DISSERTATION

IMPLICATIONS OF TEMPORALLY AND GEOGRAPHICALLY REALIZED ENERGY USE FOR ELECTRIFIED TRANSPORTATION

Submitted by

Kiran Kambly

Department of Mechanical Engineering

In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Spring 2014

Doctoral Committee:

Advisor: Thomas H. Bradley

Allan Kirkpatrick
Bryan Wilson
Peter Young

ABSTRACT

IMPLICATIONS OF TEMPORALLY AND GEOGRAPHICALLY REALIZED ENERGY USE FOR ELECTRIFIED TRANSPORTATION

Plug in electric vehicles (PEVs) are vehicles that use energy from the electric grid to provide tractive and accessory power to the vehicle. The nonexistent (electric vehicles) or reduced-sized (plug in hybrid vehicles) engine in these vehicles results in high energy conversion efficiencies, lower GHG emissions, and reduced environmental pollution. Consumer demand for these vehicles is limited by their reduced range relative to conventional vehicles. Range limitations in PEVs are primarily due to the lower onboard energy storage capacity of lithium ion (720kJ/kg) relative to gasoline (47.2MJ/kg), and the range sensitivity of PEVs to accessory loads, primarily cabin conditioning loads, is higher. The factors such as local ambient temperature, local solar radiation, length of the trip and thermal soak have been identified to affect the cabin conditioning power requirements and to therefore affect vehicle range. The steady increase in consumer demand for PEVs has resulted in research initiatives by USDOE, the automotive industry and utility industry to overcome these range limitations.

The focus of this research is to develop a detailed systems-level approach to connect HVAC technologies and usage conditions to social, environmental, and consumer-centric metrics of performance. This is accomplished through the development of a toolset that consider transient environmental parameters, real world driver behavior, charging behavior, and regional passenger fleet population for HVAC system operation. The resulting engineering toolset can be used to determine geographical distribution of energy consumption by HVAC systems in electric vehicles,

identify regions of US where EVs can elicit positive user response, evaluate the sensitivity of PEV range to the local weather conditions, identify times of use to extract maximum performance from PEVs, establish HVAC component specifications, and optimize vehicle energy management strategies and technologies. A case study with the alternative accessory technology such as a combination of phase change materials to provide for heating and cooling is explored. The results of this research show that PEV HVAC energy consumption is geographically and temporally disparate, that range variability may be more of a driver of consumer dissatisfaction than actual range, and that HVAC energy management and technologies can reduce the variability in PEV range and may thereby improve PEV consumer acceptability.

ACKNOWLEDGMENTS

I joined Dr Bradley's group in Dec 2009. I moved to Fort Collins, Colorado from Atlanta, Georgia and it was a big change. Dr Bradley advised me to think twice before making my decision to move. I had already fallen in love with the mountains and the serenity of the town during my lab visit trip on Nov 2, 2009. It was an easy decision. I made the commitment to pursue my PhD at mechanical engineering department, Colorado State University.

Naturally, like any graduate student, I was curious to know more about my advisor. I learnt a lot about him by interacting with his students. They all unanimously seemed to be in awe of his personality. I was told that he is like a butterfly, never in one place and always on the move between engineering building, engines lab and MERC. During my first few interactions with him, I would always notice at least two other parties waiting for his appointment. It seemed like everybody wanted a piece of his time and he was doing his best in satisfying the ever-increasing demand, with a smile on his face. Always.

Basavanna, a great medieval Kannada poet from India once said "Kaayakave Kailasa", loosely translated into English, as "Work is Worship". Dr Bradley is a true epitome of that. During my early days of this long journey, he made sure that I had all the freedom to define and pick my research interests. Never once I was forced to work on something that didn't interest me. This unconditional quality of nurturing student's interests has helped me stay inspired throughout my stay. Of course, he will forever be seen as a brilliant academician, teacher, mentor, friend and colleague. I envy him for the dexterity with which he shuffles between these roles so effortlessly while maintaining a sense of tranquility in going about his daily duties.

Dr Bradley has played a great role in helping myself and other students kick start our professional careers. It is his extraordinary nature that he regards his student's success as his own by placing their interests ahead of him. It has been an honor and a privilege to work under his supervision. As I move onto the next phase of my life, I will strive to uphold and imbibe Dr Bradley's passion for excellence with utmost sincerity and dedication. Without doubt, in every true sense of the word, he is one of the most amazing human being that I have come across in my life.

Thank you Sir.

I would also like to extend my heartfelt gratitude to Dr Allan Kirk Patrick for not only accepting to serve in my committee but also constantly making himself available for discussions and clarifications. I thank Dr Bryan Wilson for providing me valuable industrial insights for my research and for providing me with timely appointments despite his rigorous schedule. I first came across Dr Peter Young through his Systems Engineering class. In addition to being an excellent teacher, his homework assignments were always fun to work on without feeling the stress. I'm extremely grateful to him for accepting to serve on my committee in such short notice. During all of my industrial experience in Fort Collins, I have been apprised of all my committee members' career achievements, time and again. I feel extremely proud and honored to have them on my committee.

I also thank my friends and fellow graduate students Benjamin Geller, Baha al alawi, Mathew Fox, Nicholas Echter, Eric Wood, Tim Campbell, Nick Wagner, Justin Wagner, Jason Quinn, Casey Quinn, Shawn and Jake for their support during the last 4 years.

Lastly, I would like to thank my parents and my brother for their unconditional love and support in my every pursuit. Shruti, you were my savior in so many occasions when I first started my PhD program. I have no words to describe your support in this journey. Please forgive me for not living upto your expectations. But I promise, to be a good friend for the rest of my life. Thank you.

DEDICATION

For Anusha, who helped celebrate the leaps, mourn the falls, and gave a good kick when I needed one. Love you.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 INTRODUCTION

The focus of this dissertation is the modeling, analysis and evaluation of heating, ventilation and air conditioning (HVAC) system performance for electric vehicles (EVs). This chapter presents an introduction and motivational background to the topics of personal transportation, electric vehicles, and HVAC systems.

1.1 Personal transportation system introduction

Personal transportation accounts for a large fraction of global and US energy demand. Globally, 30 billion barrels of crude is produced to generate 3.23 billion barrels of fuel oil per year [1], and the United States accounts for 26% of world's oil consumption [2]. As shown in Figure 1-1, 70% of the total annual gasoline consumption is utilized by the US transportation sector. US Department of Transportation reports that on average 678 gallons of gasoline is consumed per vehicle in the passenger vehicle fleet, 10% of which is used towards operating the vehicle air conditioning systems. This is 0.46 million barrels of crude oil per day. With a total of 250 million registered vehicles in passenger fleet in 2008 [3], the energy utilized for vehicle air conditioning is roughly equivalent to the energy consumed by 40 million US homes (9000 kW-hr per annum).

Today, the personal transportation vehicle fleet is made up of a diversity of technologies and systems to provide tractive energy and passenger comfort [4]. In a conventional vehicle, the energy from liquid fuel powers the vehicle's tractive and accessory loads. The accessory loads are comprised of power steering, power brakes, radio, vehicle controls, lighting systems, heating and cooling systems. The engine powers the cooling systems by driving a refrigerant compressor to provide air conditioning (AC). Waste engine heat from the coolant loop is used for heating the cabin air. In the present generation of electric vehicles (EVs), a tractive electrochemical battery replaces the engine as the main energy source. In EVs, only the battery is available to power the vehicle and other auxiliary systems including heating, ventilation, and air conditioning systems (HVAC).

The HVAC systems for EVs draw its energy from the main battery, thereby reducing the range of the vehicle by 35% to 50% during extreme weather conditions [5-10]. The decrease in range of EVs is detrimental to the overall objective of reducing the petroleum dependency of the passenger fleet in the transportation sector and to meet consumer's performance expectations of these emerging technologies.

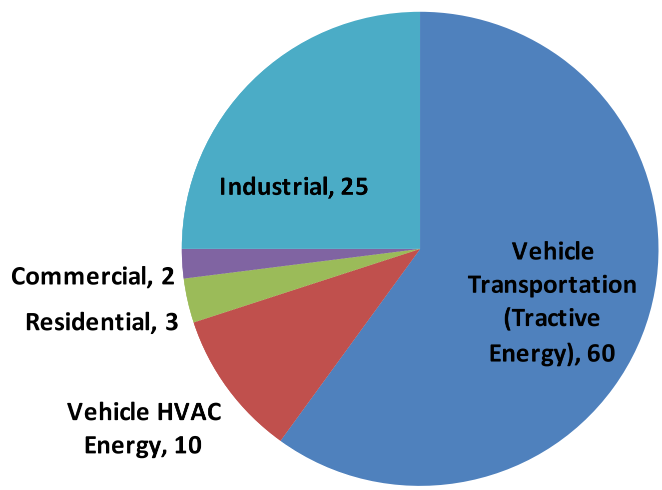


Figure 1-1: Consumption of gasoline in the US divided among the industrial, commercial and transportation sectors. The transportation sector is further divided into energy that goes to vehicle traction and passenger comfort conditioning. The gasoline consumed in transportation air conditioning is larger than the gasoline consumed in the commercial and residential sectors combined[11].

1.2 The role of electric vehicles in reducing impacts of personal transportation

The amount of fuel used for climate control in vehicles affects the energy security of US significantly as it lowers the fuel economy of the 250 million light-duty conventional vehicles in use in the United States [12]. Advanced vehicle technologies such as EVs are increasingly regarded as a means to allow the personal transportation sector to consume less primary energy with less emissions than fossil fuel vehicles of the same weight and performance (excluding driving range)[13]. A direct comparison of EVs against conventional vehicles is presented in terms of various efficiencies to objectively justify the emphasis on EVs in this dissertation research.

The Tank to Wheel energy efficiency, i.e. ratio of energy transmitted to the wheels divided by the final energy (gasoline, diesel or electricity) input to the vehicle under standard test conditions is represented in Figure 1-2. The Tank to Wheel energy efficiency for the best internal combustion vehicles under normal operating conditions is less than 22% for diesel and 18% for gasoline, while the rest is lost as heat [14, 15]. It is 60 to 72% for electric vehicles power by lead acid and lithium ion batteries[14, 16]. The electric vehicle consumes 3 times less final energy compared to a conventional fossil fuel vehicle. The Well to Wheel efficiency of a vehicle is the ratio between the final energy transmitted to the wheel divided by the primary energy at the source. It is equal to the Tank to Wheel efficiency multiplied by the Well to Tank efficiency, which is the efficiency from the source of final energy to its introduction into the vehicle (fuel tank or electrical plug). The Well to Tank efficiency (Figure 1-3) for fossil fuel and EV powered vehicle is approximately 83% and 37% respectively [15] by taking into consideration the factors such as energy consumed by the production, refining and transport of the fuel in case of fossil fuels and type of power plant (conventional power plant, combined-cycle gas power plants), energy efficiency of electricity distribution for EVs. The Well to Wheel efficiencies are shown in Figure 1-4. The nominal Well to Wheel efficiencies of EVs is approximately 1.5 times and 1.8 times better than the diesel and gasoline power conventional vehicles respectively.

The real world efficiencies in EVs can significantly vary based on driving conditions (rural, urban), real traffic conditions, hard acceleration during the driving cycles, constant large accessory power draws such as HVAC systems. The power draw by the HVAC systems strongly depends on the local ambient conditions, prior activity inside the vehicle and parking scenarios [8, 17]. As the market penetration of EVs increases (Figure 1-5), it will become imperative to quantify the real world energy consumption of EVs (including HVAC loads) in order to understand 1) their true energetic and environmental benefits over conventional vehicles, 2) the geographic sensitivity of these costs and benefits as a function of climate, electric grid, and vehicle types, and 3) the system level effects of emerging alternative accessory technologies including vehicle preconditioning, ARPA-HEATS-type thermal storage systems, and fuel cells.

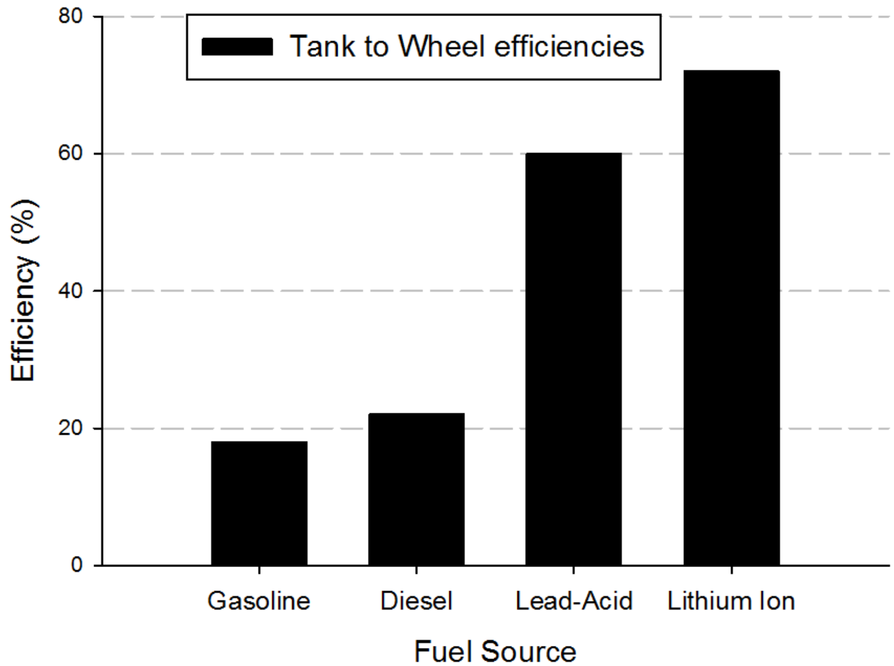


Figure 1-2: Tank to well energy efficiencies for conventional (gasoline, diesel) and electric (Lead-acid, Li-ion) powered vehicles.

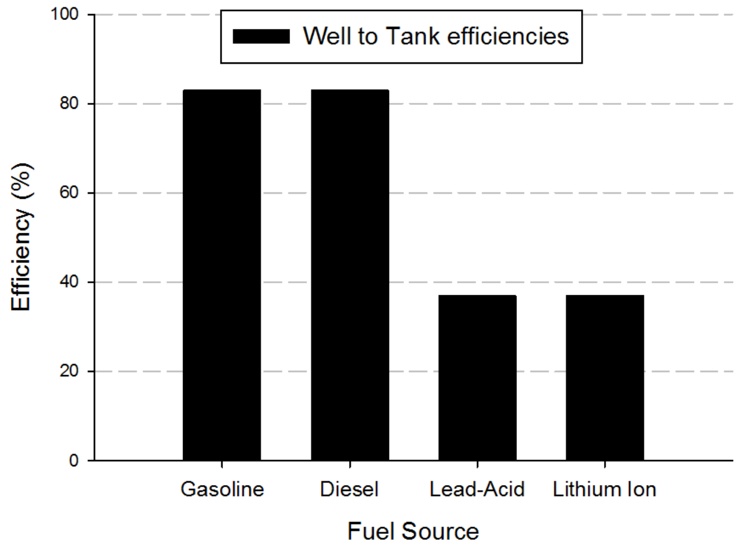


Figure 1-3: Well to tank energy efficiencies for conventional (gasoline, diesel) and electric (Lead-acid, Li-ion) powered vehicles.[14, 15]

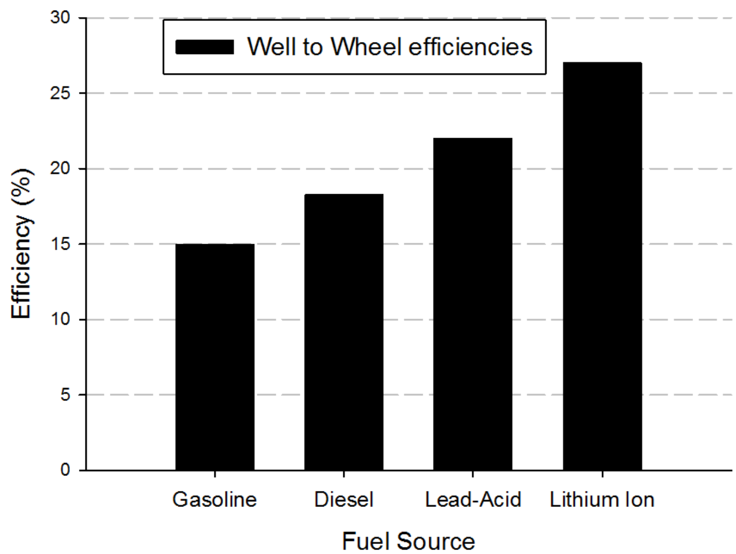


Figure 1-4: Well to wheel energy efficiencies for conventional (gasoline, diesel) and electric (Lead-acid, Li-ion) powered vehicles.

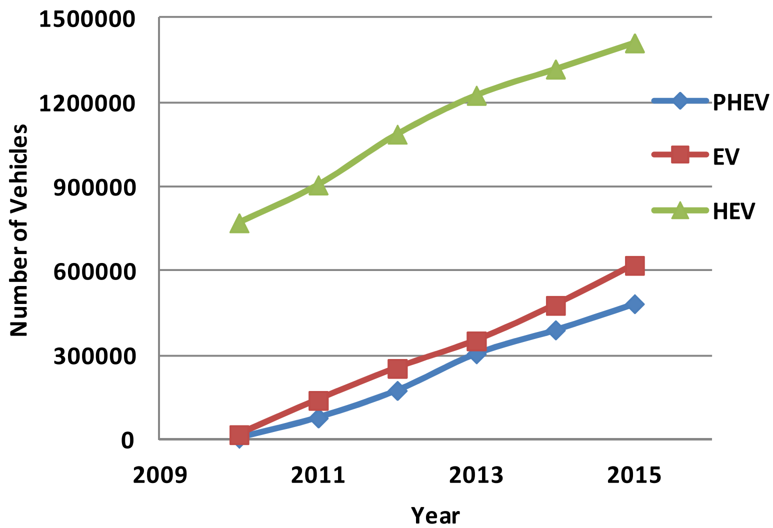


Figure 1-5: Market penetration forecast for HEV, PHEV and EVs [3].

1.3 State of the art in vehicle HVAC

Reducing the dependence on the gasoline increases the nation's energy security [4, 7, 16, 18]. Transportation sector is one of the biggest consumers of gasoline resulting in (large) contribution towards greenhouse gas (GHG) emissions in US [2, 11, 19]. With significant advances in the battery technologies and higher Well to Wheel efficiency, EVs are increasingly being considered as a future of passenger fleet [20-23]. With EVs, fossil fuels are displaced at the wheels. The additional demand on the grid due to increased fleet charging activities needs to be accommodated by increased power generation by the utilities [12, 24, 25]. By optimizing the energy management at the system level, the additional power generation at the source can be minimized.

In an EV, the energy expended for thermal comfort (cabin cooling and cabin heating) is the second largest energy load, after traction loads [18, 26]. It is therefore important to consider the role of HVAC loads in predicting EV performance. Complications arise in that the conditions of operation, the ambient conditions, and therefore the performance of HVAC systems vary geographically and temporally. Researchers and regulators have not been able to consider the transient ambient variations prevalent across US, and have instead defined thermal comfort requirements on the basis of constant average ambient conditions [5, 7, 16, 19]. Energy for cabin heating was not considered since in conventional vehicles the waste heat rejected by the engine is utilized for cabin heating. This is not the case with EVs since energy for both cabin heating and cabin cooling has to come from the onboard energy storage device. These assumptions propagated large uncertainties in energy consumption estimations. Also, current vehicle simulation software's such as Advisor, and Autonomie represent HVAC loads as a non-dynamic constant. To accommodate for the fluctuations in HVAC loads, the onboard battery storage device is overdesigned resulting in successful but not necessarily an optimized functioning [22]. For example, a 40mile range plug in electric vehicle designed with 16kWh battery storage (8kWh usable) might draw 2kW peak accessory load, thereby reducing the EV range by 25%.

