of stochastic simulation processes, which generate temporal electricity consumption profiles for all appliances of each household separately on the hourly time scale and sums the individual appliances to generate an electricity load profile for an average household.

The agent-based modeling differs from those generally used for prediction in a number of significant ways. Firstly, the statistical models that use historical data have difficulty in modeling a new device like an EV. The widespread adoption of EVs will have a significant impact on the electrical load profile of the system. The bottom-up approach provides an accurate representation on the EV adoption and hence benefits that the macro-level predictions cannot provide. Furthermore, because of the flexibility in programming, the EV adoption can be incorporated while accounting for localized effects. For instance, the driving pattern differs for each part of the system under consideration. The EV system parameters such as time of charge and amount of charge (depends on the average miles traveled per day) can be different for different geographic parts of the system.

3.3.1 The Dataset

The main datasets used in the work are gathered from the *United States Energy Information Administration's Residential Energy Consumption Survey* [34]. The datastes used are as shown in Tables 3.2, 3.3 and 3.4.

The appliance characteristic is shown in Table 3.2. The descriptions of the columns are as follows:

- The appliance saturation level indicates the percentage of households that possess the appliance.
- Weekday/Weekend Frequency indicates the number of times an appliance is used on a given day.
- The wattage (W) specifies the range of wattages for the appliances.
- The average annual kWh consumption of the appliance. This value would be converted to average daily kWh consumption for modeling purposes.

The weekday/weekend starting probabilities is as shown in Tables 3.3 and 3.4. This data will be used in the simulation for ON/OFF switching of the appliances.

[1]Modeled with control loop and based on thermal cycles. Hence, values would vary based on the building construction area.

[2]Very negligible amount

Table 3.2: Appliance characteristics [34]

ApplianceName	**Saturation**	**Weekday Frequency**	**Weekend Frequency**	**Wattage(W)**	**Annual kWh Consumption**
Stove and Oven 1	0.70428	0.7	0.7	1200-2200	1000
Stove and Oven 2	0.70428	1	1	1200-2200	1000
Stove and Oven 3	0.70428	0.6	0.65	1200-2200	1000
Microwave Oven	0.89105	0.98	1	150-1200	209
Coffee Maker	0.63035	0.98	1	900-1200	116
Refrigerator	1	45	45	725	1239
2nd Refrigerator	0.22568	45	45	725	1239
Freezer	0.3463	45	45	375	1039
Dishwasher	0.56809	0.7	0.75	1200-2400	512
Clothes Washer	0.77432	0.88	0.88	350-500	120
Electric Dryer	0.69261	0.78	0.78	1800-5000	1079
Television	1	2.1	2.2	110-130	137
2nd Television	0.80545	0.3	0.33	110-131	138
3rd Television	0.45914	0.3	0.33	110-132	139
Set Top Box	0.78	0	0	20-25	70
Video Recorder	0.7354	0	0	20-25	70
DVD	0.80934	0	0	20-25	70
Radio/Player	0.72763	4.18	4.54	70-400	81
Prsnl. Comp.	0.69261	3	3.15	270	262
Printer	0.60311	0.78	0.85	600	216
Lighting	1	18	26	500-1500	940
Other Loads	1	5	5	100-900	1000
Central A/C	0.64202	0.85	0.95	[1]	2796[1]
Room A/C	0.29183	0.85	0.95	[1]	950[1]
Elec. Water Htr.	0.60311	11	13	4500-5500	2552
Telephone	0.80545	0	0	[2]	[2]
Answering Machine	0.54864	0	0	[2]	[2]
Elec. Spc Hting.	0.40856	2.5	2.75	[1]	3524[1]
Pool Pump	0.03113	10	12	1000	1500

Table 3.3: Appliance weekday starting probability [34]

	Hour																							
ApplianceName	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Stove and Oven 1	0.21	0.21	0.21	1.07	3.20	4.27	4.27	4.27	4.27	4.41	4.58	4.43	4.15	4.76	6.18	7.72	12.13	12.13	7.72	4.41	1.88	1.10	0.33	0.40
Stove and Oven 2	0.21	0.21	0.21	1.07	3.20	4.27	4.27	4.27	4.27	4.41	4.58	4.43	4.15	4.76	6.18	7.72	12.13	12.13	7.72	4.41	1.88	1.10	0.33	0.40
Stove and Oven 3	0.21	0.21	0.21	1.07	3.20	4.27	4.27	4.27	4.27	4.41	4.58	4.43	4.15	4.76	6.18	7.72	12.13	12.13	7.72	4.41	1.88	1.10	0.33	0.40
Microwave Oven	0.20	0.20	0.40	0.40	1.78	2.59	3.19	3.83	3.70	4.13	4.29	4.15	3.89	4.46	5.79	8.76	10.00	10.30	9.24	8.15	5.82	2.79	1.51	0.36
Coffee Maker	0.20	0.20	0.40	0.40	1.78	2.59	3.19	3.83	3.70	4.13	4.29	4.15	3.89	4.46	5.79	8.76	10.00	10.30	9.24	8.15	5.82	2.79	1.51	0.36
Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
2nd Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
Freezer	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
Dishwasher	2.33	2.33	2.33	2.42	2.59	3.46	4.06	4.32	4.32	4.15	3.98	3.89	4.15	4.67	4.93	5.19	5.62	6.40	7.09	7.52	5.62	3.46	2.85	2.33
Clothes Washer	2.60	1.80	1.60	1.60	1.60	2.08	3.20	4.40	5.60	5.64	5.20	4.80	4.40	4.40	4.80	5.00	5.32	5.40	5.48	5.60	5.72	5.80	4.80	3.20
Tumble Dryer	2.60	1.80	1.60	1.60	1.60	2.08	3.20	4.40	5.60	5.64	5.20	4.80	4.40	4.40	4.80	5.00	5.32	5.40	5.48	5.60	5.72	5.80	4.80	3.20
Television	0.73	0.37	0.37	0.37	0.73	1.10	1.46	1.83	2.19	2.56	2.92	3.65	4.02	4.38	4.74	5.47	6.93	9.12	12.04	13.87	11.31	6.20	2.55	1.10
2nd Television	0.73	0.37	0.37	0.37	0.73	1.10	1.46	1.83	2.19	2.56	2.92	3.65	4.02	4.38	4.74	5.47	6.93	9.12	12.04	13.87	11.31	6.20	2.55	1.10
3rd Television	0.73	0.37	0.37	0.37	0.73	1.10	1.46	1.83	2.19	2.56	2.92	3.65	4.02	4.38	4.74	5.47	6.93	9.12	12.04	13.87	11.31	6.20	2.55	1.10
Set Top Box	2.40	1.20	0.70	0.60	0.70	1.30	2.10	2.45	3.35	3.20	3.20	3.84	3.84	4.00	4.80	6.39	7.99	7.99	7.99	9.59	7.99	6.39	4.80	3.20
Video Recorder	2.40	1.20	0.70	0.60	0.70	1.30	2.10	2.45	3.35	3.20	3.20	3.84	3.84	4.00	4.80	6.39	7.99	7.99	7.99	9.59	7.99	6.39	4.80	3.20
DVD	2.40	1.20	0.70	0.60	0.70	1.30	2.10	2.45	3.35	3.20	3.20	3.84	3.84	4.00	4.80	6.39	7.99	7.99	7.99	9.59	7.99	6.39	4.80	3.20
Radio/Player	2.40	1.20	0.70	0.60	0.70	1.30	2.10	2.45	3.35	3.20	3.20	3.84	3.84	4.00	4.80	6.39	7.99	7.99	7.99	9.59	7.99	6.39	4.80	3.20
Personal Computer	2.40	1.20	0.70	0.60	0.70	1.30	2.10	2.45	3.35	3.20	3.20	3.84	3.84	4.00	4.80	6.39	7.99	7.99	7.99	9.59	7.99	6.39	4.80	3.20
Printer	2.40	1.20	0.70	0.60	0.70	1.30	2.10	2.45	3.35	3.20	3.20	3.84	3.84	4.00	4.80	6.39	7.99	7.99	7.99	9.59	7.99	6.39	4.80	3.20
Lighting	1.89	1.68	1.89	2.10	3.15	4.20	3.99	3.36	3.15	2.94	2.73	2.10	2.10	2.10	2.31	3.15	4.20	8.40	11.55	11.55	9.45	6.30	3.36	2.31
Other Occasional Loads	1.03	0.83	0.83	0.83	1.03	2.04	3.06	3.24	3.44	3.54	3.64	3.74	3.94	4.14	4.55	4.96	5.79	6.70	7.71	8.51	9.01	8.10	5.67	3.66
Central Air Conditioning	1.49	1.22	1.02	0.68	0.54	0.50	0.45	1.04	1.22	1.63	2.85	3.73	5.15	7.18	9.19	10.57	11.25	10.98	9.08	6.50	5.15	3.73	2.85	2.03
Room Airconditioning	1.49	1.22	1.02	0.68	0.54	0.50	0.45	1.04	1.22	1.63	2.85	3.73	5.15	7.18	9.19	10.57	11.25	10.98	9.08	6.50	5.15	3.73	2.85	2.03
Water Heater	1.40	0.80	0.90	1.10	2.00	4.40	8.90	10.70	8.90	6.60	5.20	3.80	3.60	3.30	3.20	2.60	4.20	4.80	5.20	4.70	4.20	3.90	3.60	2.20
Telephone	3.40	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.40	3.88	4.85	4.85	5.93	6.13	6.80	6.80	6.80	7.77	8.25	6.80	5.34	4.85	3.88
Answering Machine	3.40	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.40	3.88	4.85	4.85	5.93	6.13	6.80	6.80	6.80	7.77	8.25	6.80	5.34	4.85	3.88
Electric Space Heating	3.44	2.99	3.01	3.14	3.31	4.12	5.37	5.59	5.54	5.05	4.64	4.43	4.17	3.69	3.57	3.48	3.93	4.73	4.85	4.81	4.64	4.17	3.95	3.39