The HVAC systems have been traditionally designed for maximum capacity, not efficiency. This is another contributing factor for lower fuel economy in conventional vehicles and reduced range in EVs. The stringent corporate average fuel economy (CAFÉ) standards necessitate greater optimization of energy systems at the component level [27]. Moving away from the traditional vapor compressor refrigeration systems in EVs, a combination of several alternative accessory technologies such as thermo-electrics, thermal storage devices, fuel cells and flow batteries may be integrated into the EV for providing thermal comfort with minimum drain on the onboard storage device. The immediate benefit is the increase in the electric range of the EV and subsequent increase in positive user experience.

The objective of the current research is to understand the system level impact of EV on the nation's electric grid to bring about a net reduction in GHG emissions. This will be achieved by developing a generalized thermal comfort model taking into consideration the wide variations in US ambient conditions geographically and temporally. The results from the model will be synthesized to answer several important questions pertaining to total gasoline displacement by an EV fleet, identifying ideal geographical locations for EVs based on consistency of their performance, mechanisms to improve their performance by means of cabin preconditioning.

A phase change based thermal energy storage system as an alternative for traditional vapor compression based refrigeration system is investigated. The Phase change system is a combination of paraffin wax and ice block, for providing cabin heating and cabin cooling respectively. The dynamics of this combined system is modeled and integrated with the local ambient conditions, time of use of the vehicle and driving characteristics. The simulation studies will be used to understand the system level changes to be incorporated in the future vehicle designs.

1.4 Organization of Thesis

This chapter provides an introduction to the research project and presents general background information on the personal transportation sector, electrified transportation, and vehicle HVAC systems.

Chapter 2 presents a literature survey of the state of the field for personal thermal comfort modeling. The USDOE's previous work in the field of HVAC system modeling and analysis is critically reviewed, and HVAC system modeling in vehicle simulation software is described. This literature review focuses on those fields associated with the research gaps addressed in this dissertation.

Chapter 3 presents the research questions and tasks that are the focus of this dissertation.

In Chapter 4, the methods that have been developed to address the research tasks are scoped through a gap analysis, and are described in relevant detail. The input databases are described, and the form and function of the thermal comfort conditioning energy consumption model is defined and its outputs evaluated.

Chapter 5 presents a series of analyses that define the temporal and geographical sensitivity of HVAC energy consumption in EVs. These results are used to define the sum of EV and conventional vehicle (CV) HVAC consumption for each US state and as a function of time of day and time of year.

Chapter 6 presents an analysis that connects the temporally and geographically-realized HVAC energy consumption results to vehicle-level performance metrics including EV range. Summary statistics and performance characterizations for EVs are presented for various US cities and as a function of time of day.

Chapter 7 uses the thermal comfort conditioning energy consumption model developed for this effort to assess the vehicle-level performance of EVs including various advanced HVAC technologies.

Chapter 8 provides conclusions to this study and a summary of future work.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

In this section, prominent research from the literature associated with thermal comfort models, their application to automobile industries, US DOE Vehicle HVAC studies, vehicle simulation software's, HVAC energy consumption predictions and alternative accessory technologies for automobiles will be highlighted.

The thermal comfort models are classified into theoretical based models, empirical models and adaptive models. In the following section each of models will be discussed briefly.

2.2 Theoretical Models

2.2.1 PMV-PPD

PMV represents the 'predicted mean vote' (on the thermal sensation scale) of a large population of people exposed to a certain environment. PMV establishes a thermal strain based on steady-state heat transfer between the body and the environment and assigns a comfort vote to strain experienced. PPD is the predicted percent of dis-satisfied people at each PMV. As PMV changes away from zero in either the positive or negative direction, PPD increases[28-30].

The PMV equation for thermal comfort is a steady-state model. It is an empirical equation for predicting the mean vote on a normalized rating scale of thermal comfort of a population of people. The equation uses a steady-state heat balance for the human body and postulates a link between the deviations from the minimum load on heat balance effector mechanisms, ex, sweating. The greater the load, the more the comfort vote deviates from zero. The partial derivative of the load function is estimated by exposing large number of people to different conditions to fit a curve.

The PMV equation only applies to humans exposed for a long period to constant conditions at a constant metabolic rate. Conservation of energy leads to the heat balance equation [29]:

$$H_i - H_{vd} - H_{sw} - H_{re} - H_r = Q_{rad} + Q_{conv} \qquad \text{Eqn (1)}$$

Where,

H_i = internal heat generation

H_{vd} = heat loss due to water vapor diffusion through the skin

H_{sw} = heat loss due to sweating

H_{re} = latent heat loss due to respiration

H_r = dry respiration heat loss

Q_{rad} = heat loss by radiation from the surface of the clothed body

Q_{conv} = heat loss by convection from the surface of the clothed body

All the terms in the heat balance equation are measurable quantities from basic physics with the exception of clothing surface temperature and convective heat transfer coefficients. The heat balance equation is solved for convective heat transfer coefficients iteratively by assuming an initial value of clothing temperature.

The thermal strain or sensation, Y is defined as some unknown function of H_r and metabolic rate (met). Holding all variables constant except air temperature and metabolic rate, mean votes from climate chamber experiments are used to write Y as function of air temperature for several activity levels. Then substituting H_r for air temperature, determined from the heat balance equation above, the partial derivative of Y with respect to H_r at Y=0 is evaluated. The exponential curve fit with several metabolic rates is integrated with respect to H_r. H_r is now renamed as "PMV"

$$PMV = e^{met} H_r \qquad \text{Eqn (2)}$$

Where,

H_r=function(pressure, ambient temperature, clothing temperature)

PMV is "scaled" to predict thermal sensation votes on a seven-point scale (hot, warm, slightly warm, neutral, slightly cool, cool and cold) by virtue of the fact that for each physical condition, Y is the mean vote of all subjects exposed to that condition. The major limitation of the PMV model is the explicit constraint of skin temperature and evaporative heat loss to values for comfort and "neutral" sensation at a given activity level.

2.2.2 ET*-DISC

ET*- DISC also uses a heat balance model to predict thermal comfort, but the model evolves with time rather than being steady-state like PMV [31]. ET* stands for New Effective Temperature where "effective temperature" is a temperature index that accounts for radiative and latent heat transfers. ET* can be calculated using the '2-Node' model. The 2-node model determines the heat flow between the environment, skin and core body areas on a minute by minute basis. Starting from an initial condition at time=0, the model iterates until equilibrium has been reached (60 minutes is a typical time). The final mean skin temperature and skin wetness are then associated with an effective temperature. DISC predicts thermal discomfort using skin temperature and skin wetness.

The 2-node model was introduced in 1970 specifically to formulate a new effective temperature scale [32]. The purpose was to determine particular combinations of physical conditions producing equal physiological strain. Backed by extensive data from climate chamber experiments, it was determined that while skin temperature is a good indicator of thermal comfort sensation in cold environments, skin wetness is a better indicator in warm environments where sweating occurs because skin temperature changes are small by comparison. The model represents the human body as two concentric cylinders, a core cylinder and a thin skin cylinder surrounding it. Clothing and sweat formation is assumed to be evenly distributed over the skin surface. At time "zero", the cylinder is exposed to a uniform environment, and the model produces a minute-by-minute simulation of the human thermoregulatory system. After the user-specified time period is reached, the final surface temperature and surface skin wetness of the cylinder are used to calculate ET*. ET* is the temperature of an environment at 50% relative humidity in which a person experiences the same amount of heat loss as in the actual environment.

2.2.3 SET*

SET* numerically represents the thermal strain experienced by the cylinder relative to a "standard" person in a "standard" environment. SET* has the advantage of allowing thermal comparisons between environments at any combination of the physical input variables, but the disadvantage of also requiring "standard" people [29, 32].

Based on a laboratory study with a large number of subjects, empirical functions between two comfort indices, and skin temperature and skin wetness, were developed. These functions (both linear) are used in the 2-Node model to produce predicted values of the votes of populations exposed to the same conditions as the cylinder.

2.2.4 TSENS, DISC

Thermal sensation (TSENS), first index, represents the model's prediction of a vote on the seven point thermal sensation scale. Discomfort (DISC), the second index, predicts a vote on a scale of thermal discomfort:

DISC:

Intolerable

Very uncomfortable

Uncomfortable

Slightly uncomfortable

Comfortable

The 2-Node model has undergone many iterations and refinements. In the most recent iteration, a new temperature index, PMV*, that incorporates skin wetness into the PMV equation using SET* or ET* to characterize the environment [29, 32].

2.3 Empirical Models

Apart from the thermal comfort models described above, there are many more theoretical models, both deterministic and empirical. Some empirical models with application to building design and/or environmental engineering are outlined below.

PD or predicted percent dissatisfied due to draft is a fit to data of persons expressing thermal discomfort due to drafts. The inputs to PD are air temperature, air velocity, and turbulence intensity. PS is a fit to data of comfortable persons choosing air velocity levels. The inputs to PS are operative temperature and air velocity. TS is a fit to data of thermal sensation as a linear function of air temperature and partial vapor pressure.

A 'draft' is unwanted local cooling. The draft risk (or PD) equation is,

$$PD = 3.413(34-T_a)(v-0.05)^{0.622} + 0.369vT_u(34-T_a)(v-0.05)^{0.622}$$ Eqn (3)

$$PS = 1.13\sqrt{T_{op}} - 0.24T_{op} + 2.7\sqrt{v} - 0.99v$$ Eqn (4)

$$TS = 0.245T_a + 0.248P - 6.475$$ Eqn (5)

In the above equations, Tu is the turbulence intensity expressed as a percent. 0 represents laminar flow and 100% means that the standard deviation of the air velocity over a certain period is of the same order of magnitude as the mean air velocity. v is the air velocity (ms^{-1}) and T_a is the air temperature in degrees Celsius. The PD equation arises from two studies in which 100 people were exposed to various combinations of air temperature, air velocity, and turbulence intensity. For each combination of conditions, the people were asked if they felt a draft. PD represents the percent of subjects who voted that they felt a draft for the selected conditions.

The PS equation predicts the air velocity that will be chosen by a person exposed to a certain air temperature when the person has control of the air velocity source. T_{op} is operative temperature (in degrees Celsius). The PS equation arises from a study in which 50 people were asked to adjust an air velocity source as they pleased when exposed to a specific air temperature. PS represents the cumulative percent of people choosing a particular air velocity at the specific temperatures tested in this experiment. TS is an equation that predicts thermal sensation vote using a linear function of air temperature and partial vapor pressure. T_a is the air temperature in degrees Celsius and P is the partial vapor pressure in kPa. The TS equation arises from a study similar to the PMV-PPD study described above [30].

2.4 Adaptive Models

Adaptive models include in some way the variations in outdoor climate for determining thermal preferences indoors.

2.4.1 Auliciems [33]

An adaptive model developed by Auliciems fits sensation data based on field investigations of thermal comfort in Australia spanning several climates. The equation is,

$$T_n = 9.22 + 0.48T_a + 0.14T_{mmo} \qquad \text{Eqn (6)}$$

2.4.2 Humphreys [34, 35]

Humphrey's equation is a fit to considerable data for climate-controlled and non-climate controlled buildings,

$$T_n = 23.9 + \frac{0.295\left(T_{mmo} - 22\right)}{e^{-\left[\frac{\left(T_{mmo}-22\right)}{24\sqrt{2}}\right]^2}} 0.48T_a + 0.14T_{mmo} \qquad \text{Eqn (7)}$$

For both the Auliciems and Humphreys models, T_n is the neutral temperature, T_a is the air temperature, and T_{mmo} is the mean monthly outdoor temperature.

2.5 US DOE Vehicle HVAC Studies [5-9, 16, 18, 19, 36-38]

Efforts to understand the impact of HVAC loads on electric and gasoline fuel economy have been driven by stricter emission regulations, depleting oil resources, need to reduce foreign oil dependence, higher corporate average fuel economy standards, and steady growth of HEV, EV and PHEVs in the market. According to US Department of Energy's advanced vehicle testing activity, the range reduction due to operation of HVAC systems in hybrid and electric vehicles could be as high as 35% depending on the ambient temperature, cabin temperature and the air volume [6]. The All Electric Range (AER) of

PHEVs or EVs will be further affected due to the energy requirements of additional accessories such as power steering and power brakes.

Early efforts by NREL [8], attempted to simulate thermal comfort, fuel economy, and emissions in conventional gasoline operated vehicles. The integrated modeling approach composed of CAD, computational fluid dynamics (CFD), thermal comfort, and vehicle simulation tools. The process was broken down into steps of developing models, and creating links between the models. In association with industry, advanced vehicle simulator (ADVISOR) tool was developed. Specific issues including differing analysis time scales and automation of data transfer were addressed to a limited extent but not completely resolved. The goal was to use the integrated modeling process leading to reduction in the peak soak temperature and improve passenger comfort, ultimately improving the efficiency of vehicle climate control systems and reduced fuel use. The example peak soak temperature reduction demonstrated that fuel economy of a conventional vehicle could be improved by 9.2% with 11.6°C drop in cabin air temperature.

Johnson in 2002 [7] attempted to determine total fuel consumed by vehicle air conditioning nationwide and state-by-state fuel use impact due to air conditioning usage in light duty gasoline vehicles. The study used data from US cities, representative of averages over the past 30 years, whose temperature, incident radiation, and humidity varied through time of day and day of year and national surveys that estimated when people drive their vehicles during the day and throughout the year. A simple thermal comfort model based on Fanger's [28] heat balance equations determined the percentage of time that a driver would use the air conditioning based on the premise that if a person were dissatisfied with the thermal environment, they would turn on the air conditioning. Vehicle simulations were performed to determine the fuel economy reduction seen with AC use in typical US cars and trucks. These statistics and models were combined with vehicle and truck registrations and vehicle miles traveled resulting in a state-by-state estimate of fuel used for air conditioning in vehicles.

Rugh et.al [9] extended Johnson's [7] work to study the impact of vehicle air conditioning (A/C) systems on fuel economy, tailpipe emissions of automobiles and greenhouse gas emissions from A/C refrigerants. The study performed on light duty vehicles in US was further extended to cover Europe and Japan. With the assistance of the automotive climate control community, the analysis was updated to include demisting, soak temperatures that vary with vehicle type, simplified clothing assumptions, and A/C compressor power definition. The study showed that the United States uses 7.0 billion gallons (26.4 billion liters) of fuel a year for vehicle air conditioning, equivalent to 5.5% of the total national fuel use and 9.5% of the imported crude oil. If all vehicles had air conditioning, the EU would use 1.8 billion gallons (6.9 billion liters) of fuel per year or 3.2% of total vehicle fuel consumption. Japan would use 0.5 billion gallons (1.7 billion liters) or 3.4% of total vehicle fuel consumption. The fuel consumption data was converted into the metric of CO_2 emissions to determine the indirect impact of air conditioning on the climate. The study also determined the magnitude of the potential reduction in fuel use due to incremental improvements in A/C coefficient of performance (COP) over a baseline and the potential fuel saved per vehicle. For example, with a 25% improvement in A/C COP, a car in Arizona was found to save 15.7 gallons per year. These data highlights the potential to reduce operational costs, A/C fuel use, CO_y emissions and eventually the amount of imported oil by implementing advanced vehicle climate control technologies.

Farrington et.al [5] studied the impact of vehicle air-conditioning on fuel economy, tailpipe emissions of conventional and hybrid electric vehicles and electric vehicle range. In addition, a new U. S. emissions procedure, called the Supplemental Federal Test Procedure (SFTP), was investigated for reducing the size of vehicle air-conditioning systems in the United States. The SFTP intends to measure tailpipe emissions with the air-conditioning system operating. Current air-conditioning systems are shown to reduce the fuel economy of high fuel-economy vehicles by about 50% and reduce the fuel economy of mid-sized vehicles by more than 20% while increasing NO_x by nearly 80% and CO by 70%.

Kaynakli et al. [17] investigated an automotive air conditioning system in detail by varying several parameters experimentally. The temperature of ambient, the evaporator and condenser and the speed of the compressor were varied and the performance of the system was monitored. Cooling load, compressor power consumption, refrigerant mass flow rate, COP value, fluctuation of the minimum and maximum system pressures were analyzed, the results are presented in graphical form and optimum operation conditions were determined. The experimental results concluded that the cooling capacity increases with increasing compressor speed and condenser temperature but this also lead to higher compressor power consumption and hence lower COP. Changes in condenser temperature and pressure affected the system performance significantly while that in evaporator temperature and pressure did not play a major role. The refrigerant mass flow rate increases substantially with increase in the compressor speeds with little or no increase due to changes in evaporator, condenser and ambient temperatures.

Barnitt et.al [19] studied the effects of mitigating a hot or cold thermal soak to quickly attain a cabin temperature comfortable to the vehicle occupants using vehicle climate control systems (air conditioning or heat) on the range depletion and battery life of PHEVs and EVs. Depleting the battery for immediate climate control was found to reduce charge-depleting (CD) range and enhance additional battery wear. PHEV cabin and battery thermal preconditioning using off-board power supplied by the grid or a building was recommended as an option to mitigate the CD range reduction and battery life impacts due to climate control. To quantify the impact, Power train Systems Analysis Toolkit vehicle simulation program was developed. The models were validated across a blended PHEV with a 15-mile (24-km) electric range, a series PHEV with a 40-mile (64-km) electric range, and an electric vehicle with a 100-mile (161-km) electric range. Representative air conditioning and heater load profiles were constructed using data from literature. Further, PHEV performance with and without thermal preconditioning over the urban (UDDS, urban dynamometer driving schedule) and highway (HWFET, high way fuel economy test) drive cycles, and for three different ambient temperature scenarios were tabulated. Battery wear was characterized using a semi-empirical lithium ion battery life model. The analysis showed that climate control loads can reduce CD range up to 35% while, cabin thermal preconditioning increased CD range up to 19% when compared to no thermal preconditioning. In addition, this analysis also showed that while battery capacity loss over time is driven by ambient temperature rather than climate control loads, concurrent battery thermal preconditioning can reduce capacity loss up to 7% by reducing pack temperature in a high ambient temperature scenario.

2.6 Vehicle Simulation Software [39-42]

The current generation vehicle simulation software's such as Autonomie (developed by Argonne National Lab), Advisor (developed by NREL) were designed primarily for simulating the conventional vehicle performance. They regard HVAC loads as non-dynamic constants. This results in over designing the HVAC systems for maximum capacity instead of efficiency. The additional curb weight resulting from the over design further increases the fuel consumption. The electric vehicle is limited in terms of range it can deliver on a single charge. Hence the onboard storage system should be designed by accounting for the transient loads on the vehicle.

2.7 Summary

From the discussions above, it is clear that to determine appropriate thermal conditions, researchers refer to standards that define temperature ranges that should result in thermal satisfaction for at least 80% of occupants in space. The standards are based primarily on a mathematical model, developed by Fanger [28]. In particular, the researchers developed a model of whole body thermal comfort, known as PMV model . Using this as a basis, the DOE vehicle HVAC studies [5-9, 16, 18, 19, 36-38] determined 7 billions gallons of gasoline are consumed by the US light duty vehicle fleet for HVAC. Although Fanger's PMV model have become a standard for predicting thermal comfort for occupants, some researchers [43-47] question their validity. The following section highlights the limitations of Fanger's thermal comfort model.

2.7.1 Limitations of Fanger's Model

The PMV model is designed to predict the average thermal sensation for a large group of people. Within such a group, optimum thermal conditions are likely to vary between individuals by up to 3°C on the thermal sensation scale[35]. Therefore, even if the thermal environment in a space is maintained in accordance with the PMV model, there will be some occupants who are thermally uncomfortable. These differences between people are acknowledged by Fanger [28] and are also reflected in the PPD index. Thus, while the PMV model can be used to determine appropriate temperatures that will satisfy the majority of occupants, it is unrealistic to expect all occupants to be thermally satisfied.

It is also important to note that PMV model is based on the measure of how warm or cool the occupants feel. This is also defined as thermal sensation felt by the occupants. Conceptually, however this is different from the thermal satisfaction (e.g. is one satisfied or unsatisfied with the thermal conditions?), thermal acceptability (e.g. are the prevalent thermal conditions are acceptable or not?), thermal comfort (e.g. I feel comfortable or uncomfortable) and thermal preference (e.g. I would like it to be warmer or colder). The PMV based thermal sensation studies does not distinguish the differences between these terms [33, 45].