Table 3.4: Appliance weekend starting probability [34]

	Hour																							
ApplianceName	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Stove and Oven 1	0.37	0.05	0	0	0	0.17	1.72	2.65	4.37	5.94	6.97	7.86	7.92	7.15	6.39	5.89	6.78	7.41	7.32	7.23	6.93	4.09	2.3	1.02
Stove and Oven 2	0.37	0.05	0	0	0	0.17	1.72	2.65	4.37	5.94	6.97	7.86	7.92	7.15	6.39	5.89	6.78	7.41	7.32	7.23	6.93	4.09	2.3	1.02
Stove and Oven 3	0.37	0.05	0	0	0	0.17	1.72	2.65	4.37	5.94	6.97	7.86	7.92	7.15	6.39	5.89	6.78	7.41	7.32	7.23	6.93	4.09	2.3	1.02
Microwave Oven	0.37	0.05	0	0	0	0.17	1.72	2.65	4.37	5.94	6.97	7.86	7.92	7.15	6.39	5.89	6.78	7.41	7.32	7.23	6.93	4.09	2.3	1.02
Coffee Maker	0.37	0.05	0	0	0	0.17	1.72	2.65	4.37	5.94	6.97	7.86	7.92	7.15	6.39	5.89	6.78	7.41	7.32	7.23	6.93	4.09	2.3	1.02
Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
2nd Refrigerator	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
Freezer	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17	4.17
Dishwasher	1.73	0.96	0.4	0.4	0.4	0.96	1.73	2.93	3.75	4.58	4.68	4.68	4.68	4.68	4.68	6.11	6.83	7.16	7.8	8.6	8.16	7.01	5.05	2.03
Clothes Washer	1.73	0.96	0.4	0.4	0.4	0.96	1.73	2.93	3.75	4.58	4.68	4.68	4.68	4.68	4.68	6.11	6.83	7.16	7.8	8.6	8.16	7.01	5.05	2.03
Tumble Dryer	1.73	0.96	0.4	0.4	0.4	0.96	1.73	2.93	3.75	4.58	4.68	4.68	4.68	4.68	4.68	6.11	6.83	7.16	7.8	8.6	8.16	7.01	5.05	2.03
Television	3.4	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.4	3.88	4.85	4.85	5.93	6.13	6.8	6.8	6.8	7.77	8.25	6.8	5.34	4.85	3.88
2nd Television	3.4	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.4	3.88	4.85	4.85	5.93	6.13	6.8	6.8	6.8	7.77	8.25	6.8	5.34	4.85	3.88
3rd Television	3.4	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.4	3.88	4.85	4.85	5.93	6.13	6.8	6.8	6.8	7.77	8.25	6.8	5.34	4.85	3.88
Set Top Box	3.4	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.4	3.88	4.85	4.85	5.93	6.13	6.8	6.8	6.8	7.77	8.25	6.8	5.34	4.85	3.88
Video Recorder	3.4	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.4	3.88	4.85	4.85	5.93	6.13	6.8	6.8	6.8	7.77	8.25	6.8	5.34	4.85	3.88
DVD	3.4	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.4	3.88	4.85	4.85	5.93	6.13	6.8	6.8	6.8	7.77	8.25	6.8	5.34	4.85	3.88
Radio/Player	3.4	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.4	3.88	4.85	4.85	5.93	6.13	6.8	6.8	6.8	7.77	8.25	6.8	5.34	4.85	3.88
Personal Computer	3.4	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.4	3.88	4.85	4.85	5.93	6.13	6.8	6.8	6.8	7.77	8.25	6.8	5.34	4.85	3.88
Printer	3.4	1.94	0.87	0.77	0.87	0.97	0.97	1.46	2.43	3.4	3.88	4.85	4.85	5.93	6.13	6.8	6.8	6.8	7.77	8.25	6.8	5.34	4.85	3.88
Lighting	1.03	0.33	0.33	0.83	1.78	2.64	3.56	3.74	3.44	3.04	3.04	3.24	3.94	4.14	4.55	4.96	5.79	6.7	8.21	9.11	9.81	8.5	4.32	2.96
Other Occasional Loads	2.55	1.33	1.23	1.23	1.33	1.73	2.13	3.55	4.07	3.99	3.77	3.97	4.07	4.47	4.97	6	6.32	6.84	7.34	7.56	6.79	6.67	4.84	3.22
Central Air Conditioning	1.491	1.220	1.016	0.678	0.542	0.501	0.447	1.043	1.220	1.626	2.846	3.726	5.149	7.182	9.187	10.569	11.247	10.976	9.079	6.504	5.149	3.726	2.846	2.033
Room Airconditioning	1.491	1.220	1.016	0.678	0.542	0.501	0.447	1.043	1.220	1.626	2.846	3.726	5.149	7.182	9.187	10.569	11.247	10.976	9.079	6.504	5.149	3.726	2.846	2.033
Water Heater	1.8	1	0.9	0.8	1.5	2.3	2.6	4.7	7.7	8.3	7.4	6.1	5.1	4.3	3.9	3.9	5.2	5.8	5.6	5.2	4.7	4.4	4	2.8
Telephone	2.4	1.2	0.7	0.6	0.7	1.3	2.1	2.45	3.35	3.2	3.2	3.84	3.84	4	4.8	6.39	7.99	7.99	7.99	9.59	7.99	6.39	4.8	3.2
Answering Machine	2.4	1.2	0.7	0.6	0.7	1.3	2.1	2.45	3.35	3.2	3.2	3.84	3.84	4	4.8	6.39	7.99	7.99	7.99	9.59	7.99	6.39	4.8	3.2
Electric Space Heating	3.437	2.986	3.008	3.136	3.308	4.125	5.371	5.585	5.542	5.048	4.640	4.425	4.168	3.695	3.566	3.480	3.931	4.726	4.855	4.812	4.640	4.168	3.953	3.394

3.4 Agent-based Modeling using GridLAB-D™

3.4.1 Classification of Load

The open source power system simulation software GridLAB-D™ is used for load modeling in this work. It is developed by *The Pacific Northwest National Laboratory*. It has an agent-based residential building demand simulation module that is used for demand prediction of residential houses. For the purpose of modeling, end-use appliances are split into two categories: simple time invariant loads without thermal cycle and complex time variant loads with thermal cycle. The simple time invariant appliances are modeled as a voltage dependent power consuming device, and there is no control loop that turns the device ON or OFF. The power consumed is constant when the device is switched ON. On the other hand, devices with thermal cycles have a control loop to turn ON or turn OFF the device. The switch ON or OFF is managed by the control logic programmed into the HVAC controller.

Simple time invariant loads without a thermal cycle

For appliances without thermal cycle, the obtained dataset is used to model the appliance. The loads are split into two categories based on their load shape [35]: analog load shapes and pulsed load shapes.

1. Appliance with analog load shapes

   Analog load shapes (Figure 3.2) are used for loads that are constantly present in the system. The amount of power consumption varies throughout the hours. The starting probability for these loads is used as the percentage of energy consumed at that hour. So, given the total consumption over the entire day, the starting probability denotes the percentage of energy spent at that hour. In GridLAB-D™, an analog loadshape is defined using the following form [35]:

   ```
   object plugload {
   ```

```
name ‘lights‘;
shape "type: analog;
 schedule: light_start_probability;
 energy:Daily Energy Consumption";
};
```

The ‘energy’ or ‘power’ parameter could be used interchangeably as constant power (kW) over an hour is the energy (kWh) consumed in that hour. In the household model, lights and other occasional loads are modeled using analog load shapes.

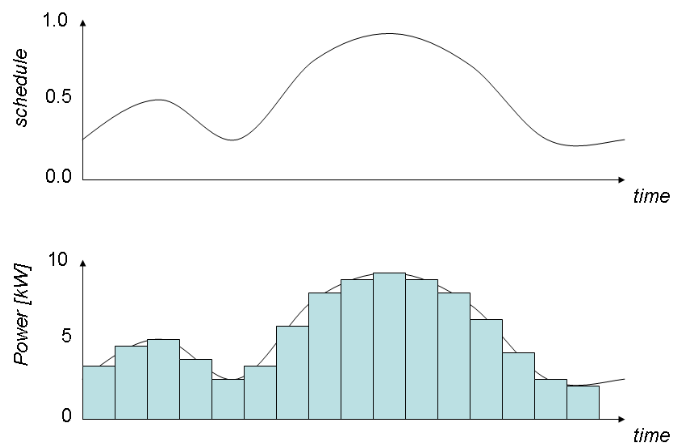

Figure 3.2.: Analog load Shapes [35]

2. Appliance with pulsed load shape

   Pulsed load shapes (Figure 3.3) are used for appliances that switch ON and switch OFF in a given time frame. In other words, these appliances consume power in the form of a pulse. Most appliances are not ON throughout the day and hence their energy consumption is modeled as a pulse. Pulsed loadshapes emit 1 or more pulses at random times such that the total energy is accumulated over the period of the loadshape. The random times are defined by the starting probabilities at each hour. In GridLAB-D™, a pulsed loadshape is defined using the following form [35]:

```
object sample {
   myshape "type: pulsed;
    schedule: schedule-name;
    energy: value kWh;
    count: value;
    power: value kW";
}
```

In this form, the 'schedule' specifies the starting probability, the 'energy' specifies the average daily energy consumption, 'power' specifies the power rating of the appliance and 'count' denotes the number of pulses, i.e. the frequency of switching-on. All these values are obtained from the dataset mentioned above. Given that the power is constant, the duration of the pulse will vary that the amount of energy consumed in the given time-period (day) is as specified.

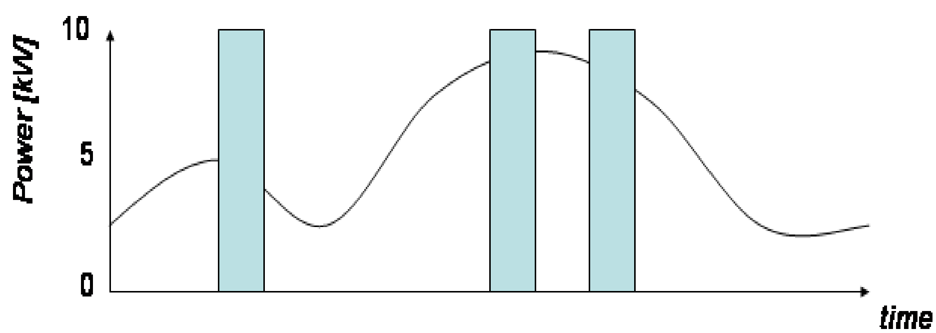

Figure 3.3.: Pulsed load shape [35]

Most of the appliances are modeled using the pulsed load shape. This model is efficient in modeling the household as it accounts for the power rating of the appliance, daily energy consumption and most importantly the occupant behavior through the starting probabilities. It is inherently simple and easy to implement provided the necessary data is available.

Complex time variant loads with a thermal cycle

Devices with thermal cycles are relatively more difficult to model. The power consumption is acquired by building a physical/engineering model of the system accurately. In addition the control logic is also specified to modulate the behavior of the system. For these devices, the control system will adjust the duty cycle such that the output energy satisfies the control requirements. Many of the large end-use appliances have thermal cycles. Basically, those devices that emit enough heat to affect the surrounding air temperature are included in the thermal model of the house. These include, but not limited to, HVAC, hot water heating, refrigerators, ovens and clothes dryers. In our model, we have used a detailed physical/thermal model of the HVAC alone. Usually, the HVAC is the largest appliance with a thermal cycle in a house. The HVAC system tries to maintain the set temperature inside the house. Several external factors such as heating degree day, cooling degree day, outside temperature and building material affect the energy consumption. To account for the interactions, a thermal model of the house is constructed using an equivalent thermal model (ETP) of the house [35,36]. The ETP model has been proved to be very efficient in providing accurate representation of building energy consumption [36].

Figure 3.4 [36] depicts the ETP model of a house. It shows the path of heat flow within a house. There are three sources of heat: solar radiation, internal gains that accumulate through heat produced by the appliances and the HVAC that is set to regulate the temperature within the house. The total heat affects the air temperature and the temperature of mass (walls, furniture, etc.) in the house. The air temperature of the house is thermally coupled with the outside air temperature, through the building material (thermal envelop), and the mass temperature. The model can be represented by a set of second order differential equations [35, 36].

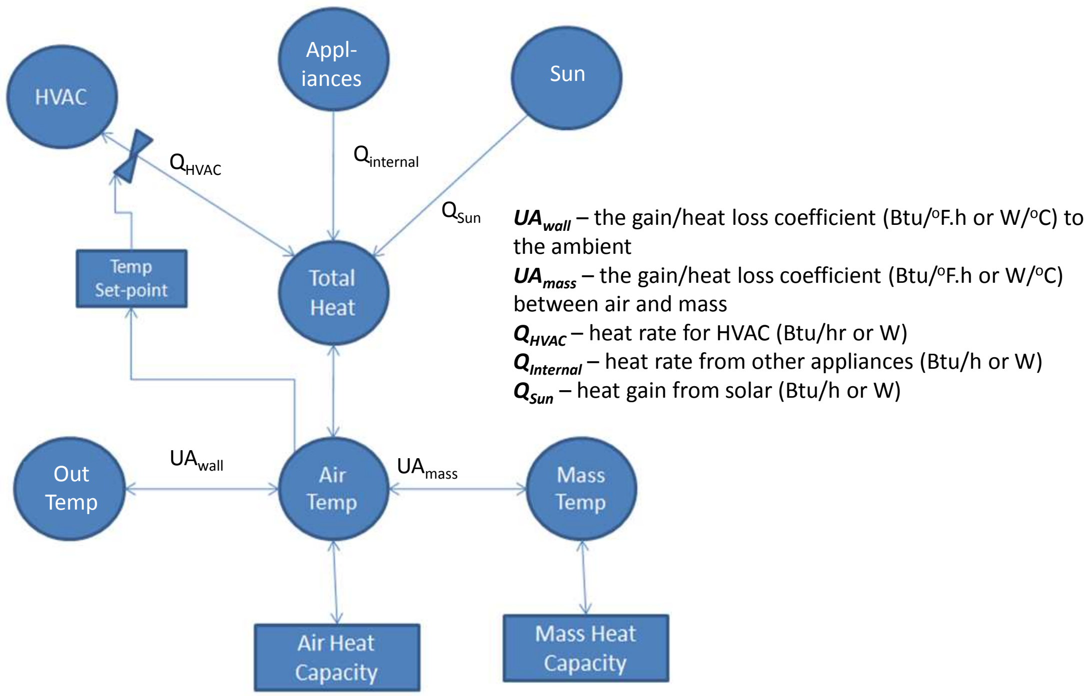

Figure 3.4.: The ETP model of a house

These equation are used in determine the important thermal characteristic of the house. The solution to these equations determines the air temperature and thereby the energy consumption of the HVAC system.