Advanced laboratory studies have shown greater discrepancies of over and under prediction of neutral temperatures that used PMV index [43-47] . Oseland and Humphrey [48] concluded that "the use of PMV encourages unnecessary heating in cool conditions and unnecessary cooling in warm conditions". In addition to the difference between actual and predicted neutral temperatures, several field studies [45, 49, 50]have suggested that occupant's sensitivity to changes in temperature differ from those predicted from PMV and the differences between the predicted and actual thermal sensation grew larger when the occupants were further away from neutrality.

The predictions of PMV model are based on experiments conducted in a climate chamber. The physical variables (air temperature, mean radiant temperature, relative humidity and air velocity) are closely monitored and controlled. The use of standardized clothing and prior activities helps to control physiological variables accurately. However, many studies [45, 48] have shown large measurement errors resulting from controlling all 6 variables accurately. The measurement difficulties have been argued to contribute to the discrepancies between PMV and actual thermal sensation. Over all, the measurement error associated with physiological variables (metabolic rates and clothing) is considered problematic to the accuracy of the PMV model.

Hence it can be concluded that the HVAC studies using Fanger's PMV model is not always a good predictor of actual thermal sensation. Discrepancies between actual and predicted neutral temperatures reflect the obvious difficulties in obtaining acceptable measure of clothing and metabolic rates. The US DOE studies use this as the basis for estimating the fuel consumed for thermal comfort in conventional automobiles. In this dissertation, a new control volume based bottom up approach is proposed. This is discussed in greater detail in Chapter 3.

CHAPTER 3 RESEARCH QUESTIONS AND DEFINITION OF RESEARCH SCOPE

3.1 Research Questions

The literature survey and gap analysis in the previous sections allows us for the development of the following research questions. Each question posed here, is discussed individually in the following sections and is further broken down into specific tasks.

Research Question 1: How much energy (petroleum energy, electrical energy) does an electrified light-duty vehicle fleet consume compared to a fleet of conventional vehicles?

To answer this research question, a comprehensive time-resolved and vehicle-resolved model of vehicle energy consumption must be constructed specific to the EV/PHEV application. Energy consumption by HVAC system has been estimated by developing a Matlab/Simulink model of vehicle heat transfer, and HVAC system function. The environmental inputs from the National Solar Resource Database (NSRDB), light-duty vehicle fleet inputs from Mobile 6 and vehicle trip details from the National Household Transportation Survey (NHTS) will enable the characterization of the energy consumption of an electrified light-duty vehicle fleet. The geographically realized energy consumption maps will be utilized in subsequent research tasks.

Research Question 2: What is the geographical sensitivity of the accessory loads and vehicle fueling costs for HEVs, PHEVs and BEVs? Are there regions of the country that are most advantageous or that should be precluded from vehicle fleet electrification?

To accommodate large scale market penetration rates of HEVs, PHEVs and EVs it is important to identify regions of country where the technology could be most beneficial. The environmental, economic and energetic performance of nonconventional vehicles will depend on the climatic conditions in which they operate. An EV or a PHEV with a certain battery capacity may show environmental benefits in moderate climates that are not present in regions of the US with higher HVAC loads.

The results from the first research question shall be utilized to analyze and determine the regions with high energy requirements. The additional battery capacity enhancements that may be required at these high energy consuming regions shall be determined. The outcome of this analysis should help the automobile industry to understand the performance of EVs, HEVs and PHEVs as a function of the geographical variations in climate conditions.

Research Question 3: What accessory systems or technologies can improve the environmental performance and utility of HEVs, PHEVs and BEVs? What metrics or methods can be used to evaluate the economic, environmental and energy life cycle of the proposed technologies?

This question is focused on investigating alternative accessory technologies (AATs) for HEVs, PHEVs and EVs to reduce and optimize the auxiliary loads such that the vehicle can be designed to achieve system-level design criteria including petroleum displacement, CO_2 emissions, or performance robustness.

Some of the technologies and techniques to power HVAC systems in electrified vehicles in consideration are 1. Decoupling the transmission and HVAC loads from the battery pack and utilizing a reduced size engine to only accommodate for the HVAC loads, 2. Thermal storage technology similar to that defined in ARPA-E heats program by DOE to provide onboard energy storage for cabin comfort conditioning. 3. Vapor absorption AC system. 4. Thermo-chemical storage systems such as fuel cells and flow batteries.

A thermal systems model of each technology mentioned will be evaluated across different vehicle platforms and geographic areas to determine the design metrics that can be used to characterize high performance AATs based on overall system efficiency, greenhouse gas emissions, economic performance and more.

3.2 Definition of Research Scope

The program of research to answer these research questions is broken down into research tasks and subtasks, as presented in Table 1. Dates of completion and percent completed are presented for this work package. Figure 3-1 represents an overview of inputs and resulting outputs to the Accessory load model and simulation. Climate data is obtained from National Solar Resource Database (NSRDB), driver characteristics are extracted from National Household Transportation Survey, regional vehicle type and fleet population is obtained from Mobile 6 database while vehicle simulation software (Autonomie) will be used to evaluate alternative accessory technologies. The outputs from the Accessory load model are classified into tasks listed in Table 3-1.

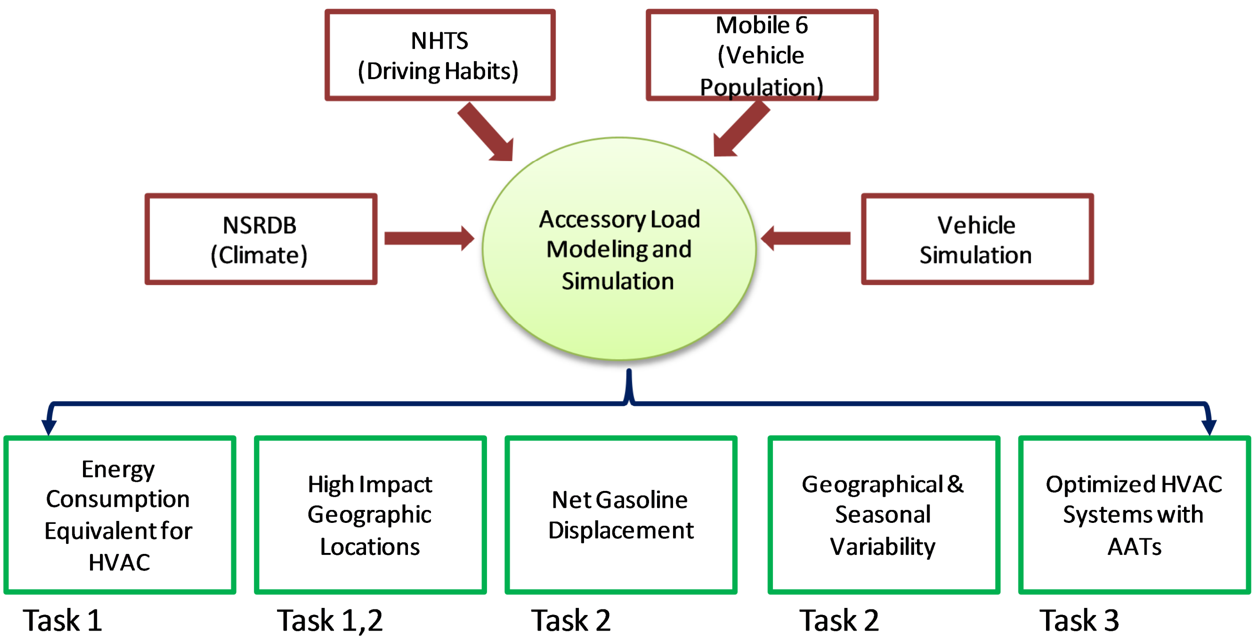


Figure 3-1 Research block diagram representing I/O and the allocation of efforts into Tasks 1 through 3

Table 3-1 Breakdown of Research Tasks

Research Tasks	Associated Research Question
Task 1.1: Database generation as a function of TOD and TOY	
Subtask: Data mining and sorting of environmental parameters from TMY3 dataset generated by NSRDB into relevant formats	I
Subtask: Generate vehicle trip and regional fleet details from the NHTS and Mobil 6 database	I
Task 1.2: Develop a generalized dynamic HVAC system model	
Subtask: Construct parametric model for vehicle windshield surface	I
Subtask: Construct parametric model for vehicle roof surface	I
Subtask: Develop control volume model for cabin space	I
Subtask: Interlinking data sets generated in Task 1.1 with the control volume model	I
Task 1.3: Determine energy consumption of HVAC systems	
Subtask: Generate geographical distribution maps of HVAC energy consumption based on a. Trip length b. Seasonal variations c. Worst case scenarios	I
Task 2.1: Construct algorithms to extract 'hotspots' across the country with high HVAC energy demand	
Subtask: Determine high return on investment (ROI) zones based on frequency of trips	II
Subtask: Determine potential zones for high impact on net GHG reduction	II
Task 3.1: Define and evaluate performance metrics for alternative accessory technologies	
Subtask: Evaluate a. Storage technologies (Sensible and Latent) b. Preconditioning c. Flow batteries and fuel cells d. Vapor absorption systems	III

CHAPTER 4 METHODS

4.1 Introduction

General thermal comfort is defined as certain thermal equilibrium conditions existing inside a zone or an indoor environment that is acceptable for dispensing regular tasks in a broader view. The thermal equilibrium is a meta-stable state and requires dynamic exchange of energy in the form of heat, mass and work transfer between environment and the zone. Any deviation from this state is perceived as lack of thermal comfort condition inside the zone. Heating, ventilation and air conditioning systems are used to restore the thermal comfort conditions.

In addition to the thermal equilibrium state, the thermal comfort or the lack of it, as perceived by an individual subject is influenced by several human thermal regulation parameters such as the physiological conditions, metabolic rates and prior activities inside the zone.

The earliest thermal comfort model was derived by Fanger [28]. According to Fanger's theory, the human body employs physiological processes in order to maintain a balance between the heat produced by metabolism and heat lost from the body. An actual comfort equation was defined based on the investigation of body's physiological processes. The physiological processes influencing the heat transfer were sweat rate and mean skin temperature as a function of activity level. The data from the study were used to derive a linear empirical relationship between activity levels, sweat rate and mean skin temperature. The relationships were based on the physics of heat transfer with an empirical fit to sensation and termed as 'predicted mean vote' (PMV). The details of PMV model and its limitations were discussed in Chapter 2 (Literature Review).

In this chapter, a gap analysis based on literature review is discussed along with methodological and design criteria research challenges. Owing to the limitations posed by PMV model, a more general control volume approach to modeling thermal comfort based on transient energy exchanges between indoor environment and outside ambient will be developed. The ability to use this model for much accurate estimations of HVAC energy consumption over DOE HVAC studies for conventional vehicles and its subsequent applicability to electric vehicle HVAC energy consumption will be highlighted.

4.2 Gap Analysis

The DOE/National Renewable Energy Laboratory (NREL) thermal comfort studies have clearly shown that vehicle auxiliary loads consume significant amount of energy. Based on the literature survey in chapter 2, there exist some methodological and applications-based gaps in modeling thermal comfort and their application for understanding of the impact of HVAC loads on charge depleting energy storage device that is used in electric vehicles based on real world conditions.

4.2.1 Thermal comfort modeling challenges

Fanger's PMV model combines two physiological variables (personal metabolism rate and clothing insulation) with four physical variables (relative humidity, air velocity, average radiant temperature and air temperature) into an index that can be used to predict average thermal sensation of a large group of people in a space. In the literature review we discussed some major theoretical and measurement errors giving rise to discrepancies between predicted and measured thermal sensation. It was also discussed that controlling all the 6 variables together for generating PMV was a challenge. The PMV itself is based on averaged environmental parameters. Hence the PMV scale does not take into account the fluctuating weather patterns prevalent across US. However, for estimating thermal comfort and subsequent energy required to provide thermal comfort, it is very important to develop a model that takes into account the transient weather conditions. Since the PMV model was developed back in 1970, the lack of environmental data across US may have posed as a major deterrent for incorporating transient ambient conditions. However, the weather monitoring stations set up across several locations in US ad improvements in reporting hourly weather data with minimal measurement enables us to use the recorded database for developing a thermal comfort model that closely captures the HVAC loads based on local conditions. The transient weather data base is parsed using advanced data mining algorithm to develop a transient thermal comfort model using a control volume based bottom up approach. The results from the model will be compared against a PMV based thermal comfort model developed by NREL for estimating HVAC energy consumption in conventional vehicles.

4.2.2 Methodological Research Challenges

The models of passenger vehicle occupant temperature that are used in previous work were built upon the premise of Fanger's [28] description of person's thermal sensation vote (PMV). The person's thermal sensation is related to the heat balance on the body as a whole. The metric 'predicted percent dissatisfaction' (PPD) was defined as a function of deviation in person's heat balance from a thermally neutral sensation. A positive deviation is representative of the person likely to feel too hot. Under these assumptions, PPD is treated as a statistical representation of the fraction of time the air-conditioning is turned on. However, negative deviations indicative of cold cabin conditions were not considered. Therefore, the model based on thermal sensation is more leaning towards statistical estimations and does not consider the time resolved temperature fluctuations in the cabin space arising due to changes in real world environmental parameters. AC and heating requirements need to be considered with equal weights as both cabin cooling and cabin heating require energy and both limit vehicle range.

The current generation of DOE vehicle simulation software does not capture the complexity of modern HVAC operation. Popular vehicle simulation platforms like ADVISOR and Autonomie [39-41] built by NREL and Argonne national labs in partnership with automobile industries follow bottom-up approach in predicting the total energy expended for traction power requirements, while accessory loads are represented as a constant, non-dynamic load. This approach leads to over-designing the battery to accommodate for fluctuations in the HVAC loads of electric vehicles. Over-designing the batteries can lead to reduction in electric range because of increased total curb weight. Hence a more integrated approach towards EV design should incorporate an accurate representation of dynamic HVAC power requirements.

In previous studies, PHEV/EV grid interactions are not modeled with the complexities required to predictively model the environmental and energetic response of the electric sector. Previous studies do not use time-resolved modeling of vehicle charging and therefore cannot capture the types of marginal electricity generation that are powering electric transportation and cabin preconditioning loads. A fully time-resolved driving/charging simulation would be required to interface with conventional utility generation modeling environments.

4.2.3 Design Criteria Research Challenges

There have been few investigations [17, 21, 23, 51-54] on integration of alternative accessory technologies with HVAC systems for HEVs PHEVs and EVs. Since the market for electric vehicles has grown only in last decade, lack of sufficient research on HVAC components exclusive for electric vehicles has prevented any standardization of technologies or systems. Instead, existing HVAC systems for EV/HEVs use the same technology as HVAC systems for conventional vehicles. These systems are slightly modified and made functional to suit the electric vehicle [55] resulting in either over designing of the HVAC system or the development of a system that is only fully functional for certain weather conditions.

To date, no studies have attempted to develop integrated design metrics for EV/HEV HVAC systems. Alternative technologies, such as ARPA-E storage systems, flow batteries, fuel cells, small engine powered AC compressor, vapor absorption systems and preconditioning for running the auxiliary systems in HEVs, PHEVs and BEVs have not been evaluated on the basis of their system-level impacts. Fundamentally, these HVAC technologies are developed so as to be able to improve metrics such as CO_2 emissions, vehicle market penetration, and other high-level design criteria. As such, they must be modeled and designed in a way that can evaluate them on these bases.

4.3 Overview of automobile thermal comfort model

In this section an overview of simulation architecture with respect to the thermal comfort model for an automobile will be described at a higher level. The relations between all the data bases and their interaction with the main model will be highlighted.

The Figure 4-1 represents an overview of the simulation architecture. The main data base inputs to the model are obtained from National Solar Resource Database (NSRDB), National Highway Transportation Survey (NHTS) and US light duty fleet distribution census data. The format and content of the above mentioned data bases are discussed in the subsequent sections. At the core of the model architecture is the generic control volume based dynamic thermal comfort algorithm that evaluates existence of thermal comfort conditions inside the control volume (cabin space of automobile) as desired by the user. The algorithm is built using MATLAB Simulink platform. In addition to the inputs from the NSRDB and NHTS databases, the vehicle characteristics comprising of vehicle type, vehicle physical dimensions, front and rear wind shield configurations, and individual component material properties for the glass windshield, car roof, dash board and doors are fed into the algorithm in the form of a MATLAB input file. The algorithm comprises of control strategy to dynamically determine the deviations from the set thermal comfort limits. The comfort limits are specified in terms of lower and upper temperature and humidity bounds based on user requirements. The model includes a standard automobile HVAC system. Upon detecting any deviations from the user defined temperature and humidity bound, the controls for the HVAC system will be triggered in an effort to reestablish the thermal comfort.

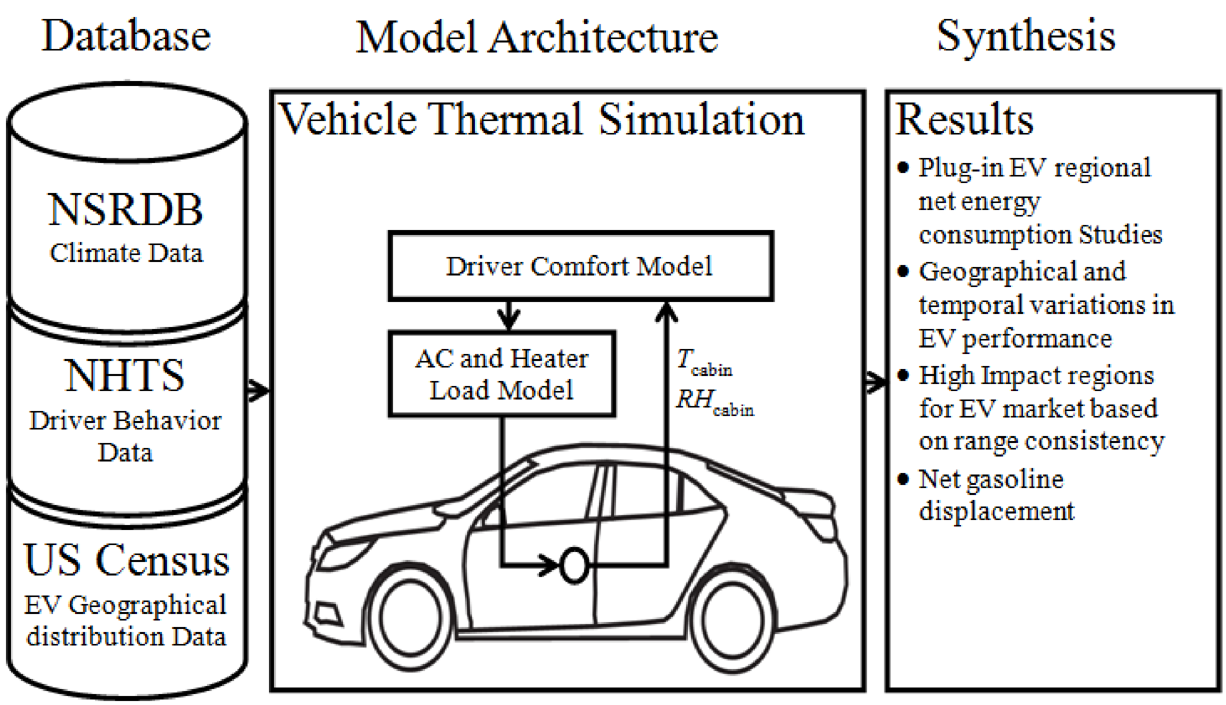


Figure 4-1 Simulation architecture for cabin comfort conditioning thermal model.

Referring to Figure 4-1, the cabin space is subjected to changing environmental conditions (ambient temperature T_{amb}, relative humidity, total solar irradiation Q''_{solar}). The fluctuations in the ambient conditions results in transient temperature changes inside the cabin (T_{cabin}).