3.4.2 Household Model Simulation

To simulate the electricity consumption of the household, the open-source GridLAB-D™ simulation environment is used. All the devices in the appliance list are included in the model. Only HVAC is modeled as a time-variant complex system with thermal cycles. All the other devices are modeled as a simple time-invariant system without a thermal cycle. The starting probability of the devices reflects the occupant behavior most effectively. The HVAC system operates based on the outside temperature. Figure 3.5 shows the simulated power consumption of the HVAC, and also depicts the relation between the outside temperature and the HVAC energy consumption. As outside temperature increases above a certain point, the HVAC works to cool down the house and hence consumes more energy. Similarly, as outside temperature decreases below a certain point, the HVAC works to heat-up the house. This relationship is well observed in the model.

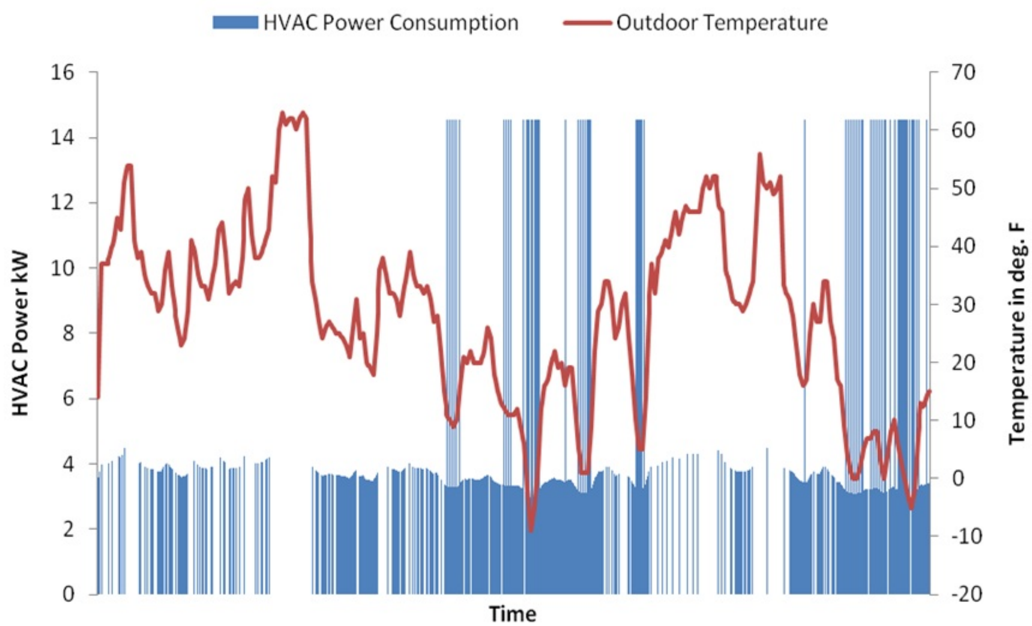

Figure 3.5.: Relationship between the outdoor temperature and HVAC power consumption

The other simple appliances use the power schedule obtained from national averages in the modeling. The switch-ON/switch-OFF characteristics and power consumption pattern of the appliance are as shown in Figure 3.6. The simulation environment provides measurement at different time intervals. The total power consumption of the household is as shown in Figure 3.7.