The transient ambient conditions are obtained from NSRDB. The NSRDB contains hourly averaged environmental data for 365 days of the year across 1019 locations within US. The hourly averages are generated based on best estimates over 15 year period. The locations are classified as Class 1 2 and 3 based on different confidence levels of the best estimates. Class 1 location indicates 99.8% confidence level of the data.

During an automobile trip, the use of HVAC systems may or may not be desired based on factors such as prior activity inside the cabin and ambient conditions. In order to quantify the net energy consumed by an EV during real trips due to HVAC, the time of use of light duty fleet is approximated from NHTS database. The NHTS database holds passenger survey data. The survey data comprises of trip details of 234000 survey takers on a randomly chosen day of the year. For the purpose of approximating the time of use of light duty fleet, trip start and end times, length of the trip, trip location (rural, urban), driving condition (urban driving, highway driving) is synthesized. The percentage of fleet population on road at any given time of day is as shown in Figure 4-2 (a).

The transient inputs from NSRDB and NHTS is fed into the dynamic thermal comfort model. For this study, the thermal comfort inside the cabin space is defined as a specific temperature range and relative humidity value. Accordingly cabin temperature between 23 and 27 °C with 50% relative humidity is set as thermal comfort. The vehicle characteristics such as size of the vehicle, window configurations, and material properties are used to evaluate the conduction and convection losses. The control volume based approach, dynamically evaluates the power required by HVAC to maintain the set thermal comfort.

The outputs from the resulting simulations are used to synthesize net energy consumed by EVs both at vehicle level and fleet level, geographical variations in net HVAC energy consumption across US, performance of EVs across US using all electric range as a metric and net gasoline displacement. The following section describes the modeling method in more detail.

4.4 Input Databases

4.4.1 National Highway Transportation Survey (NHTS) data base [56]

The research presented here is focused on the energy consumed by HVAC systems in EVs as they replace conventional passenger vehicle fleet. For real world representation of time of use of HVAC systems, it is important to know priori the time of use of the vehicle, vehicle trip start and end times, type of vehicle used and typed of driving encountered. The NHTS data information for 2009 contained 150,147 survey takers over the designated 24 hour period on the beginning and end of the trip times, the trip length and the type of vehicle used for the trip, location of the trip and driving conditions (urban, highway). The NHTS survey data are normalized using appropriate weights to ensure equal representation of survey data based on rural urban population distributions.

For this study, each driver is assumed to have the same distribution of driving behavior as does the NHTS, independent of geography, demography or any potential vehicle range limitations. Each light-duty vehicle trip is performed in a vehicle with a tractive energy consumption of 300 DC Wh mile^{-1} (186 DC Wh km^{-1}). Each vehicle is assumed to charge before each trip from home.

The minute-by-minute percentage of vehicles on road throughout the 24 hour survey time from NHTS survey database is parsed and presented in Figure 4-2 (a). The percentage of trips is seen to be increasing during the early portion of the day as the survey takers drive to work and other intermediate locations. Between 10 AM and 3 PM, approximately 62% of the survey fleet is at rest, parked either at home, work or other intermediate locations. [57]

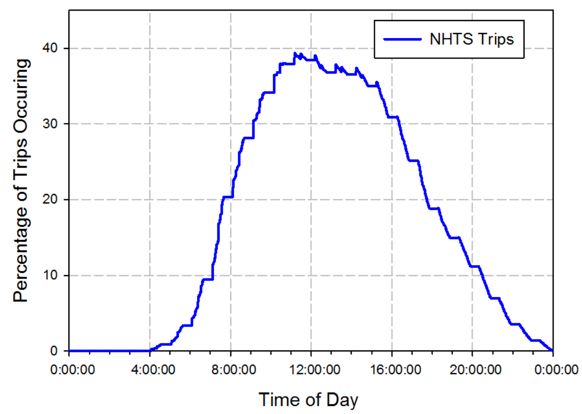
4.4.2 National Solar Resource Database [58]

NSRDB comprises of historical collection of hourly environmental data across 1019 US locations. Based on the measuring certainties, all the NSRDB stations are classified as class 1 2 and 3 zones. The data from the class 1 zone is regarded to have minimal measurement certainties. The most recent 15 yearly historical data from each zone is sorted using standard statistical methods to predict best day-to-day environmental conditions in that zone within a certain confidence level. The refined dataset is called as “Typical Meteorological Year 3 (TMY3)”. The zones are set up and concentrated based on prior observed fluctuations in local weather and the geographical size of the state. The states of US exhibiting large variations in local weather conditions contain more NSRDB stations of different classes as against a single location in smaller states. For ex, state of Texas has greater than 24 NSRDB locations as against Delaware with only 4 stations. For this study, EVs are simulated at every NSRDB station.

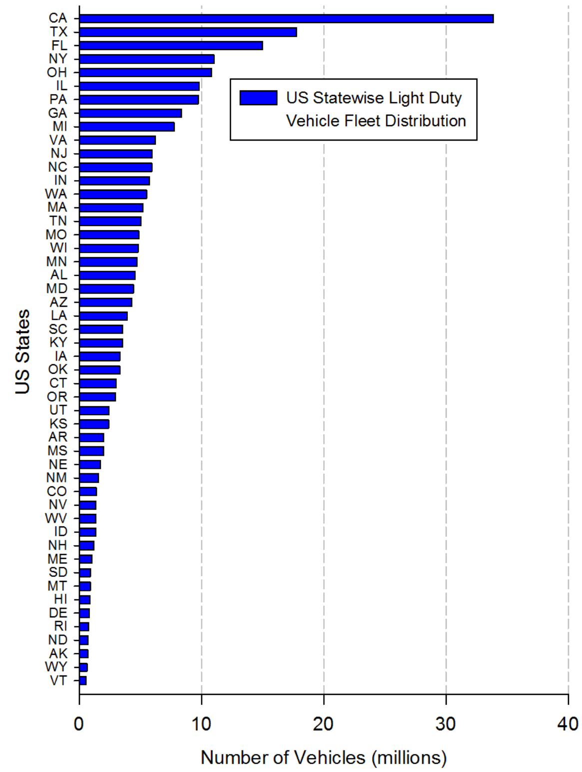
The important parameters required for the thermal comfort modeling are ambient temperature (T_{amb}), relative humidity (RH), solar irradiation (Q''_{solar}) and the local wind speed. The TMY3 dataset contains hourly averages of T_{amb} and Q''_{solar} ($Q''_{solar, diffuse}$, $Q''_{solar, direct}$) for all 365 days of the year. The RH is calculated based on dry-bulb and dew-point temperature

4.4.3 EV geographical distribution data

The light duty passenger vehicle distribution in US across different states is dependent on several factors such as availability of mass transportation facilities, surge in population growth, rapid urbanization, and increases in personal and household income, regional migration, trip distributions for work and non-work purposes and state transportation policies. The state-wise vehicle population distribution is extracted from the census bureau record, 2009 [57] and is presented in Figure 4-2 (b). California has approximately 14% of the 241.8 million registered light duty vehicles in US.



(a)



(b)

Figure 4-2 (a) Percentage of trips occurring as a function of time of day, (b) Passenger light duty vehicle fleet distribution across US.

4.5 Modeling methodology

In this section, dynamic thermal comfort model as applied to a passenger EV is discussed in more detail. The model is based on fundamental control volume approach to determine the dynamic state of a closed system and is more comprehensive in terms of regulating the cabin temperature by accounting for the changes effected due to transient environmental parameters [59]. As discussed in the gap analysis, it was found from the literature review that most of the previous work focused on creating a statistical model based on thermal comfort sensation to determine the usage of HVAC system. The current approach is a fundamental control volume approach to determine the dynamic state of the cabin space based on factors that affect the cabin space temperature. It can be seen that major governing factors affecting the cabin space of an automobile and the HVAC system usage is the local ambient temperature, local solar radiation, local humidity, length of the trip, type of automobile, occupant clothing, recent occupant activity, outdoor or indoor parking. This model is also forward facing approach as requirements of HVAC system would be established instead of utilizing existing design specifications of HVAC components.

The cabin space comprising of the driver and passenger compartment of an EV is chosen as the control volume. The control volume along with all the energy interactions with the environment across the boundary is represented in Figure 4-3. Unlike the PMV based physiological model, thermal comfort in this approach is defined as a scenario when the cabin space temperature (T_{ci}) and relative humidity is bound within a range of values decided by the user. Accordingly, the temperature and humidity values defining thermal comfort is set as $23\ °C < T_{ci} < 27\ °C$. The values were chosen based on widely accepted limits from the ASHRAE code defining thermal comfort conditions inside a control volume [60].

Figure 4-3 represents energy interactions at the boundary of control volume. The local solar radiation G_s, ambient temperature and relative humidity vary as a function of time of day (TOD) and time of year (TOY). The cabin space temperature is intended to be maintained within the range defined for T_{ci}. Due to continuous energy interaction between the cabin space boundary and the environment, the cabin space temperature varies. The state inside the cabin space is reestablished to that of comfort conditions by addition or extraction of heat energy. This is physically achieved by operating heater or AC system. The cabin space of the EV is not completely insulated resulting in conductive and convective energy losses across the boundaries.

The governing equation representing transient energy exchange across the boundary of cabin space is given by Eqn (8) where, $\dot{Q}_{heater}$ and $\dot{Q}_{AC}$ represents the DC electric power required to operate the heater and AC respectively. They are coupled to the cabin interior temperature using energy balance across the heater element and evaporator coil. They are based on average energy exchange between ambient air passing over the heater and evaporator coils as shown in Figure 4-4. $\dot{Q}_{losses}$ represent the conductive and convective heat lost through the vehicle interiors. $\dot{Q}_{glass}$ and $\dot{Q}_{roof}$ represent the heat gain or loss through front and rear windshield and the vehicle roof [61, 62]. The dynamics of the temperature of air leaving the surface of heater and evaporator coils are not considered, since the transient fluctuations of the air temperature passing over the heater and AC last for a non-significant time period. Also, the heater and AC are assumed to operate in steady state conditions.

As mentioned earlier, since the cabin space is not perfectly insulated, energy losses comprising of conductive and convective losses occur across the cabin. This is represented using Eqn (8) and computed from an equivalent conductive and convective thermal resistance for energy flow. The details can be found in Appendix.

$$\dot{Q}_{roof}+2\dot{Q}_{glass}+\dot{Q}_{conv,i}+\dot{Q}_{AC}+\dot{Q}_{heat}-\dot{Q}_{losses}=MCp\frac{dT_{ci}}{dt} \qquad \text{Eqn (8)}$$

$$\dot{Q}_{AC}=\dot{m}_{air}\left(\tilde{T}_{evap}-T_{ci}\right) \qquad \text{Eqn (9)}$$

$$\dot{Q}_{heater}=\dot{m}_{air}\left(\tilde{T}_{heater}-T_{ci}\right) \qquad \text{Eqn (10)}$$

$$\dot{Q}_{losses}=\frac{\left(T_{amb}-T_{ci}\right)}{R_{eff}} \qquad \text{Eqn (11)}$$

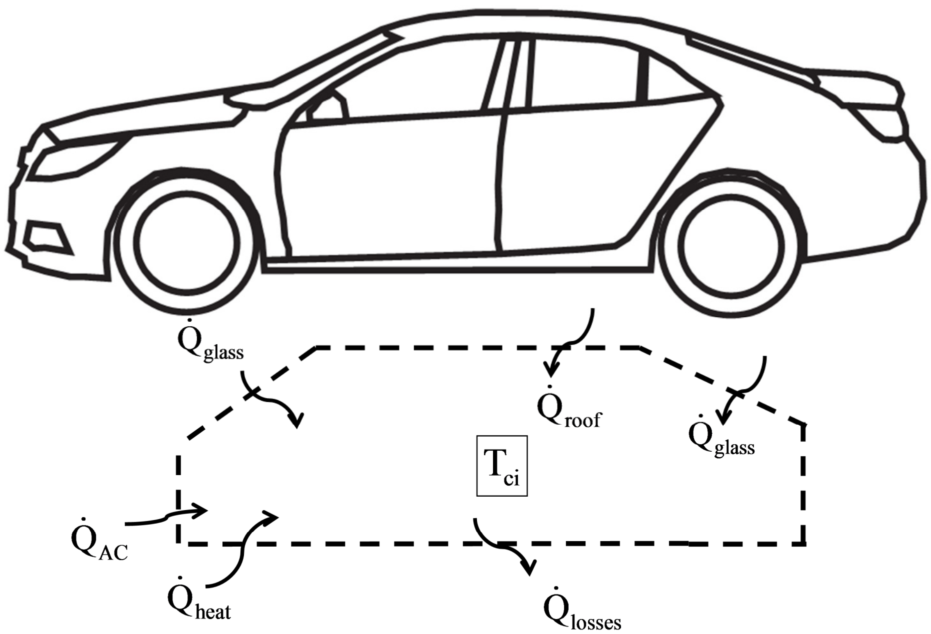


Figure 4-3 Energy balance for cabin space.

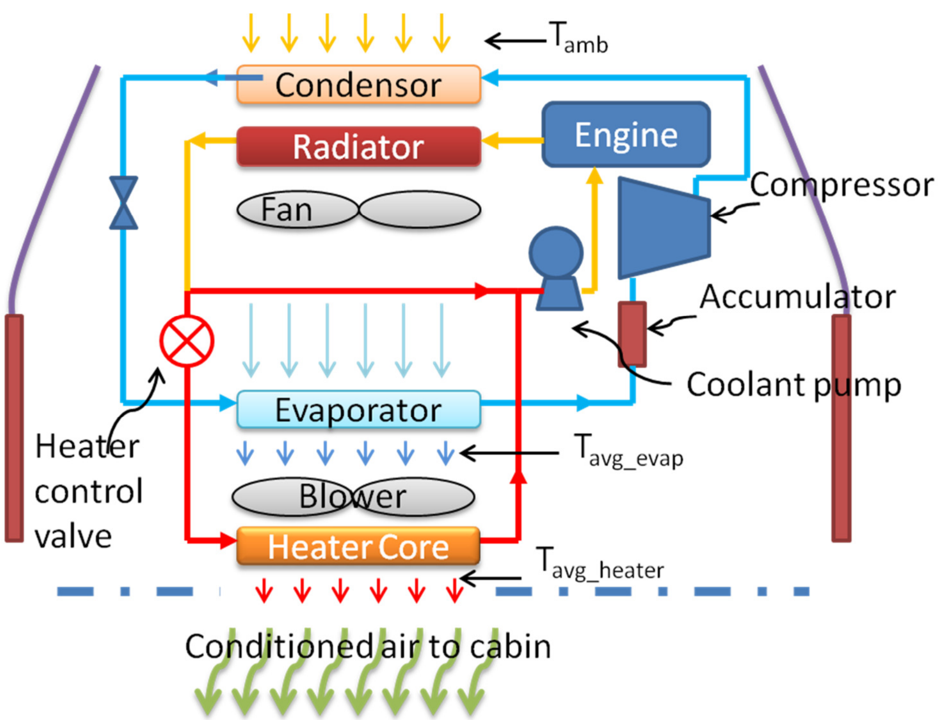


Figure 4-4: Car HVAC system [17].

The MATLAB SIMULINK model for thermal comfort is shown in Figure 4-5. The coupled governing equations are solved numerically using the ODE86 solver with automatic time steps [63]. The local ambient temperature is used as initial conditions to capture thermal soaking inside the cabin space. The DC electrical power required by the AC and heater is an output from the Simulink model.

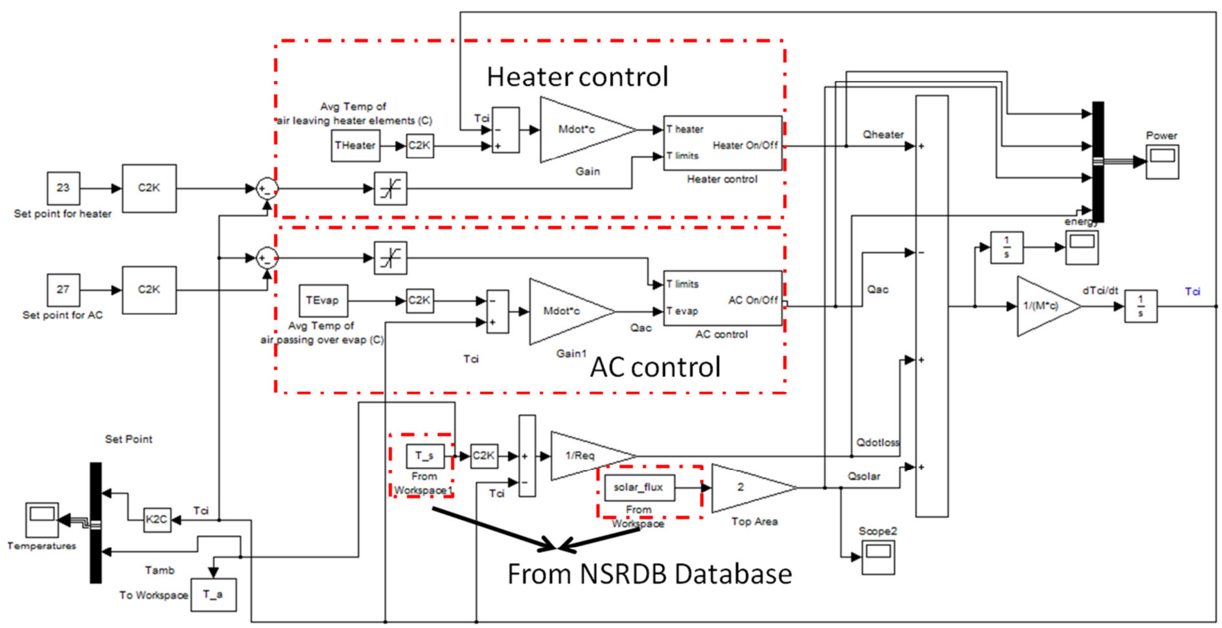


Figure 4-5: Snapshot of the Simulink model for cabin space control volume.

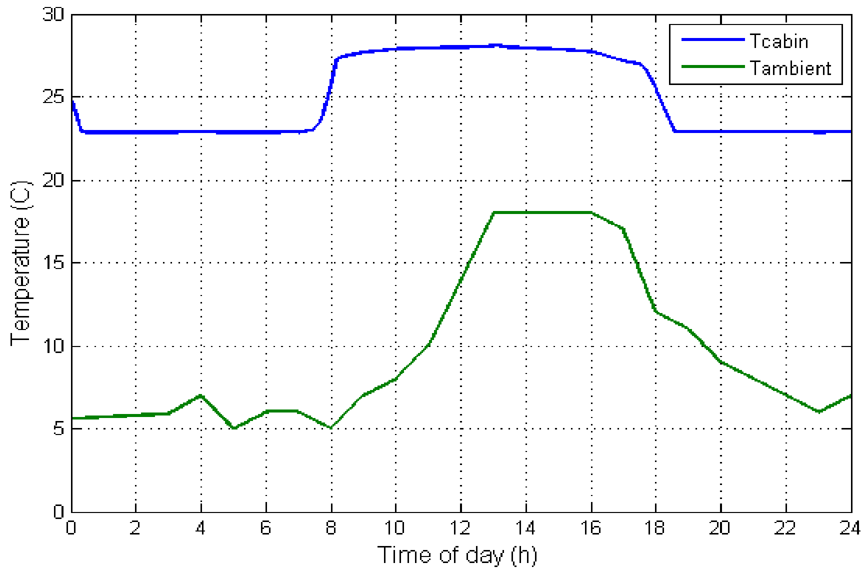
4.5.1 Case A: Trip starting with pre-conditioned cabin

In this case, consider a scenario where an EV is operated from the class 1 NSRDB station at 29 Palms, California by using the hourly average local environmental parameters from the TMY3 dataset. The simulation is performed by assuming that EV is continuously operated from 0hr to 11 59hr on the 1st day of January. It is also assumed that the prior to the beginning of the trip, the EV cabin is already preconditioned such that the thermal comfort requirements are established inside the cabin. Due to the continuous energy interactions across the boundary of vehicle's cabin space with the environment, the electrical power required to operate HVAC is not constant. The variations in ambient temperature and the corresponding cabin space temperature fluctuations at 29 Palms, California during the time of use is represented in Figure 4-6 (a). The ambient temperature is seen to increase with the TOD and is varying between a minimum of 5 to maximum of 18 °C and the peak occurring between 1PM to 4PM in the noon. The HVAC system maintains the cabin temperature between 23 and 27 °C throughout as is represented in Figure 4-6 (a). The heater and AC electrical power curves along with ambient solar irradiations, conductive and convective losses due to imperfections in the cabin space insulations are represented in Figure 4-6 (b). It can be seen that at 29 Palms, California, on 1'st of January, the solar irradiation varies from a minimum of 0 W to maximum of 1820 W. The peak solar irradiation occurs between 10 AM and 1PM. It is interesting to note that the time of peak temperature occurrence does not correspond to peak solar irradiation. This is due to the prevailing wind conditions at the location. The losses are more during the time of peak solar irradiation as against the time of peak ambient temperatures. It can be seen from Figure 4-6 (b) that the AC power curve is a strong function of solar irradiation while the heater power curve is a strong function of ambient temperature. By integrating the power curves over their time of use (in this case from 0hr to 11 59hr), electrical energy consumed by the HVAC system in an EV for providing thermal comfort is determined. The accurate predictions of HVAC energy consumption depends on time of use of the vehicle. As described in the earlier sections, the time of use is estimated using NHTS data base.

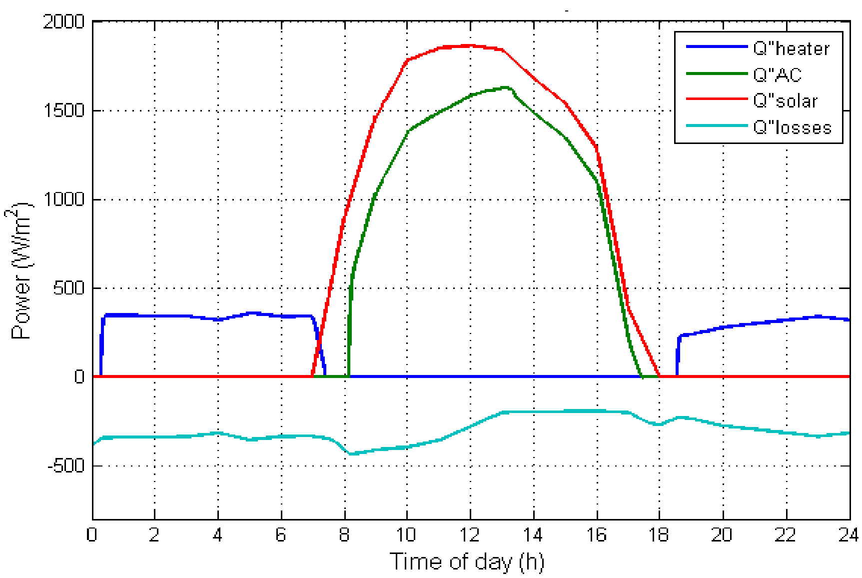
4.5.2 Case B: Trip starting at certain time of day

In this case, consider a scenario where an EV is operating at a class 1 NSRDB station at 29 Palms, California. The EV is parked such that the cabin space is soaking under direct sunlight. It is assumed that the EV is in thermal equilibrium with the environment at the beginning of the simulation. Due to the incident solar irradiation, the cabin temperature inside the cabin increases steadily with the time of day. At 11 AM in the morning, the user starts a trip. Due to high soak temperature of the cabin, the AC system is turned on. The AC control system maintains the temperature within the thermal comfort bounds until the end of trip at 13 hour. After the trip, the EV is again parked such that it is exposed to open ambient conditions. This variation in cabin temperature for the scenario is represented in Figure 4-6a. The temperature inside the cabin is seen to be slightly lower than the ambient temperature and is steadily rising at the start of the day. The rise in temperature corresponds with the increase in the intensity of the incident solar irradiation. At the start of the trip, the cabin temperature has reached a maximum of 35C. The vehicle HVAC system is turned on as indicated in the power curve (Figure 4-6b). Due to the thermal soaking of the cabin, the AC requires a peak power of ~7.7kW. After the initial ramp down of the soak temperatures, thermal comfort is established and AC system operates under steady state conditions with an average power of 1.2kW until the end of the trip (13 h). The initial transient state lasts for ~400s (< 7 min). After the trip, the vehicle is turned off and the cabin is further soaked under direct solar irradiation. The cabin temperature subsequently reaches the thermal equilibrium conditions. The no trip case in Figure 4-6a represents the cabin temperature profile for a scenario when the EV is parked under the direct sunlight all day and night. The total HVAC electrical energy (0.52kWhr: transient, 1.91 kWhr: steady-state, inclusive of system COP) for the sample trip is computed by integrating the HVAC loads during the length of the trip.

This process is repeated across all the 1019 NSRDB stations in US for all days of the year. The resulting database is post processed and several statistical analyses are performed to answer several high-level questions pertaining to the EV performance. The post-processing steps are described in more detail in the next section.

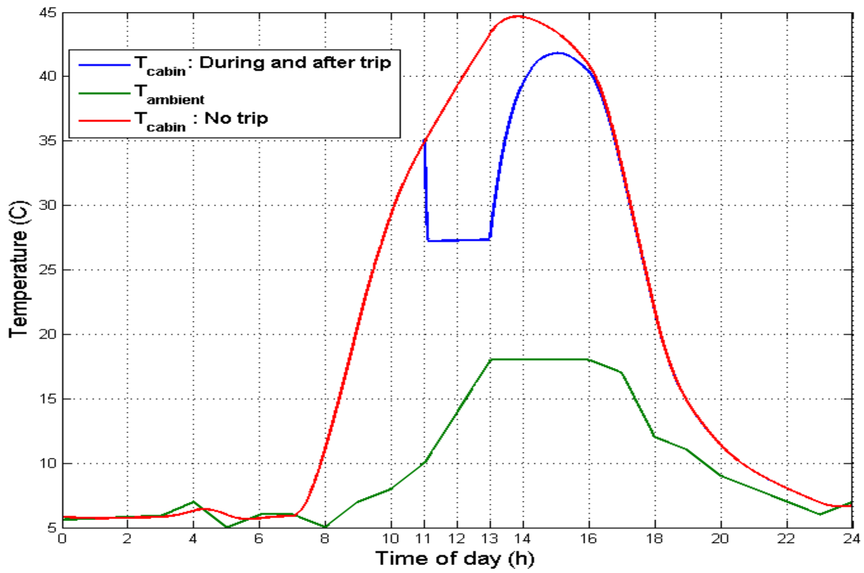


(a)

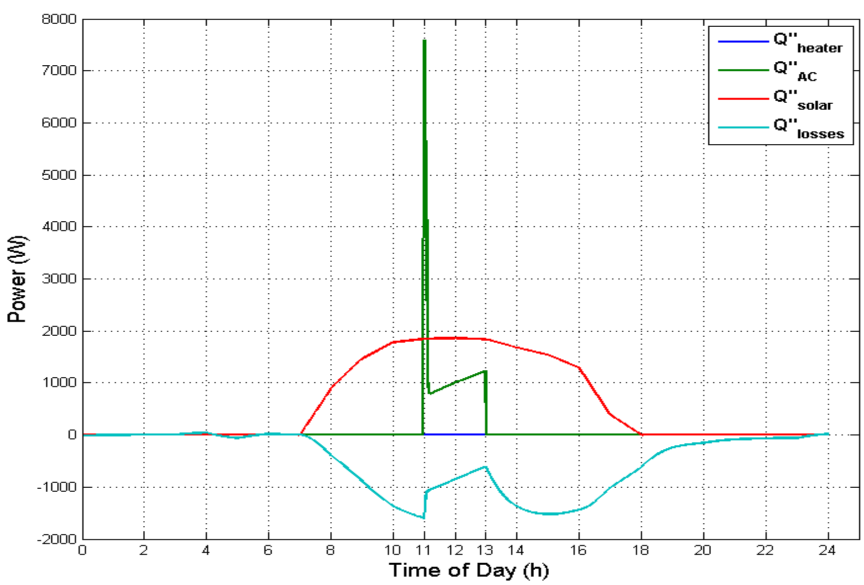


(b)

Figure 4-6 (a) Case A: Sample temperature curves for location, (29 Palms CA), over a period of 24 hours, (b) Case B: Sample power curves for location, (29 Palms CA), over a period of 24 hours.



(a)



(b)

Figure 4-7 (a) Case A: Sample temperature curves for location, (29 Palms CA), over a period of 24 hours, (b) Case B: Sample power curves for location, (29 Palms CA), over a period of 24 hours.

4.6 Post processing

In the previous section a sample simulation result for 29 Palms, California was discussed in detail using case A and B. The process of estimating EV HVAC energy consumption for real world driving conditions was outlined. The thermal comfort simulation is repeated for 1019 NSRDB stations across US. The resulting electric power curves for AC and heater are integrated over the time of use of passenger fleet from the NHTS survey data for all 365 days of the year and 24 hours of the day.

The output database is structured and processed for investigating the potential of EVs to replace the conventional vehicle fleet and their impact on increase in the US energy independency through reduced oil imports. The results will be used to synthesize annual HVAC energy consumption across US at the vehicle and fleet level, expected loading on the grid due to consumers charging the vehicles prior to peak hour travel, geographical and temporal variations in the consumption of HVAC energy, benefits of cabin preconditioning if any towards extending EV range, sensitivity of EV range as a function of TOD and TOY and identifying regions of US that are optimal for EV use.

4.7 Summary

In this chapter, the methods relating to the development of thermal comfort model was described in detail. The outputs from the sample thermal comfort simulation of an EV at 29 Palms, California for 1st day of January was presented for case A in which the cabin was assumed to be preconditioned at the start of the simulation and case B where the cabin was in thermal equilibrium with the environment and a trip was simulated between 11AM and 1PM to highlight the thermal soak, transient and steady state behavior of AC system to pull down the cabin from soak temperature to comfort limits. The process to evaluate HVAC energy consumption from the power curves based on the vehicle TOU from the NHTS survey data resulted in estimating the energy required for transient and steady state operation of HVAC system. By repeating the simulations for 1019 NSRDB stations across US, a massive database consisting heater and AC electric loads based on real world conditions was obtained. The resulting database will be further used to investigate a) Vehicle level HVAC energy consumption, b) Fleet level HVAC energy consumption, c) Potential savings by reduction of gasoline consumption d) EV performance in terms of day to day variations in EV range e) geographical variations in terms of charging characteristics f) frequency of EV range consistency g) minimum maximum and mean EV range in all of US states h) pre-conditioning of cabin as a feasible solution to increase day to day EV range.

CHAPTER 5 VEHICLE AND FLEET LEVEL HVAC ENERGY CONSUMPTION

5.1 Introduction

As highlighted in the gap analysis, previous HVAC energy consumption studies were focused on passenger conventional vehicle fleet. In the conventional vehicles, the waste engine heat is utilized for winter conditions and hence the energy for heating the cabin space of the vehicles were not considered in the PMV based thermal comfort model. However, in electric vehicles, in addition to the energy required for AC, energy for heating the cabin space during winter conditions need to be accounted for since the energy for both heating and AC is provided by the on board energy storage device. In this chapter, the results from the thermal comfort model are post processed to evaluate HVAC energy consumption at the vehicle level and fleet level. The evaluated HVAC energy is based on real world environmental conditions. The energy consumed for both heating and AC is clearly determined separately and their relative magnitudes are evaluated so as to highlight the importance of designing efficient HVAC systems based on their variability. The thermal comfort modeling simulations are performed over 1019 locations across US. Every US state has more than three weather monitoring stations located in different regions of the state. For state-wise representation, average HVAC energy consumption is determined for individual state by grouping and averaging HVAC energy consumption for all the monitoring stations that lie within a given state. In the subsequent sections of this chapter, the state-wise annual average HVAC energy distributions at the vehicle (section 5.2) and fleet level (section 5.3) will be presented. In addition to the vehicle and fleet level HVAC energy consumption, of particular importance is to estimate HVAC energy consumption for peak hour travel conditions. This is presented in section 5.4.

5.2 State-averaged fleet PEV HVAC energy consumption

A PEV is powered by the on board energy storage device like Li-ion batteries. The frequency of charging and discharging the battery varies based on the users driving characteristics. The electrical energy consumed by the user directly replaces the gasoline there by eliminating the tail pipe emissions.

However, the electrical energy drawn from the grid during the process of charging the battery needs to be accounted for by generating additional power at the source. Figure 5-1 represents the average HVAC electrical energy consumed by an PEV user in a year across all the states in US states and for 12,000 mi (19,312 km) of annual driving distance. The tractive energy is not included since it will remain constant for a given drive cycle and is independent of local weather conditions. The total HVAC energy consumption consists of two components, the energy expended for heating and the energy expended for AC. Arizona tops the list of US states in terms of annual average HVAC energy consumption per vehicle with ~2754 kWh and 437 kWh towards AC and heat respectively, while 1329 kWh and 742 kWh is required for similar PEV in West Virginia in accordance with the associated local conditions.

The ratio of AC load to heater load is highest in Arizona (6.3) and lowest in Alaska (0.48). Figure 5-2 shows that for similar driving and discharge conditions, a PEV in Arizona requires approximately 1000kWh (~30gallons gasoline equivalent) of more electrical energy for passenger comfort conditioning compared to a PEV in West Virginia. This translates into the need for PEV user in Arizona to charge ~54 times more often as compared to PEV user in West Virginia. The large differences in frequency of charging results in unsatisfactory user experience across US deterring large scale adoption of PEVs in to the passenger fleet. The current generations of PEVs are frequently recalled from the market since their energy storage systems are designed without accommodating for these fluctuations [64].

Traditionally the HVAC systems in the conventional vehicles are designed for maximum capacity[6, 65, 66]. However, in case of electric vehicles, optimizing the HVAC systems for maximum efficiency will result in significant improvements in terms of increase in electric distance travelled, reduction in the electrical energy consumed and hence net displacement of gasoline and associated tail pipe emissions.

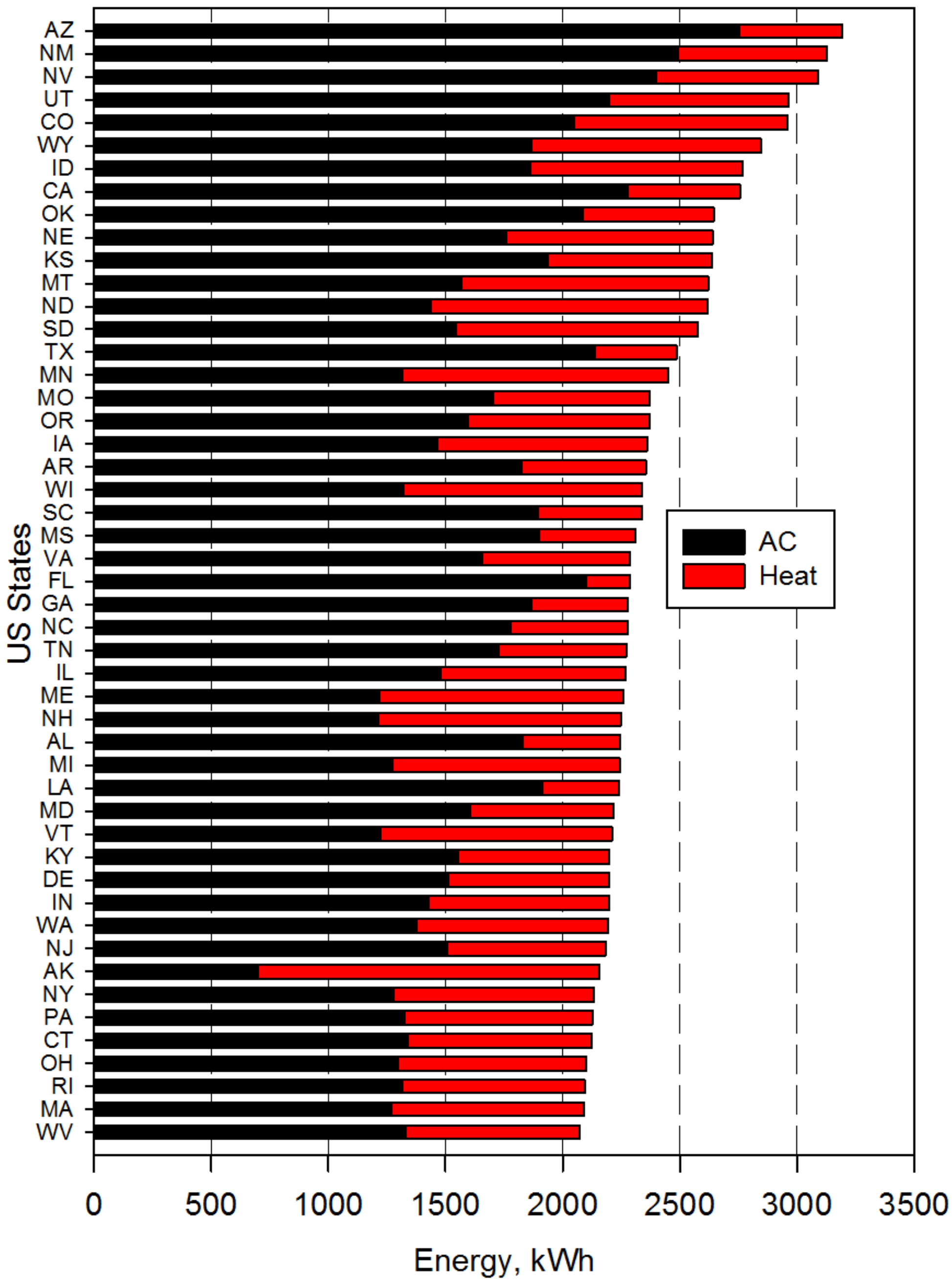


Figure 5-1 Annual average HVAC energy consumption per light duty vehicle in individual states of US.

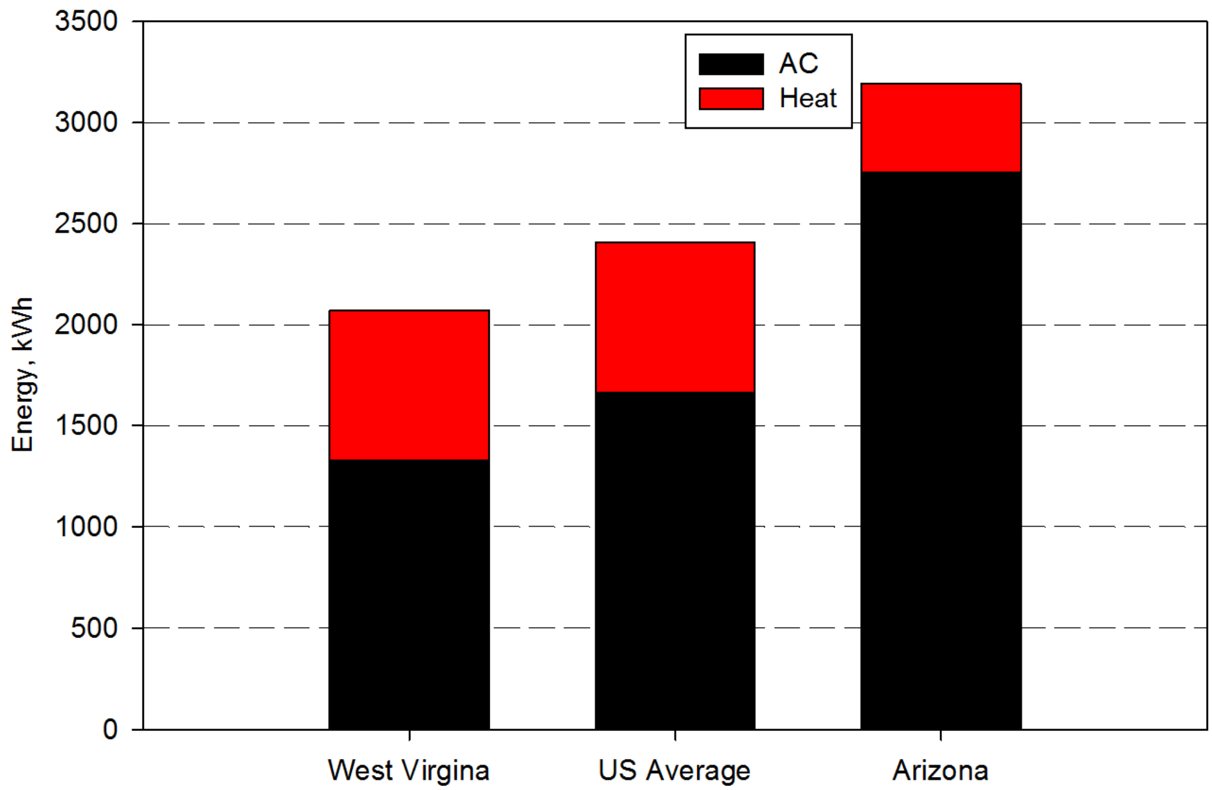


Figure 5-2 States with minimum and maximum HVAC energy consumption per light duty vehicle per year.