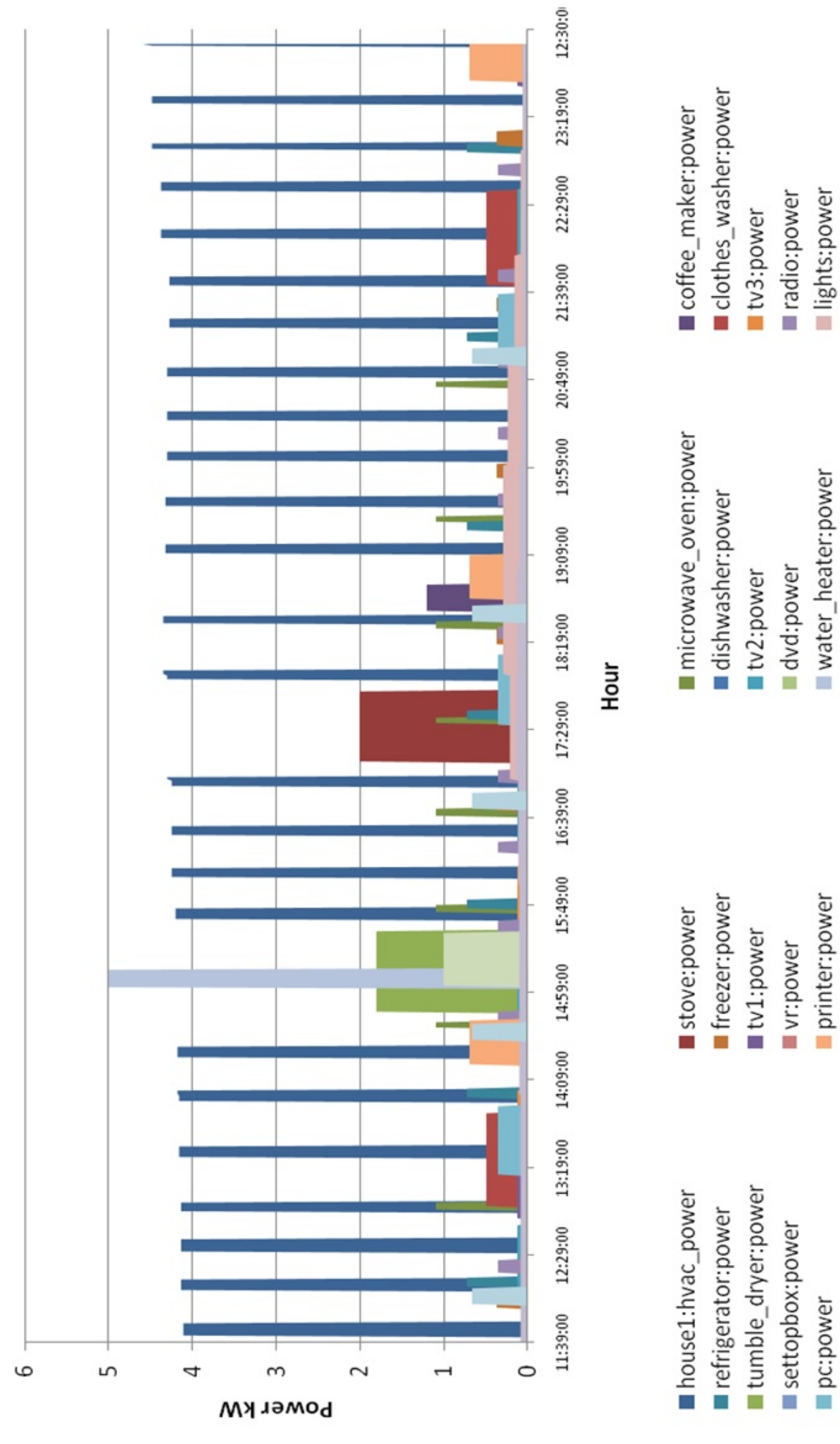

Figure 3.6.: Power consumption characteristics of the appliances

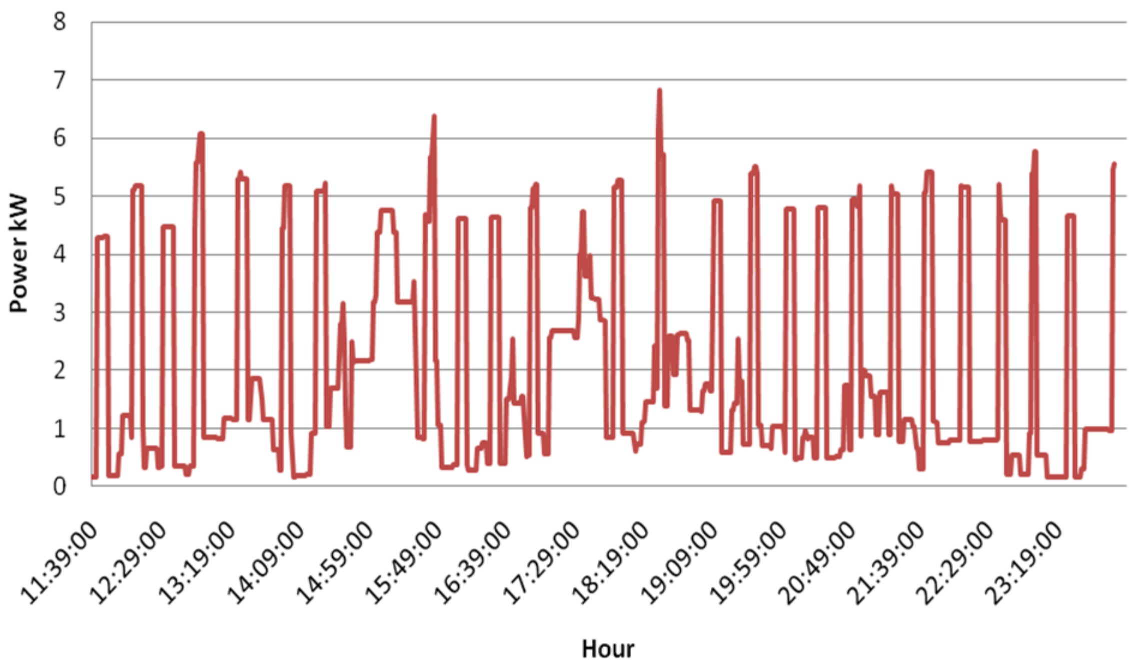

Figure 3.7.: Total household power consumption

4. DISTRIBUTION SYSTEM IMPACTS - TRANSFORMER MODELING

4.1 Introduction

Distribution systems function as the serving end of a power system. Distribution transformers are responsible for stepping-down distribution level voltage (7.96kV/13.8kV) to residential level voltages. Depending on the household characteristics of the customer, the number of customers connected to a single transformer varies. In all cases, transformers are designed for specific load capability based on the expected power demanded by the customer(s). When EVs are connected to the grid, it manifests as a large unexpected load that is not accounted for in the distribution system planning. The distribution system is planned to withstand momentary heavy loads. But a sustained heavy load such as EVs would pose certain complications. This chapter explains how the impact on the distribution level transformer is evaluated.

To evaluate the impact of this scenario on the system, it is necessary to model the distribution system. The modeling procedure consists of four procedures: residential household modeling, center-tapped transformer modeling, electro-thermal transformer modeling and loss-of-life calculation. The residential household containing standard appliances and EV is modeled in GridLAB-D^{TM}. Demand is simulated for an entire year, taking into account the weather conditions. The distribution transformer serving the household(s) is also modeled in the simulation. This simulation model will be elaborated later in terms of power flow in the distribution. Using the power flow module of the simulation, the current flow through the transformer for a particular household load pattern is obtained from the model.

The study focuses on evaluating the capability of a power system to handle new loads. The transformers are an integral component of the distribution system that is more likely to be affected due to localized heavy loads. The heavy loads draw large currents from the secondary (customer-end) of the transformer causing rise of temperature in the different transformer components. An electro-thermal model of a transformer is used to evaluate various components of the system and subsequent evaluation of the adequacy of the system and/or the evaluation of the risk of failure. For the transformers, we can evaluate the loss of life for specific temperature profiles of the transformer.

Simulations are performed using two systems in the study. The residential household and center-tapped distribution transformer is modeled in GridLAB-D™, while the electro-thermal model and loss-of-life calculation of the transformer is performed in Matlab. Using the household and transformer simulation, the currents through the transformer winding is calculated. With knowledge of the currents in the transformer windings, the temperature of the windings can be calculated using a simplified first-order electro-thermal model. The temperature evolution is computed from the electro-thermal model of the system components. Based on transformer winding temperature, the hot spot temperature of the transformer, loss of life, and expected life can be calculated over a planning period.

Two scenarios are examined. In the first case, the homeowners do not own any EVs. In the second case, we assume that each homeowner owns one EV. We focus on the impact on distribution transformers. Specifically, we compare the loss of life and expected life of a distribution transformer for these two cases.

The test system, consists of a medium voltage distribution transformer (7.96 kV to 120/240 V, 15 kVA) feeding a residential circuit. Three-phase overhead transmission lines deliver the power to the center-tapped distribution transformer that serves three houses. To charge the EVs, the following assumption is made. The owners of the house use their 120 V, 15 A garage outlets to charge their cars.

4.2 Residential Household Model

A customer's household is modeled by using the residential module of GridLAB-D^{TM}. Estimating end-use consumption that accurately reflects the magnitude, average hourly shape, and probability and variance of the load is critical for the household simulation to work. The household simulation accounts for the simulation of standard home appliances in a typical house. Since only the effects on a single distribution transformer are studied, a house from a wealthy neighborhood is simulated using the simulation methodology described in the previous chapter. The EV is added as another appliance to evaluate its impacts on the transformer.

4.2.1 EV Electrical Load

The added electric load due to EV charging is based on two parameters that are obtained from the EV modeling. The arrival time of the vehicles and the distance traveled by the vehicle are used in calculating the consequent EV demand. For the high incomes zones, arrival time (Figure 2.5) and trip distance (Figure 2.6) distribution are used to generate the required parameters.

Along with the residential model, the EV is added as an appliance by employing these parameters. In the GridLAB-D^{TM} model, the hourly vehicle flow is translated as schedule and the vehicle miles traveled is converted to energy consumption. For a Nissan Leaf, 24 kWh battery capacity can be used to travel 100 miles. That would be translated to .24 kWh/mile. In essence, the electric vehicle charging characteristic are derived from the conditional miles driven and arrival time probabilities as shown in Figure 4.1, which is similar to the charging pattern used in Taylor at al. [30].

4.3 Center-Tapped Single Phase Distribution Transformer

The power-flow module of GridLAB-D^{TM} is used in the computation of the currents through a transformer. The power-flow module is a fundamental power system

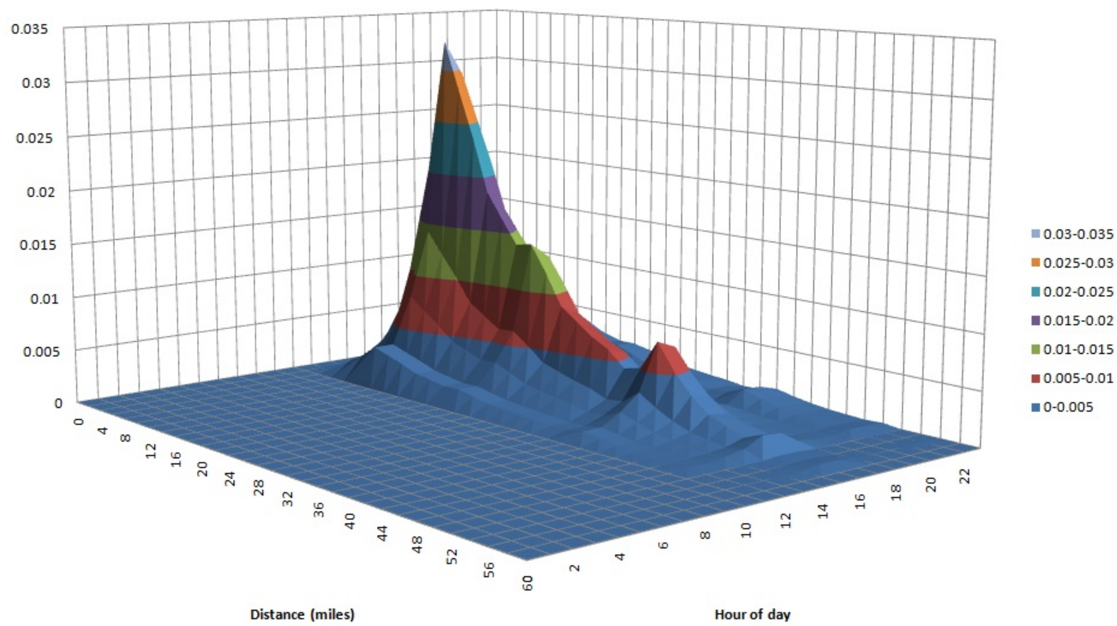

Figure 4.1.: Conditional miles driven and arrival time probabilities

analysis tool. Given the voltage of the three-phase distribution feeder (a conductor which carries power from one equipment to another) and the load on the transformer, it determines voltage at all points (nodes, transformers) on the distribution system. This in turn defines the currents on the system and indicates if the system is properly loaded.