5.3 US light-duty vehicle fleet level HVAC energy consumption

The light-duty passenger vehicle fleet distribution across US as represented in Figure 4-2 (b) highlights the regions where PEVs can have maximum impact by means of replacing a certain percentage of conventional light-duty passenger vehicle fleet over a period of time. To estimate the total annual HVAC energy required by a hypothetical 100% PEV US light duty vehicle fleet, the HVAC energy consumed by a single PEV across different states (Figure 5-1) can be combined with the vehicle fleet distribution (Figure 4-2b), as represented in Figure 5-3. For this hypothetical 100% PEV fleet, we estimate that 565 billion kWh of energy would be required annually for thermal comfort, as shown in Table 5-2. AC electrical energy requirements exceed heating electrical energy requirements by ~2.75

times. This is equivalent to 17 billion gallons of gasoline consumption (~13.7% of 2011 US annual oil imports).

Of course, a 100% PEV light-duty fleet is not representative of any near-term feasible scenario, but the presentation of results in this format allows for the simple calculation of the HVAC energy consumption of near-term light-duty fleets through multiplication of either national or state-level energy consumption by the PEV fleet penetration fraction. For example, at present, there are 59,952 PEV in the US light duty vehicle fleet, which represents 0.03% of the 2009 census value of 242 million vehicles. At present, the energy allocated to heating and cooling PEVs in the US is approximately 0.14 billion kWh_{DC}.

The scale of the energy involved in thermal comfort conditioning of PEVs justifies the treatment of PEV HVAC systems design as means for achieving significant transportation system energy consumption reductions. The results presented in Figure 5-3 are averaged across entire state. The fleet level annual average HVAC energy consumption results can be further resolved at the city level based on the scale of urbanization. This will help in the identification of EV friendly hotspots within every state. Currently, as can be seen from the results presented in this section, the variation in the user experience can lead to inappropriate assessments of EV technology. By targeting the promotion of EV technology at the identified hot spots, a more structured policy and EV promotion strategies specific to individual hotspots can be brought about. This shall not only increase the awareness of the general user in terms of the expectations from EV, but also, over time can result in higher acceptance of the EV technology.

From Figure 5-4, it can be seen that with 14% of total light duty passenger vehicle fleet concentration, California exceeds the total US average annual HVAC energy consumption by 88%. Thus, with a modest 10% replacement of the conventional vehicles with electric fleet in California, approximately 2 billion gallon of gasoline can be potentially displaced.

While new policies and frame works are being recommended [4] and formulated to enhance the process of owning and operating PEVs and EVs on par with conventional gasoline operated vehicles, a scalable onboard energy storage capacity will help mitigate the inconsistencies in performance of the EVs due to HVAC loads The displacement of gasoline needs to be compensated by generating additional energy by the utilities in the upstream side. Result similar to Figure 5-3 at the county level can help the regional utilities to understand, plan and estimate additional ancillary services required to accommodate large scale market penetration of PEVs. With renewable energy based ancillary services, and controlling the emissions associated with manufacturing battery packs for EVs, a net reduction in the gasoline consumption can be brought up, resulting in lower oil imports and also cutting down all the tail pipe emissions from the conventional vehicles.

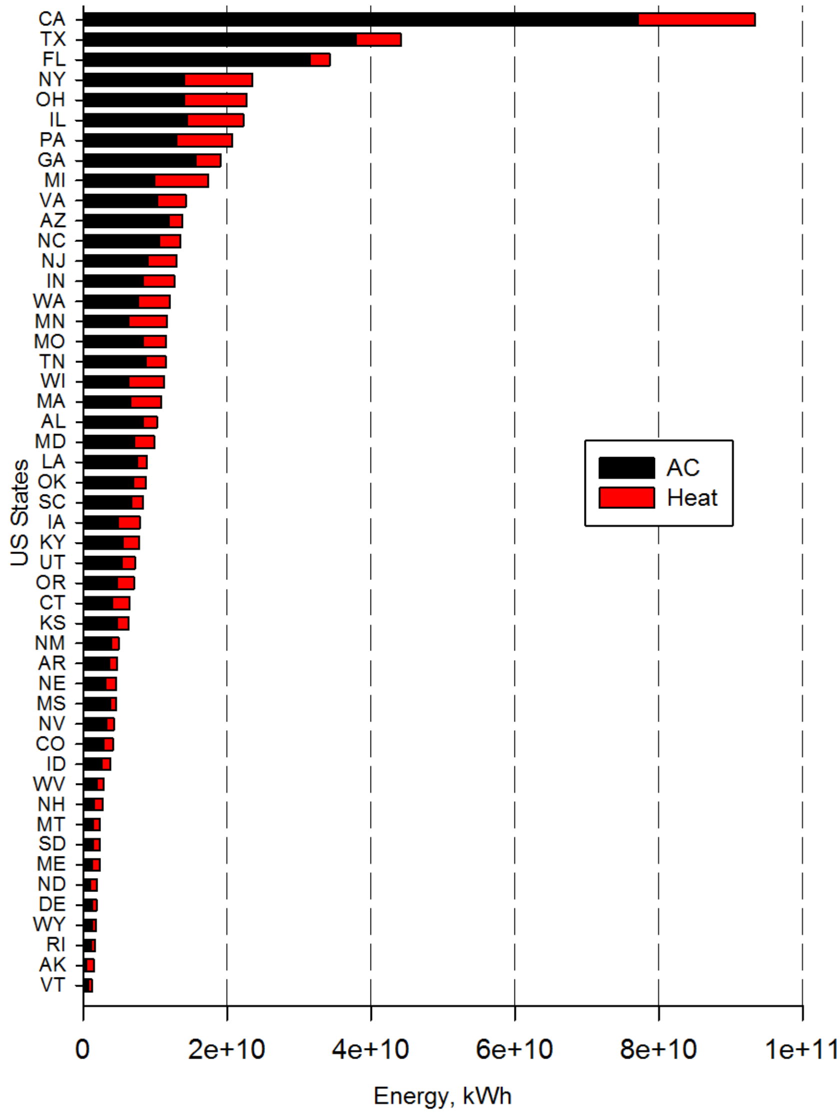


Figure 5-3 Annual total HVAC energy consumption by the light duty vehicle fleet in individual states of US.

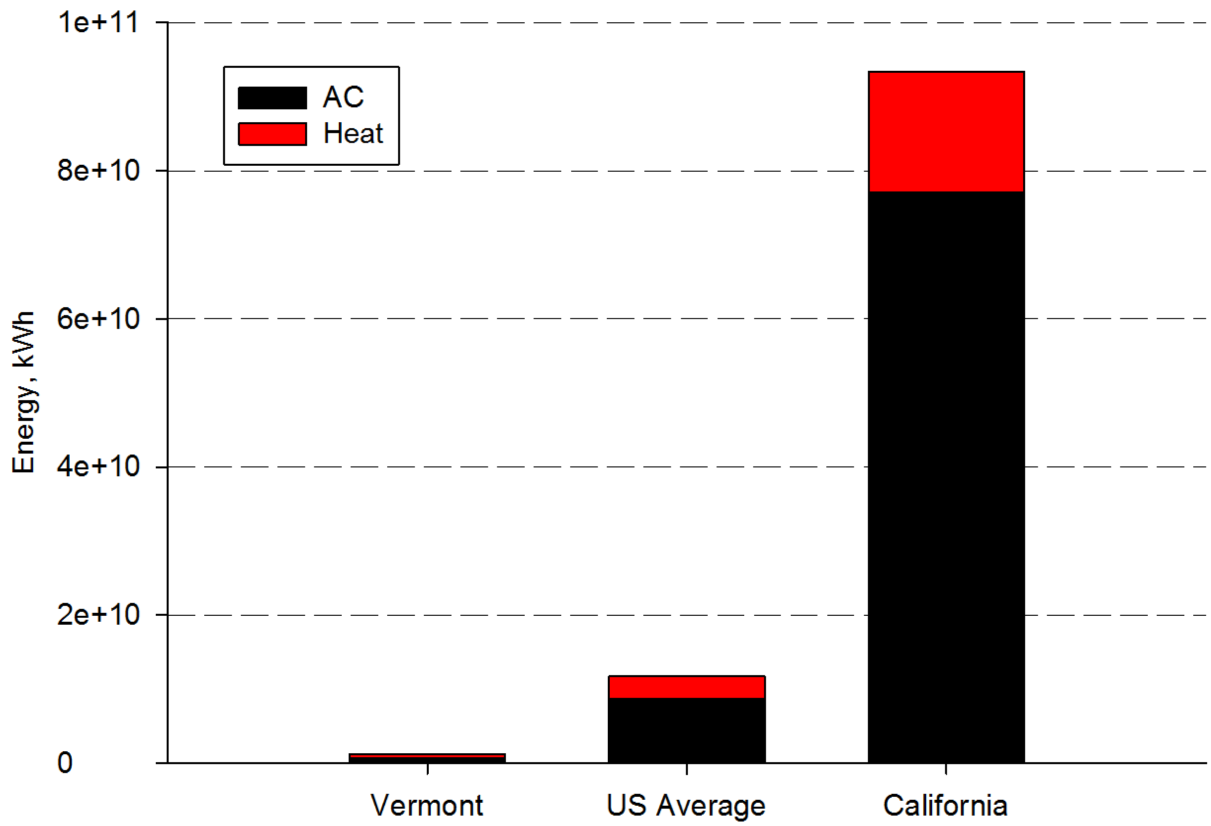


Figure 5-4 States with minimum and maximum total HVAC energy consumption by the light duty passenger fleet per year.

5.4 Peak hour travel HVAC energy consumption

The Figure 5-5, Figure 5-6, Figure 5-7 and Figure 5-8 represents HVAC load for peak hour travel during an average spring (March 21 to June 20), summer (June 21 to September 22), fall (September 22 to December 20) and winter (December 21 to March 20) day respectively. The peak hour travel is defined as the time of day when maximum percentage of trips occur [ref]. Accordingly for this study the peak hour travel is defined as all the trips occurring at 9AM and 4 PM of the day indicative of commute to and back from work.

From Figure 5-5, Figure 5-6, Figure 5-7 and Figure 5-8 can be seen that the peak load drawn by the HVAC system is greater than 2 kW on an average day except during winter. The results from the plot are summarized in Table 5-1. The differences in the HVAC loads across the states in US are due to the direct impact of environmental conditions on the cabin space. This implies that, for a similar sized HVAC system, the electric miles travelled in US is can vary significantly. For example, a 40 mile range electric vehicle designed with 16kWh battery storage (8kWh usable) can only travel a distance of 30 miles with a 2kW peak accessory load.

Table 5-1 Summary statistics for geographically-realized HVAC power calculations

Seasons	State (Maximum Power, kW)	State (Minimum Power, kW)
Spring	Arizona (2.4)	Alaska (0.72)
Summer	Nevada (2.9)	Alaska (0.88)
Fall	Arizona (2.2)	Alaska (0.63)
Winter	Alaska (1.6)	Alaska (0.78)

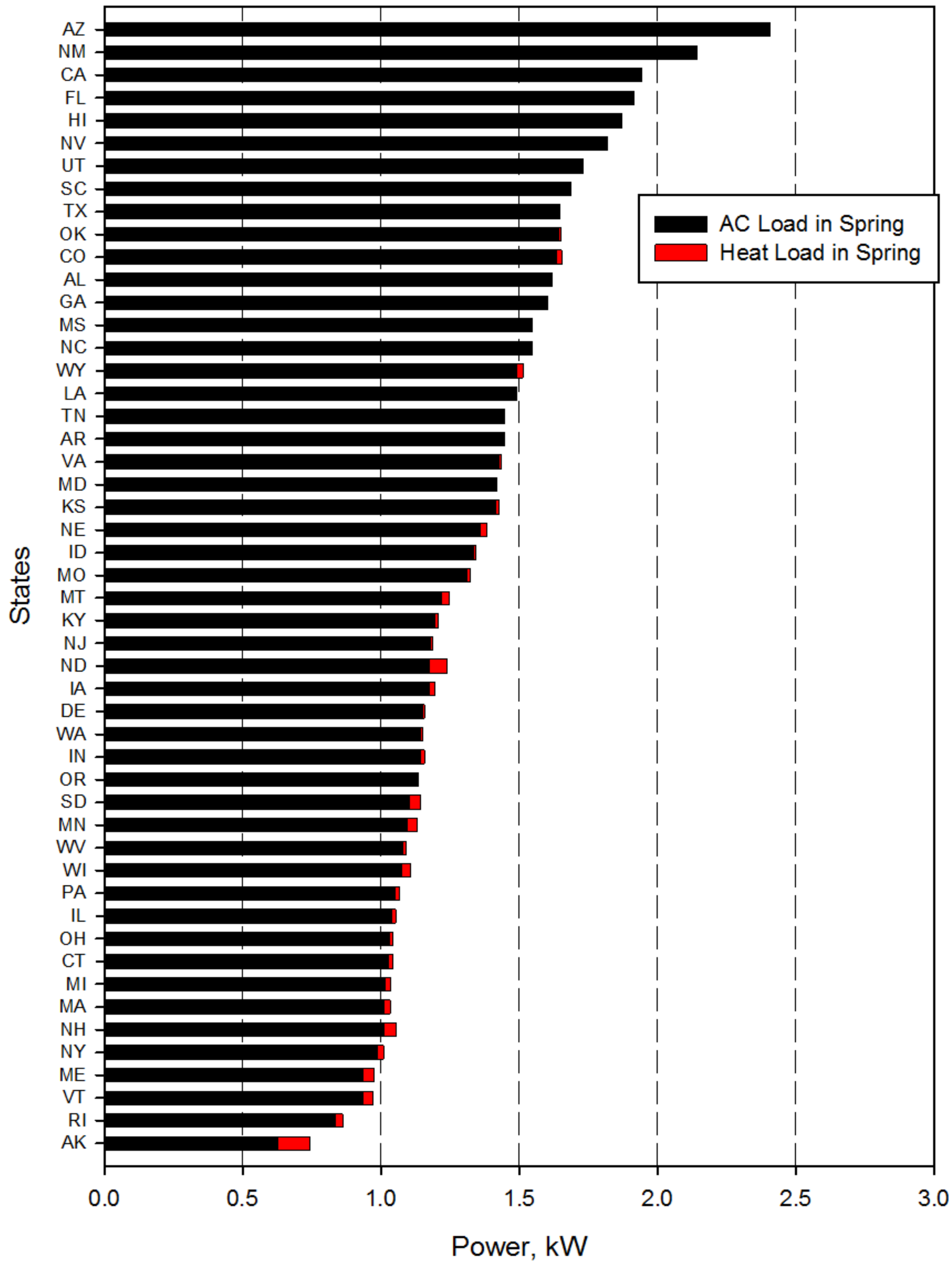


Figure 5-5 Average vehicle HVAC load for peak hour travel across US states during spring.

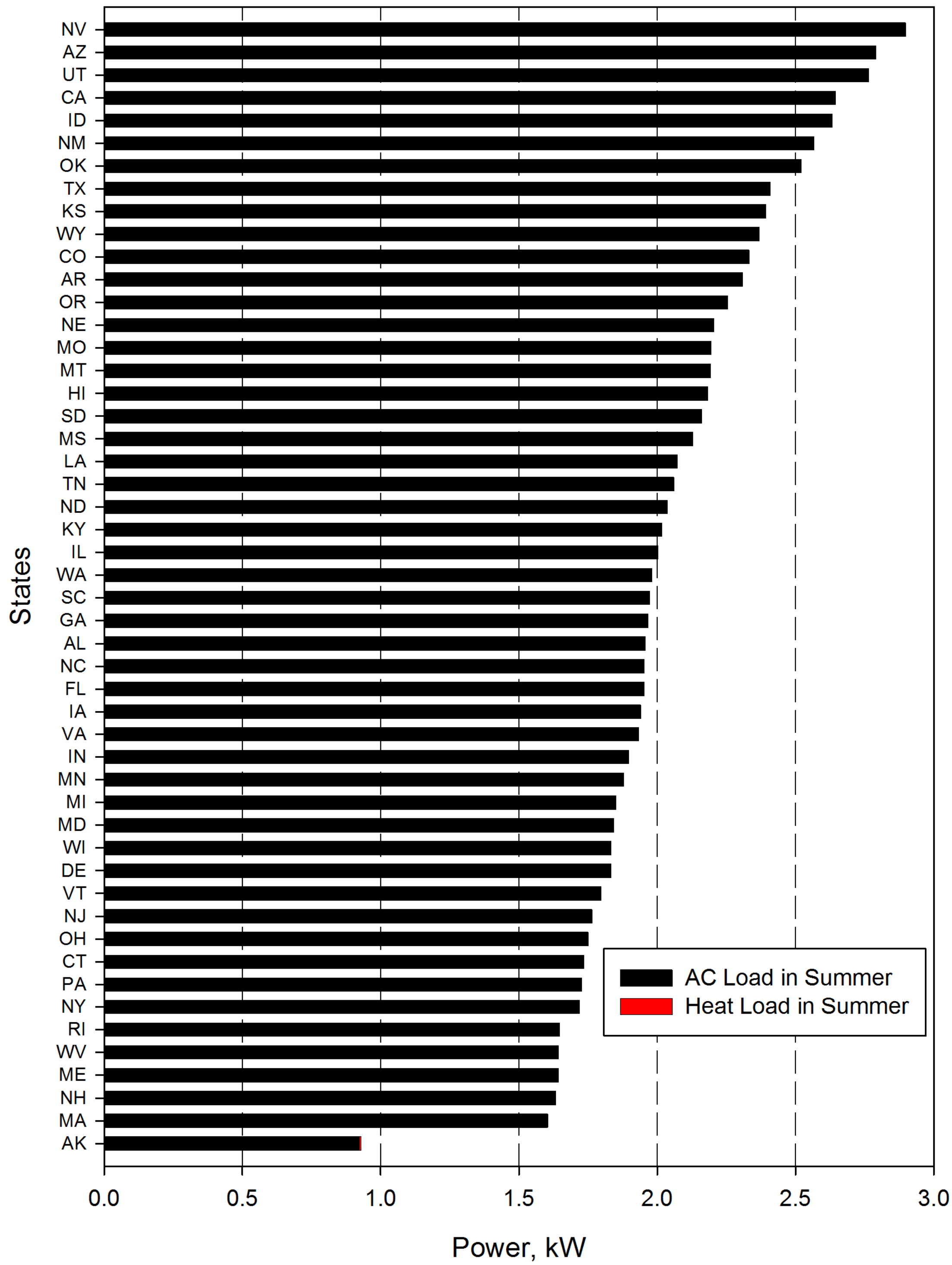


Figure 5-6 Average vehicle HVAC load for peak hour travel across US states during summer.

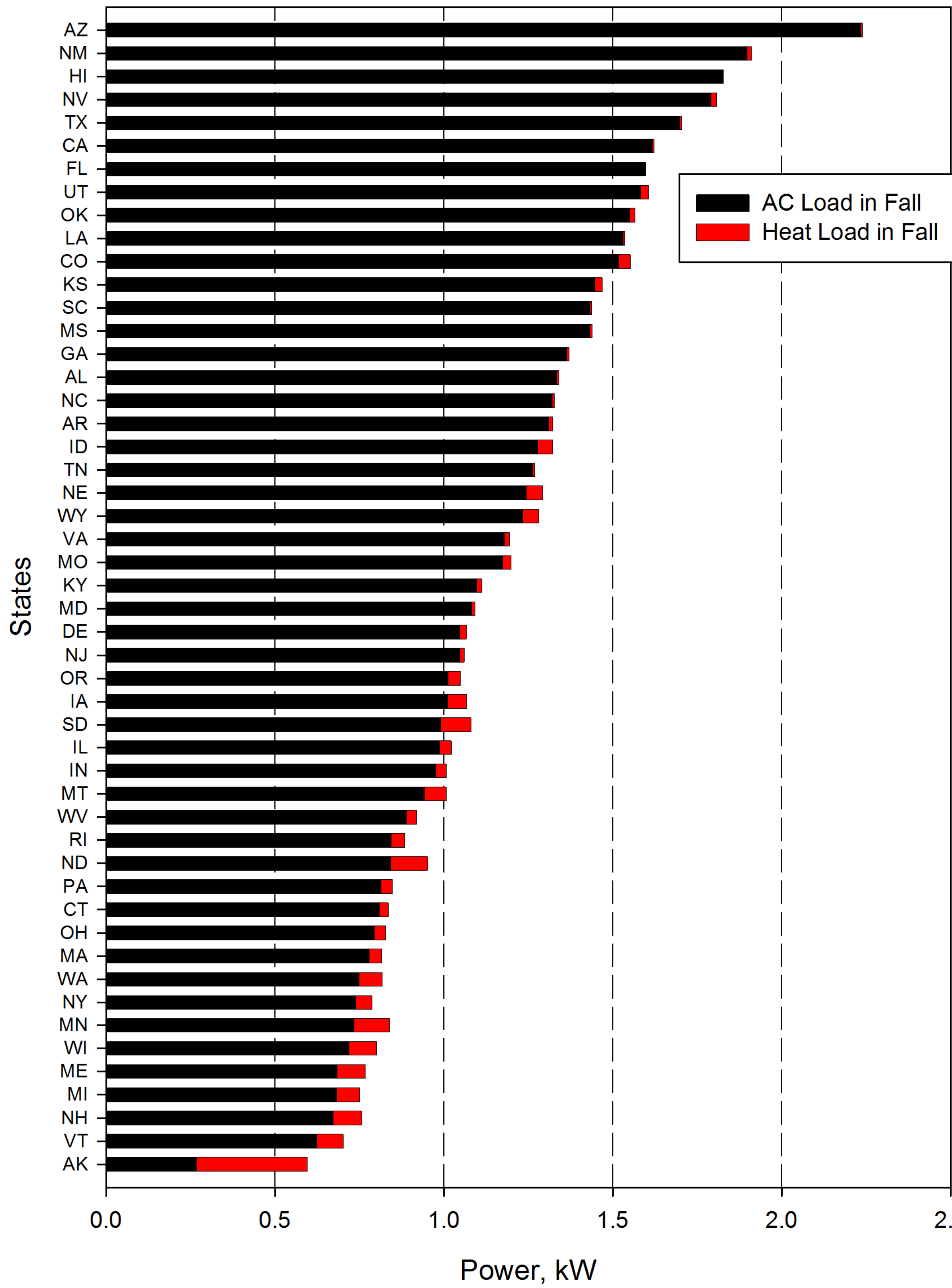


Figure 5-7 Average vehicle HVAC load for peak hour travel across US states during fall season.

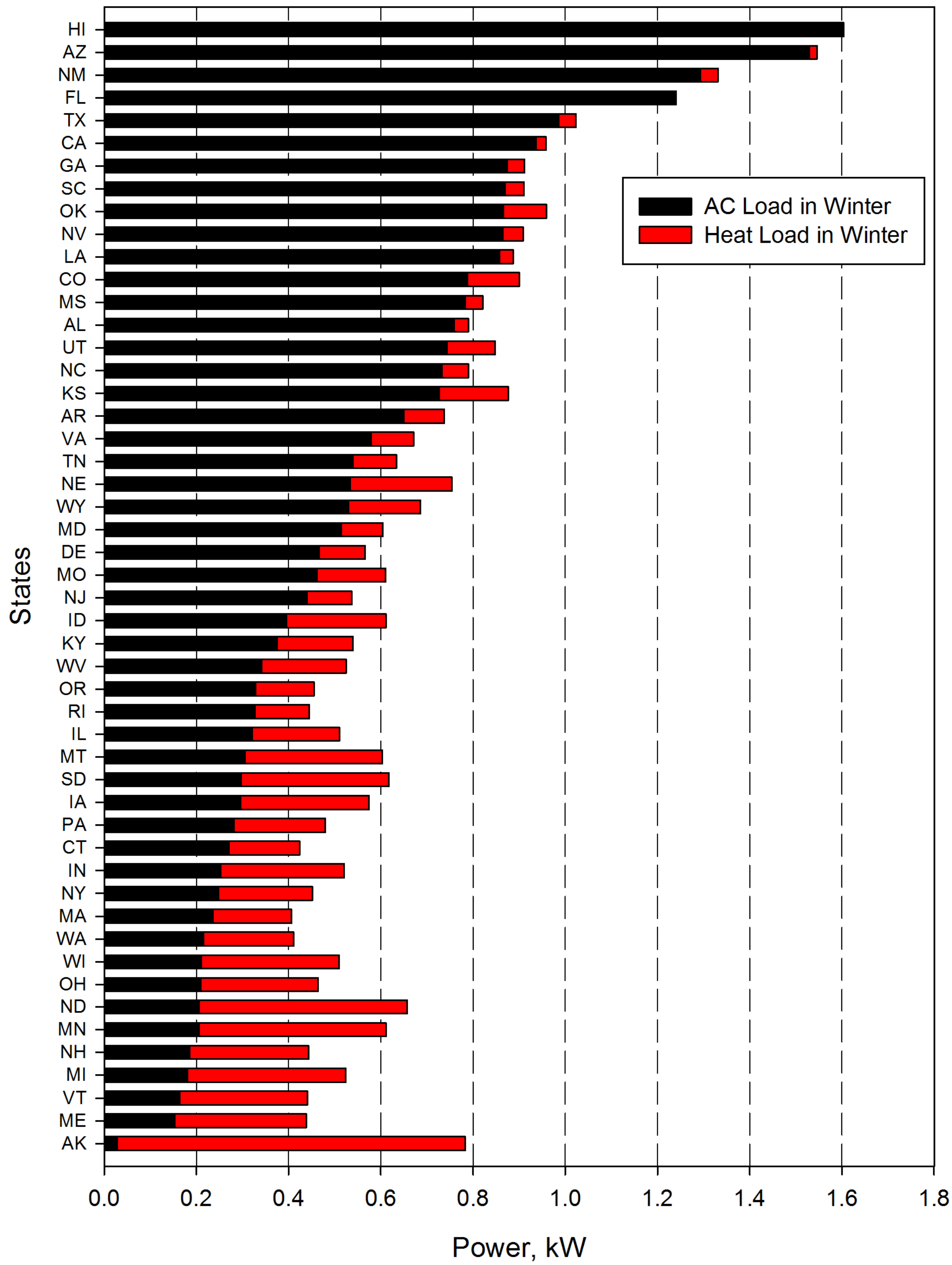


Figure 5-8 Average vehicle HVAC load for peak hour travel across US states during winter season.

5.5 Summary

This section of the research effort has allowed us to address research question 1, which is restated here: **Research Question 1: How much energy (petroleum energy, electrical energy) does an electrified light-duty vehicle fleet consume compared to a fleet of conventional vehicles?**

To answer this research question, this study has derived the state-wise annual average HVAC energy consumption at the vehicle and fleet level using the methods developed in this chapter. Previous studies of the accessory loads of conventional vehicles had considered AC loads as the only contributor to vehicle thermal comfort conditioning. Modern electric vehicles consume electric energy to provide both heating and A/C for thermal comfort conditioning. Table 5-2 shows that sum of all of the HVAC energy consumed by an EV fleet is the equivalent of 13.3 billion gallons of gasoline, with 26.5% for providing heat energy. This justifies the treatment of automotive HVAC systems design as means for achieving transportation system energy consumption reductions.

Table 5-2 Total annual energy required for operating a hypothetical 100% PEV US light-duty fleet

Air Conditioning Energy	Heating Energy	Traction Energy
415 billion kWh_{DC}	151 billion kWh_{DC}	1012 billion kWh_{DC}

A wide variety of studies[3, 4, 5, 6, 7, 9] of electrified vehicles have made comparisons between EVs and CVs on the basis of their EPA 5-cycle measured fuel economy, but the EPA 5-cycle fuel economy test does not consider the effect of heating loads on the fuel economy of EVs. Using the results of this study, we can make a comparison of the energy consumption of EVs and CVs that does consider their real-world fuel consumption due to HVAC loads. Table 5-3 shows these results and shows that inclusive of the energy consumption of EV HVAC systems, the EVs exhibit 70% annual energy savings. Previous studies [3, 9] overestimates the energy savings by 23%, resulting in inaccurate estimations of the EV range. This has important implications for consumers (to switch from CV), policy construction including CAFE and overall goal of moving towards sustainable passenger fleet transportation.

Table 5-3 Comparing the annual energy consumed by conventional and electric vehicles (12,000 mi/yr, midsized car)

	Estimated energy consumption using 5-cycle EPA test methods [3, 9]	Estimated energy consumption using 5-cycle EPA test methods including real-world heater energy
Conventional Vehicle	14.6 MWh_{LHV}	14.6 MWh_{LHV}
Electric Vehicle	3.6 MWh_{DC}	4.3 MWh_{DC}

CHAPTER 6 HVAC-INCLUSIVE PERFORMANCE EVALUATION OF ELECTRIC VEHICLES

6.1 Introduction

In Chapter 5, energy consumed by the HVAC systems at the vehicle level and the fleet level was evaluated for real world conditions across US using the control volume based thermal comfort model discussed in Chapter 4 . In this chapter, the high level EV dynamics is translated into distance travelled by the EV with a specific onboard storage capacity. For the purpose of this study, an EV with a 24kWh energy storage capacity, representative of a currently popular model in the market is chosen. The energy consumed towards traction is evaluated assuming a drive cycle similar to that of EPA 5 cycle test for electric vehicles with a constant discharge rate of 0.3kWh/mi. During the drive cycle, the energy flow from the battery for traction and thermal comfort based on real world conditions is monitored. The miles travelled are computed based on available storage energy. The procedure is simulated for all the 1019 NSRDB locations. The results are post processed to address several questions such as 1) How does day to day environmental conditions at a given location affect commute using a EV? 2) How does frequency of distance travelled using an EV change from one location to another? 3) How much impact does start time of the trip has over distance travelled using EV? 4) Under what conditions does cabin pre-conditioning assist in increasing the EV range? 5) What percentage increase in EV miles can be expected due to cabin preconditioning at a given location? These questions will be quantitatively addressed in the following sections.

In section 6.2, the average minimum, mean and maximum range is evaluated for all US states. The thermal comfort conditions are simulated across 1019 locations in US for travel during 365 days of the year and 24 hours of the day. Every state has more than one NSRDB stations. The range is averaged across all the stations within a given state. The minimum mean and maximum range for every US state is quantified.

The widely varying HVAC energy requirements are clearly due to the variations in real world environmental conditions prevailing across the US. The recurring theme throughout this dissertation is the impact of the environmental conditions on the thermal comfort requirements and the subsequent taxing on the on board energy storage device. In section 6.3, the temperature contours for five cities: Anchorage (AK), Atlanta (GA), Detroit (MI), Los Angeles (CA) and Phoenix (AZ) is presented as a function of TOD and TOY. The cities chosen are representative of the wide spectrum of weather conditions prevalent across US.

In section 6.4, the EVs real world range at the five cities is discussed as a function of TOD and TOY. Of particular interest to EV user is the consistency with which one can travel a given distance throughout the year. This question is answered by means of histogram plots in section 6.5. The results in this section has the potential to assist the EV user in creating pre-informed travel routine without stretching the expectations beyond the EVs capabilities, thereby increasing the user satisfaction.

Amidst all the discussions regarding the limitations of EVs range, a microscopic look at the energy flow diagram of the onboard storage device reveals that HVAC systems consume significant energy next only to traction requirements [51]. The energy consumed by the HVAC system is dispensed towards reducing the transient loads due to thermal soaking and subsequent steady state loads. The energy to pull down the transient loads on a hottest or a coldest day can be as much as 30% of the total HVAC energy consumed [19, 67]. Previous studies have qualitatively recommended preconditioning the cabin prior to the trip as one of the possible solutions towards extending the EV range. This is based on the assumption that the user has the access to the grid electrical energy. However, none of the studies quantify the benefits of cabin preconditioning for real world driving conditions. In section 6.6, a qualitative and quantitative analysis of thermal comfort results without and with preconditioning is discussed. Specifically, the benefits if any of preconditioning the cabin and associated conditions and assumptions when they apply will be discussed in more detail.

6.2 State-wise minimum, mean and maximum range estimates

With the increasing push towards reducing global green-house gas emissions, several automakers have taken the lead in introducing EVs into their fleet of passenger light duty vehicles. The early adopters of EV technologies have reported less than satisfactory performance of their respective vehicles[68]. Several reports have tested and compared EVs available in the market at different locations. The widely varying results are attributed to the driver behavior, trip characteristics (city vs. highway), battery chemistry and environmental conditions. In this section, the impact of widely prevailing weather conditions across US states on the EV range is presented using Figure 6-1.

The simulation results are daily-averaged across several NSRDB stations within individual states for 365 days of the year. The minimum, mean and maximum expected range is obtained from the matrix of stations in each US state. The minimum and maximum range for a particular state in Figure 6-1 indicates that at any given location within the state, the range obtained from a 24kWh EV and average speed of 60 mph is bounded by the limits. For example, on any given day in CO, with the prevailing weather conditions, the daily averaged expected range is between 66.5 to 71.2 miles.

The result from Figure 6-1 assists in understanding the EV performance across all the states in US. The states are sorted out based on the mean range values. Accordingly, an EV in Alaska has the highest mean EV range of 75.8 miles while it is lowest in Arizona with 67.9 miles. The EV range spectrum for individual states will assist the policy makers in devising smart strategies that can be targeted selectively at specific states. The automakers can use Figure 6-1 to understand the requirements of storage system such that EV performance variations across the country can be minimized.

From the users perspective, it is important to note that the minimum, mean and maximum values is of less significance as compared against consistency with which a certain range can be obtained on day to day basis during the course of travel. In many scenarios, due to the constraints on the energy storage capacity, it is most beneficial to operate and EV over a pre-determined route. Using Figure 6-2, it is now possible to identify the states where the fluctuation in EV range is lowest. It can be readily seen that Delaware has the lowest fluctuation of the EV range and hence greater consistency and reliability for travel using EV in comparison to driving a similar EV in California. California has the highest concentration of passenger fleet vehicles with approximately 33 million registered light duty vehicles in 2008. From Figure 6-2, clearly, the prevailing weather conditions in California leads to poor user experience as a result of large fluctuations in EV range. This highlights the need for customized design for the EVs intended to be introduced in CA, in terms of energy management and energy storage. The drastic difference in fluctuations between Alabama and other states leads to questioning the veracity of the environmental data obtained from NSRDB database and hence Alabama is not considered in the present discussion.

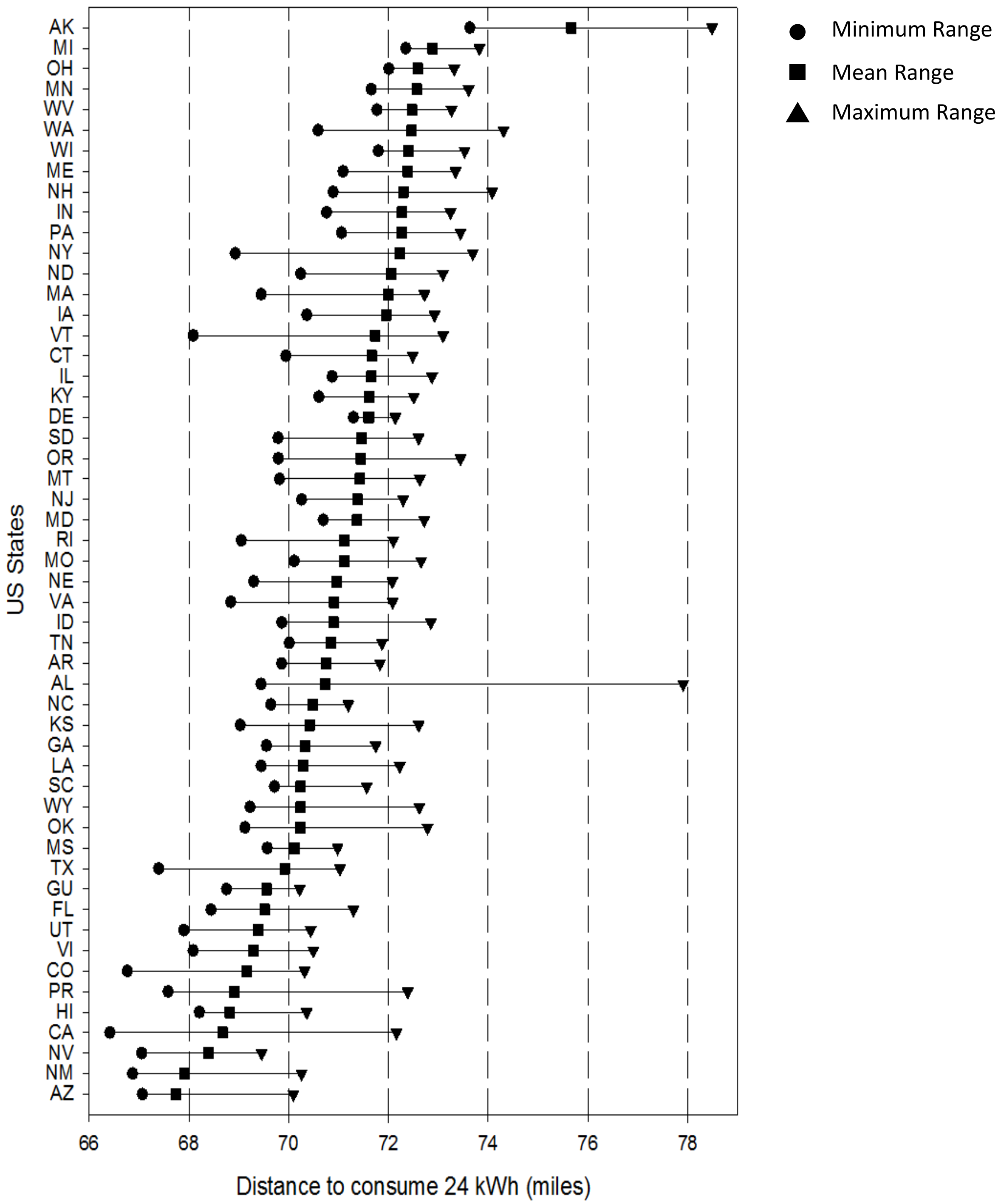


Figure 6-1: Average minimum, mean and maximum range distribution across US states.