The typical residential distribution system distribution transformer model is used to compute the expected transformer currents for a specified electric load demand. The model, shown in Figure 4.2, is fully described in [37]. The specific scenario modeled here is a single phase distribution transformer feeding a house. The transformer is a 7.960 kV to 120/240 V transformer rated at 15 kVA. The transformer has a series resistance R_A and reactance X_A of 0.007 p.u. and 0.035 p.u. respectively [37].

Figure 4.2 shows a center-tapped single phase distribution transformer. Z_0, Z_1, and Z_2 are transformer winding impedances. Usually, three wires (triplex) are available

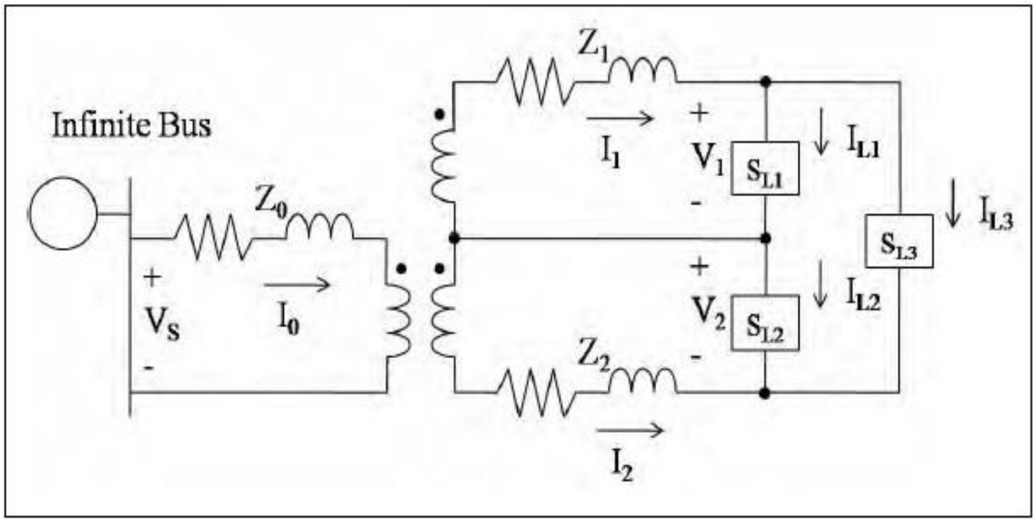

Figure 4.2.: Equivalent circuit of a split-phase transformer model [37]

at the customer end. S_{L1} and S_{L2} are 120V (V_1 and V_2) loads. Loads that require 240V (V_1 + V_2) is represented by S_{L3}. To compute the winding impedances Z_0, Z_1, and Z_2 the interlaced transformer design equations are used [37].

To compute the winding currents I_0, I_1, and I_2 in the above figure an iterative process from [37] is utilized. The GridLab-D^{TM} simulation uses the forward-sweep and backward sweep procedure [37] to calculate the winding currents. The method outlined in [10,37] to compute the transformer currents is an iterative process consisting of a forward sweep and a backward sweep. The forward-sweep/backward-sweep method is a fast algorithm that is used to solve for power-flow equations in distribution systems. Figure 4.3 shows the simulation results for the base case scenario (BC) and again for the EV scenario. These currents form the input to the electro-thermal transformer model, which is in turn used to compute the expected distribution transformer temperature, and thus the distribution transformer loss-of-life.

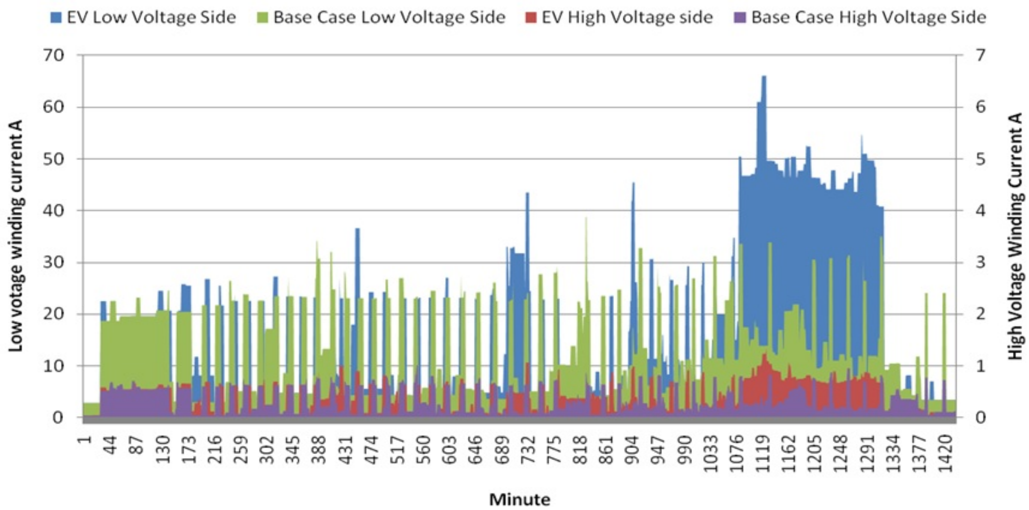

Figure 4.3.: Sample scenario transformer current for the low voltage (Low V) and high voltage (High V) side windings

4.4 Hourly Electro-Thermal Hot-Spot Temperature Computation

A simplified electro-thermal transformer model [10] of a center-tapped single phase convection cooled distribution transformer is shown in Figure 4.4.

The nodes in Figure 4.4 represent:

- The high voltage winding (node h).
- The low voltage winding center tap 1 (node 1).
- The low voltage winding center tap 2 (node 2).

Each circuit element represents a thermal phenomenon: the conductance components ($G_{x,x}$) represent heat transfer within and between the transformer windings (estimated from temperature gradients between transformer windings [10]); the capacitive components ($C_{x,x}$) represent transformer winding thermal inertia (computed from the winding mass and winding specific heat constant [10]); and the current sources represent heat sources in the form of ohmic losses in each of the transformer windings.

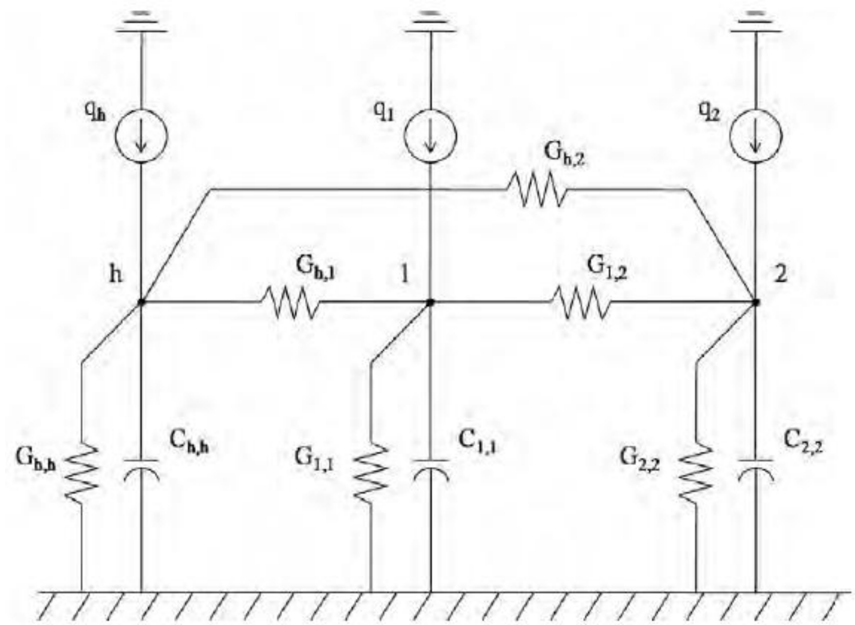

Figure 4.4.: Electrothermal model of a transformer [10]

The detailed description of the modeling procedure and dynamics of the transformer winding temperatures is found in AP Meliopolous et al [10, 11]. The numeric values of the circuit parameters chosen were analytical computed and experimentally verified [10].

The input to the above model is the transformer currents I_h, I_1, and I_2 over a specific time period, typically one day. The result from the modeling is the estimated transformer temperature over the simulated time span. In the mentioned models, the circuit parameters of the electro-thermal model are dependent on ambient temperature. A flat ambient temperature of 20° C is assumed for simplicity and ease of calculation.

The hot-spot temperature is defined as the maximum winding temperature in a given hour. Thus, the transformer currents, from the center-tapped single phase distribution transformer, are sampled every 10 seconds as input to the electro-thermal transformer model simulation. The final result of this simulation (Figure 4.5) is the hot-spot temperature of the distribution transformer, which is the maximum temperature observed from each hour of the simulated day.

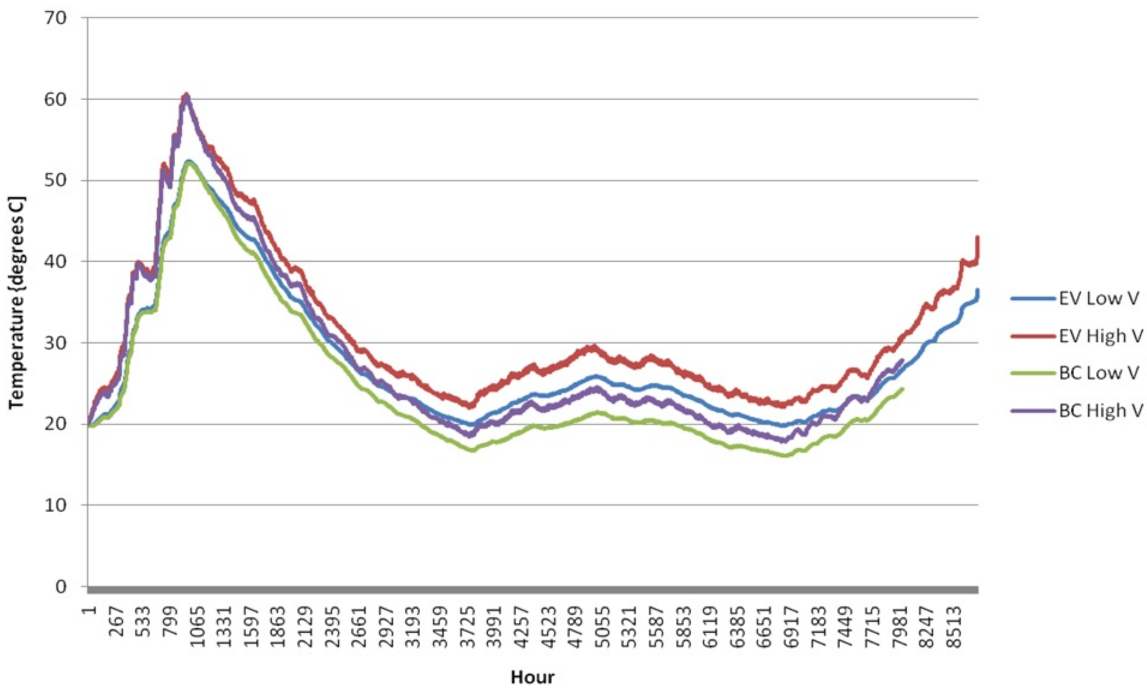

Figure 4.5.: Simulated high/low voltage side winding temperature

In both scenarios the high voltage winding currents are significantly smaller in amplitude then the low voltage winding currents; as shown in Figure 4.3. The next step in the transformer impact simulation is to compute the hot-spot winding temperature for both scenarios ("BC" and "EV"). The hot spot temperature ($\tilde{T}$) is the maximum winding temperature(T) in a given hour. Based on the winding temperatures in Figure 4.5, the windings hot-spot temperatures is obtained and shown in Figure 4.6.

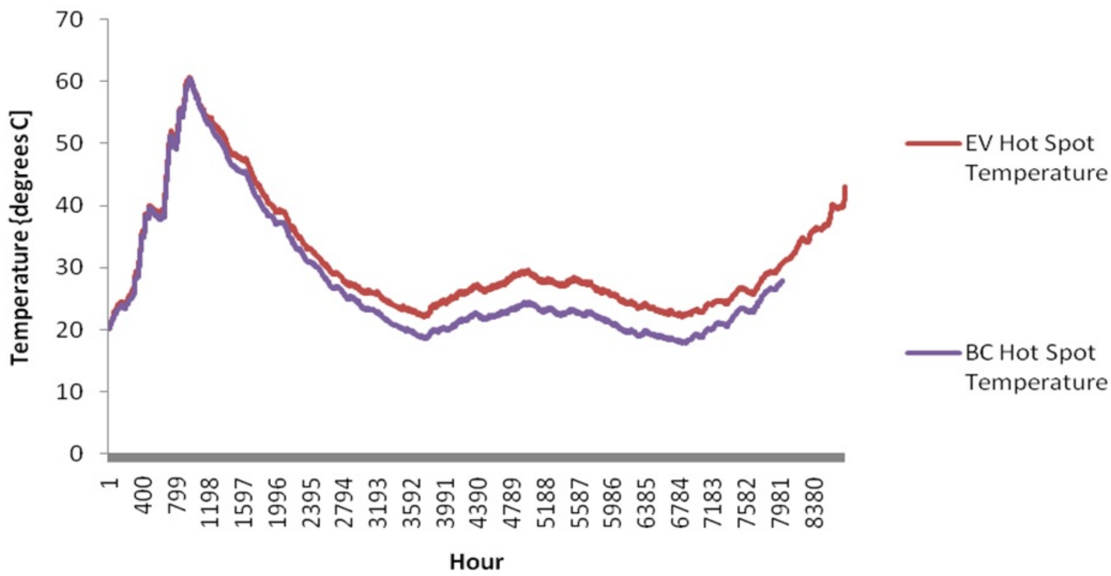

Figure 4.6.: Hot-spot temperatures

4.5 Transformer Loss-of-Life Computation

The fourth step in the distribution system impact analysis is the transformer loss-of-life calculation. The process of insulation degradation, for oil filled transformer, is a function of three phenomena (1) temperature, (2) moisture, and (3) oxygen content [10, 38]. The later two consist of water and oxygen contamination of the oil inside the transformer and can be controlled through "oil preservation systems" and thus are not considered in the analysis. The method described in [10, 38] is used to calculate the transformer loss-of-life.

The transformer hot-spot temperature ($\tilde{T}^{\circ}$ C) is used to calculated the aging acceleration factor θ_u. The aging acceleration factor is used to translate the transformer temperature to insulation degradation. The formula for calculating θ_u at time u is as follows:

$$\theta_u = exp\{\frac{B}{383} - \frac{B}{(\tilde{T}_u + 273)}\}, \tag{4.1}$$

where, B is the aging rate constant in Kelvins [10]. 273 is added to $\tilde{T}_u$ to convert it to Kelvins[K], and 383K is the boiling point of water [10]. θ_u is further used in obtaining the equivalent life E_L of the transformer. The equivalent life is percieved as the loss-of-life of the transformer. For a typical day, the equivalent life is the summation of the hourly aging acceleration factor.

$$E_L = \sum_{u=1}^{U} (\theta_u * \Delta t_u) \tag{4.2}$$

where, Δt_u is 1 hour and U is 24. The loss-of-life, P_L[%], is a function of the equivalent life, E_L, and the normal insulation life, N_L [10,38].The formulation of the loss of life, P_L, is as follows:

$$P_L = \frac{E_L * 100}{N_L}, \tag{4.3}$$

The loss-of-life calculation variables E_L and θ_u are computed for each hour of the simulated day based on the simulated hot-spot temperature $\tilde{T}_u$ in that hour (the maximum simulated transformer winding temperature for a given hour). The loss-of-life constants N_L and B are selected based on the values used in [10, 38].

Using the described method, the loss-of-life is computed for each simulated day for both scenarios, without EV charging (base case) and with EV charging. The simulation is performed for a whole year. Figures 4.7 and 4.8 show the daily loss-of-life distribution for an entire year. By the law of large number, the mean of the results will be the mathematical expectation. For the EV case, the mean loss of life was 7.9237E-05 and for the base case the mean loss of life was 7.06938E-05. Therefore, by having one EV in the system the loss of life of transformers increase by 12.08% 4.4.

$$[1 - (\frac{7.9237E-05}{7.06938E-05}) * 100] = 12.08\%, \tag{4.4}$$

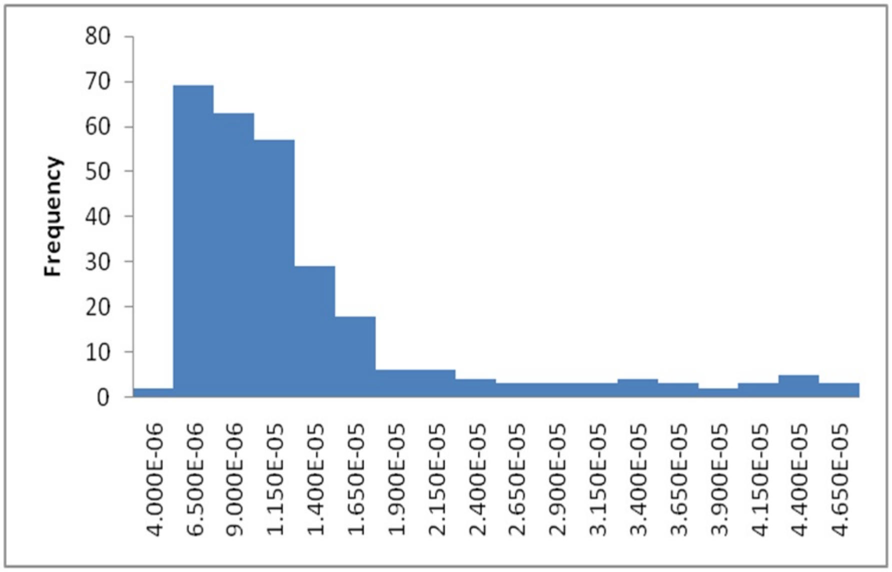

Figure 4.7.: EV loss-of-life histogram-(P_L)

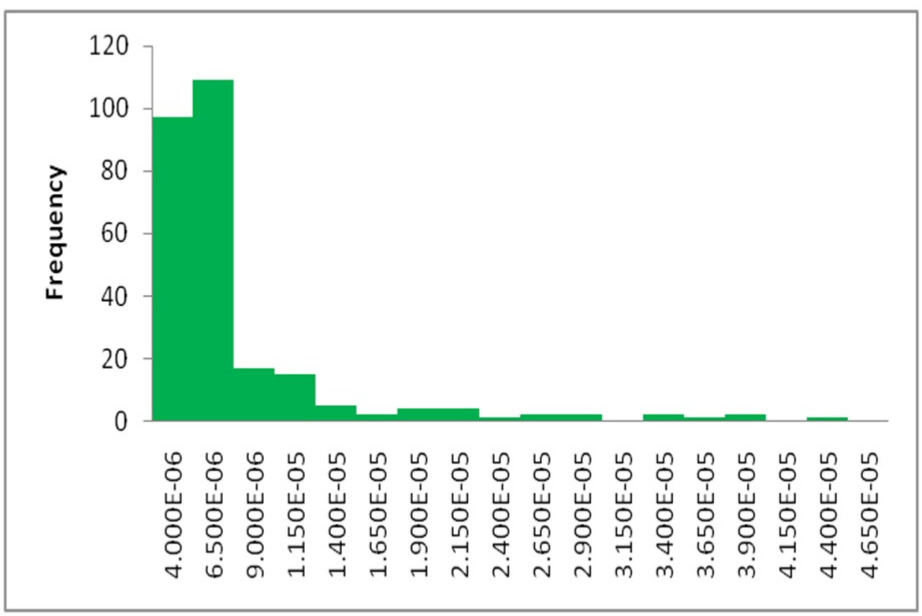

Figure 4.8.: Base Case loss-of-life histogram-(P_L)

5. CONCLUSIONS AND FUTURE WORK

Electric vehicle technology is on the cusp of widespread acceptance. These electric vehicles draw energy from the power grid. As a result, utility companies have an opportunity to increase their revenue by selling more energy. However, utility companies must ensure that the current distribution systems are able to serve the new increased demand. This thesis has elaborated on a detailed modeling mechanism to serve this purpose.

Electric vehicle charging may be controllable (using advanced control mechanisms) or uncontrollable. In either case, there would be an apparent increase in load. As identified in the study, there are three constituent systems: transportation system, residential electricity demand and distribution system (transformers). Earlier studies have concentrated on one or two of the constituent systems [3–9]. To the author's knowledge, no other study had done a detailed modeling of each of the constituent systems. In addition, this study is very practical; the data for traffic analysis is available with most metropolitan transport planning organizations. Other data are obtained from government websites. The work also provides a method which used available data to identify zones that are more likely to be affected first. Utility companies could initially concentrate on the more affluent zones.

The focus of this study has been the relative increase in loss-of-life of transformers due to an electric vehicle. For the given zone, the results show that the increase in loss of life to be around 12%. This value is very similar to the result observed in AP Meliopolous et al. [10]. If the utility company had installed a distribution transformer expecting it to last for 10 years, the life would be reduced to 8.8 years with one electric vehicle in the households connected to that distribution transformer. Charging more electric vehicles would substantially reduce the life of the distribution transformers.

The utility companies could use this study to evaluate the need to upgrade their distribution transformers. Utility companies can either decide to restrict the number of electric vehicles charged from a distribution transformer or install transformer with higher kVA ratings.

The work presented in this thesis is an initial attempt to model the interactions in the electricity system. It has several possible and promising extensions, which could be effectively applied to real world analysis. Firstly, certain analyses can be performed to obtain definite conclusions without modifications to the current model. The residential demand simulation can be run for a long period of time (for example, 5 years or more) to obtain the electric vehicle energy sales. This can be used to calculate the rate of return on tranformer investments. As an extension, different electricity pricing schemes (flat-rate, time-of-use etc.) for electric vehicle charging could be analysed. Similarly, the impact on transformers due to different charging schemes ("instant charging", "as late as possible (ALAP) charging" etc. [9]) could be studied.

Secondly, detailed distribution system studies could be performed. Some of the distribution system impacts that could be studied are: thermal loading, voltage regulation, unbalanced load and losses [8]. Most devices in the distribution system are designed for a particular rating. It is usually designed to withstand short periods of heavy loading (emergency rating). But, prolonged and frequent heavy loading could potentially damage the devices. Thermal loading analysis can be used to measure the strain on the devices and thereby aid in choosing the correct rating of the devices. In a distribution network, the energy consuming devices are expected to be using power at a constant voltage (120V or 240V). This is not the case always. Most devices consume power at varying voltage levels. Because EVs are a major load, the varying voltage levels of EV power consumption could affect the system stability. Detailed analysis could help in distribution system voltage regulation. The three-phase electricity system is built on the premise that the load at each of the phases will be the same. If all the EVs in a distribution system are connected to the same phase, there would serious imbalance in the system. The effects of such an occurance can be analysed. In electricity networks, losses (ohmic) are propotional to square of current flow. For a constant voltage, higher power rating would require more current flow, and thereby more losses. Since EVs have high power rating, having it in the distribution system would increase the losses. It would be very beneficial to analyse the increase in losses. These analyses would require a thorough understanding of the GridLAB-D™ power-system module.

Finally, the model could be expanded to a larger area. For example, the distribution transformer study could be expanded to include the entire distribution network. Sub-station level analysis would be very interesting as large-scale distributed generators are connected to the sub-stations. Also, the potential of using distributed generation to relieve localized effects on tranformers, sub-station, etc. could be studied. In electricity markets, the possibilities and opportunities for change and improvement are great. Detailed modeling and analysis would help in building a stronger and resilient electricity system.

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