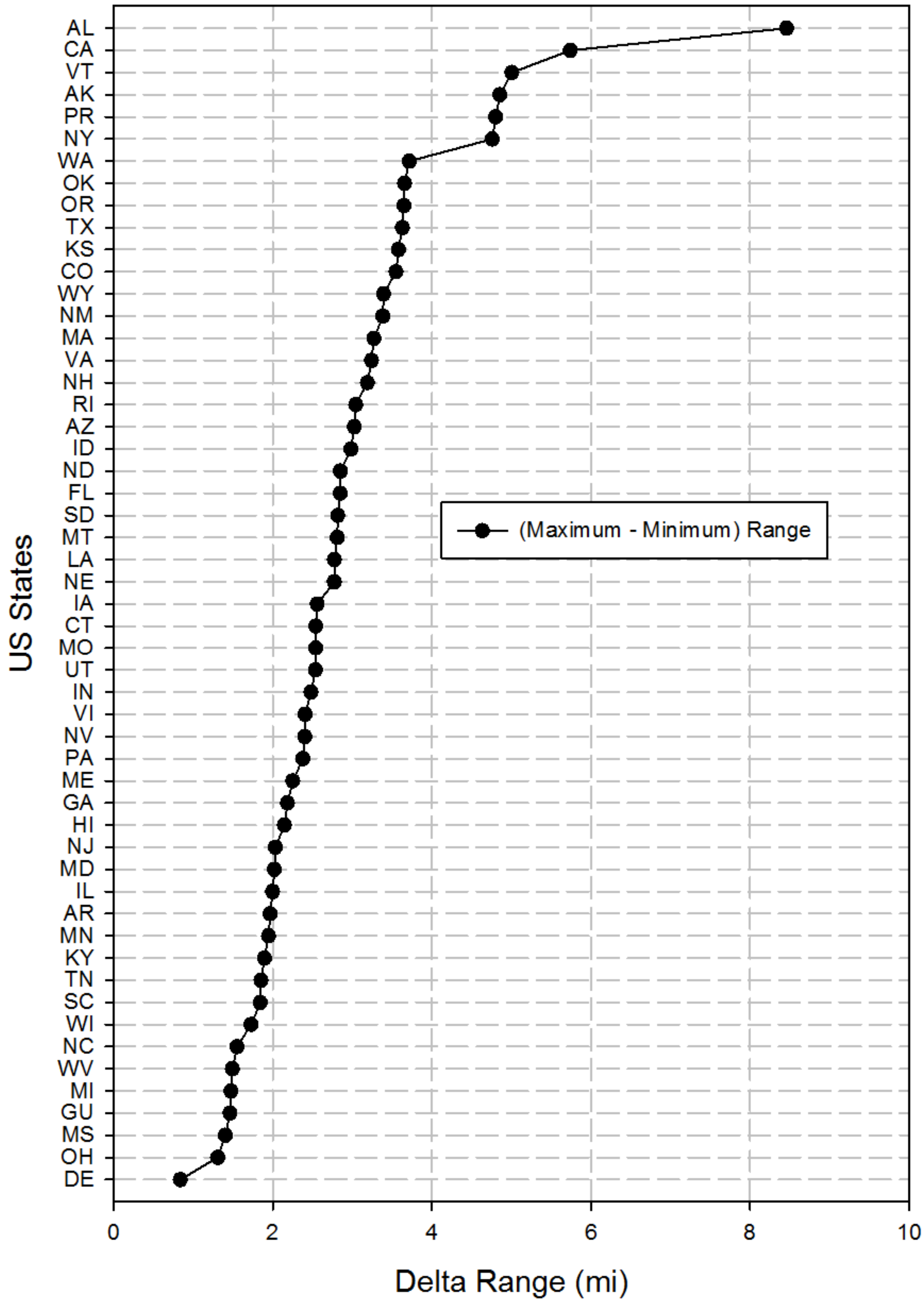


Figure 6-2: Difference between maximum and minimum EV range across all US states.

6.3 Temperature fluctuations across US cities

The day to day weather conditions across US vary widely. In order to visualize this trend, hourly averaged ambient temperatures are plotted as a function of TOD and TOY. This is represented in Figure 6-3 through Figure 6-7 for 5 cities Anchorage (AK), Atlanta (GA), Detroit (MI), Los Angeles (CA) and Phoenix (AZ). A uniform temperature scale ranging between -20°C to 40°C captures the seasonal changes. Clearly, Anchorage (AK) and Phoenix (AZ) are in the two ends of the temperature spectrum. The average summer and winter temperatures in Arizona can be seen to be in excess of 40°C and 20°C respectively, while in Alaska, the average temperatures during summer and winter range between 25°C and -10°C. The thermal comfort requirement in any location is a strong function of ambient temperatures. Similar variations can be seen in the solar irradiation levels across 5 cities.

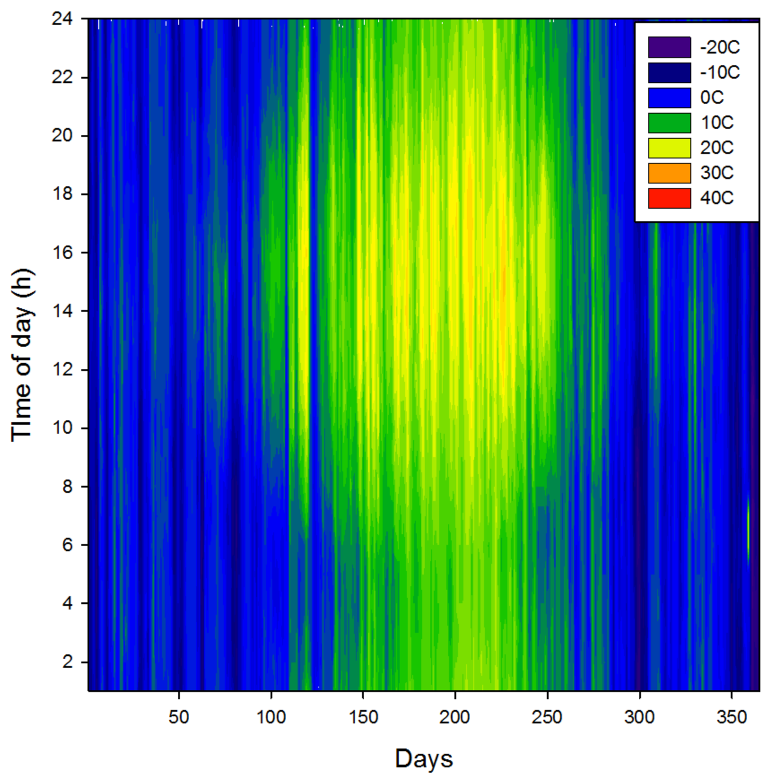


Figure 6-3: Ambient temperature in Anchorage, AK as a function of TOD and TOY.

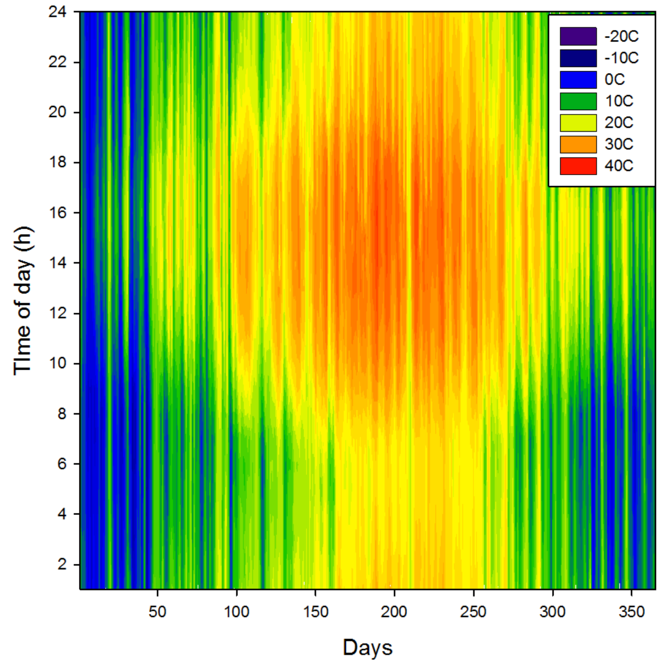


Figure 6-4: Ambient temperature in Atlanta, GA as a function of TOD and TOY.

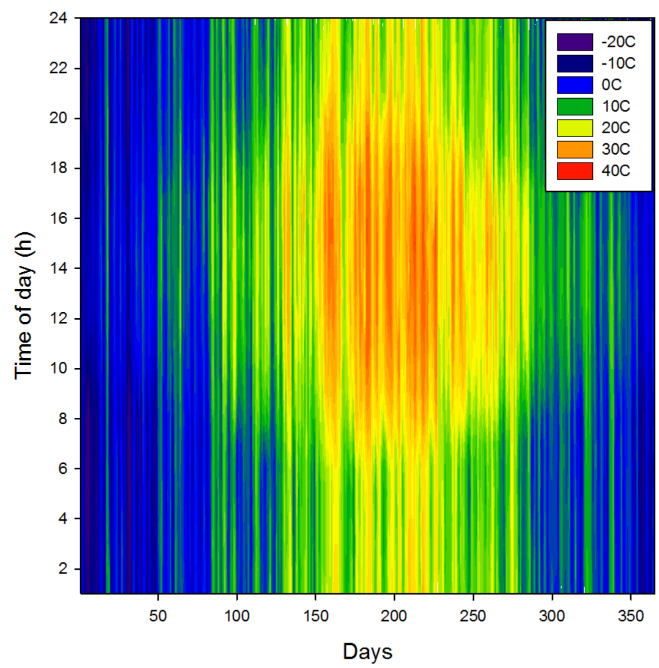


Figure 6-5: Ambient temperature Detroit, MI as a function of TOD and TOY.

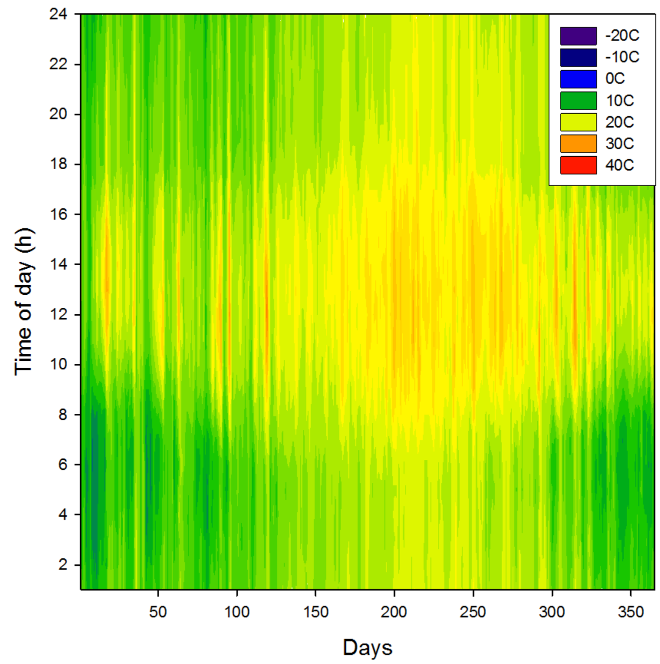


Figure 6-6: Ambient temperature in Los Angeles, CA as a function of TOD and TOY.

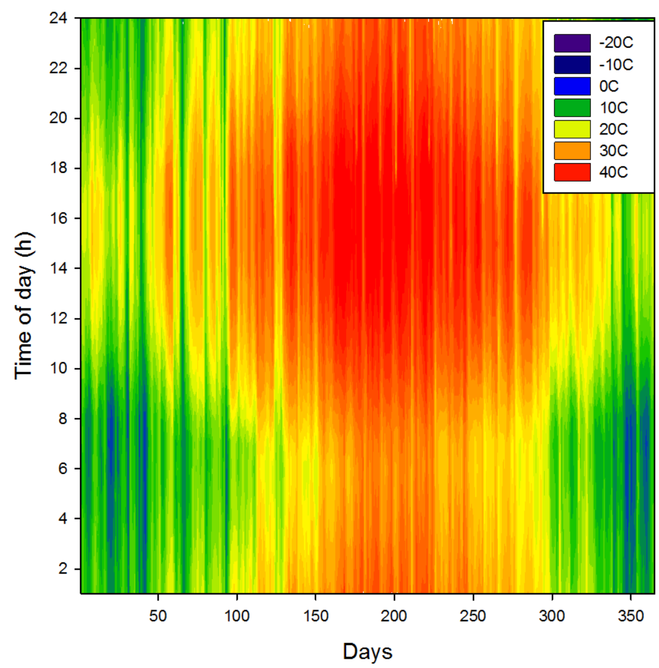


Figure 6-7: Ambient temperature in Phoenix, AZ as a function of TOD and TOY.

6.4 Geographical and Temporal distribution Variations in EV Range

The energy from a fully charged on-board storage device of a 24kWh EV is distributed between traction and thermal comfort requirements. Without the need for thermal comfort, assuming a uniform discharge rate of 0.3kWh/mi, the maximum range that can be travelled is 80mi. In situations when HVAC systems are turned on to heat or cool the cabin space for comfortable driving conditions, the distance travelled is lower than 80 mi. The decrease in range is a strong function of prevailing local ambient conditions such as local temperature and incoming solar irradiation and vehicle drive cycle. For EPA-5 cycle average speed of 27.6 mph, the impact of the environmental parameters on the EV range is represented in Figure 6-8 to Figure 6-12 for Anchorage (AK), Atlanta (GA), Detroit (MI), Los Angeles (CA) and Phoenix (AZ). The contours are represented as a function of TOD and TOY. The figures also highlight the temporal variations in EV range over different seasons of the year. The general variation across TOD is such that the expected range is higher for travel in the beginning of the day. With increase in ambient temperature and solar irradiation, the energy consumed for restoring the thermal comfort increases thereby decreasing the EV range. This decrease in EV range can be seen to progressively increase with changing seasons, with summer being the worst.

The Table 6-1to Table 6-5 Average monthly variation in electric miles through TOD in Phoenix, AZ summarizes the variations in EV range for Anchorage (AK), Atlanta (GA), Detroit (MI) and Phoenix (AZ). For travel at 12 noon through each month, the EV range decrease by a minimum of 2% to maximum 14% in Anchorage, AK, while in Phoenix, AZ the minimum to maximum variation is between 14 to 22%.

In Figure 6-8 to Figure 6-12, it can be seen that there exists conditions such that the range is close to the maximum value of 80miles. This is representative of the fact that, naturally there exist conditions when the need for thermal comfort is minimal, thereby leveraging all the energy only towards traction.

Table 6-1 Average monthly variation in electric miles through TOD in Anchorage, AK

Month	EV Range without Pre-conditioning									
	8:00 AM		10:00 AM		12:00 AM		2:00 PM		4:00 PM	
	mi	Percent decrease	mi	Percent decrease	mi	Percent decrease	mi	Percent decrease	mi	Percent decrease
Jan	76.1	5%	77.1	4%	76.9	4%	75.6	5%	75.3	6%
Feb	77.3	3%	78.0	2%	78.0	2%	77.0	4%	75.8	5%
Mar	76.6	4%	75.7	5%	75.8	5%	77.0	4%	77.1	4%
Apr	72.9	9%	71.9	10%	72.5	9%	74.6	7%	77.3	3%
May	72.3	10%	71.8	10%	72.1	10%	73.9	8%	76.5	4%
Jun	70.1	12%	68.9	14%	69.1	14%	71.6	11%	75.1	6%
Jul	73.0	9%	71.8	10%	71.6	11%	73.1	9%	76.1	5%
Aug	73.8	8%	72.7	9%	72.0	10%	74.1	7%	77.4	3%
Sep	75.0	6%	73.6	8%	73.7	8%	75.8	5%	77.7	3%
Oct	77.4	3%	76.6	4%	77.1	4%	77.5	3%	76.0	5%
Nov	77.3	3%	77.7	3%	77.5	3%	76.4	4%	75.8	5%
Dec	75.6	6%	76.3	5%	76.1	5%	75.0	6%	74.8	6%

Table 6-2 Average monthly variation in electric miles through TOD in Atlanta, GA

Month	EV Range without Pre-conditioning									
	8:00 AM		10:00 AM		12:00 AM		2:00 PM		4:00 PM	
	mi	Percent decrease	mi	Percent decrease	mi	Percent decrease	mi	Percent decrease	mi	Percent decrease
Jan	74.0	7%	71.8	10%	72.9	9%	76.1	5%	77.6	3%
Feb	72.0	10%	70.8	11%	71.8	10%	74.9	6%	78.3	2%
Mar	70.7	12%	68.8	14%	68.9	14%	71.9	10%	78.5	2%
Apr	68.0	15%	66.8	17%	67.8	15%	70.4	12%	77.5	3%
May	66.9	16%	66.2	17%	67.6	16%	70.8	12%	77.5	3%
Jun	66.0	17%	65.1	19%	66.4	17%	69.3	13%	75.8	5%
Jul	66.8	17%	66.2	17%	66.6	17%	69.5	13%	76.2	5%
Aug	67.0	16%	65.8	18%	66.5	17%	69.7	13%	76.7	4%
Sep	69.3	13%	68.8	14%	69.4	13%	72.2	10%	78.6	2%
Oct	70.1	12%	69.2	14%	69.9	13%	74.3	7%	79.2	1%
Nov	71.8	10%	70.5	12%	71.2	11%	76.4	5%	79.0	1%
Dec	73.4	8%	72.0	10%	73.5	8%	77.4	3%	78.0	3%

Table 6-3 Average monthly variation in electric miles through TOD in Detroit, MI

Month	EV Range without Pre-conditioning									
	8:00 AM		10:00 AM		12:00 AM		2:00 PM		4:00 PM	
	mi	Percent decrease	mi	Percent decrease	mi	Percent decrease	mi	Percent decrease	mi	Percent decrease
Jan	76.9	4%	75.6	6%	77.0	4%	77.1	4%	74.9	6%
Feb	74.2	7%	74.1	7%	74.3	7%	76.5	4%	76.4	5%
Mar	76.1	5%	75.2	6%	74.9	6%	76.5	4%	77.5	3%
Apr	70.6	12%	69.4	13%	70.0	12%	73.5	8%	78.1	2%
May	71.7	10%	71.2	11%	72.1	10%	74.3	7%	78.2	2%
Jun	68.0	15%	67.1	16%	68.6	14%	71.1	11%	75.8	5%
Jul	66.5	17%	66.5	17%	66.9	16%	69.2	14%	75.0	6%
Aug	68.6	14%	68.4	15%	68.6	14%	70.9	11%	77.2	4%
Sep	71.4	11%	70.5	12%	70.7	12%	73.9	8%	79.0	1%
Oct	74.6	7%	73.9	8%	75.4	6%	77.7	3%	78.1	2%
Nov	76.4	5%	76.2	5%	77.1	4%	78.2	2%	76.8	4%
Dec	76.9	4%	76.2	5%	77.1	4%	77.6	3%	75.8	5%

Table 6-4 Average monthly variation in electric miles through TOD in Los Angeles, CA

Month	EV Range without Pre-conditioning									
	8:00 AM		10:00 AM		12:00 AM		2:00 PM		4:00 PM	
	mi	Percent decrease	mi	Percent decrease	mi	Percent decrease	mi	Percent decrease	mi	Percent decrease
Jan	71.1	11%	70.4	12%	72.5	9%	78.1	2%	78.7	2%
Feb	70.4	12%	69.8	13%	72.4	9%	77.5	3%	79.0	1%
Mar	68.9	14%	67.8	15%	69.7	13%	75.4	6%	79.4	1%
Apr	67.4	16%	66.0	17%	67.9	15%	73.4	8%	79.3	1%
May	67.8	15%	67.1	16%	68.1	15%	72.6	9%	79.2	1%
Jun	66.5	17%	65.2	19%	65.8	18%	70.6	12%	78.9	1%
Jul	64.6	19%	64.2	20%	65.8	18%	70.6	12%	79.0	1%
Aug	65.9	18%	65.1	19%	66.2	17%	71.4	11%	79.1	1%
Sep	66.6	17%	65.2	18%	66.7	17%	73.0	9%	79.7	0%
Oct	68.6	14%	67.1	16%	69.6	13%	77.1	4%	79.6	0%
Nov	68.0	15%	68.0	15%	70.9	11%	78.5	2%	79.1	1%
Dec	69.7	13%	69.3	13%	72.4	10%	78.8	2%	78.7	2%

Table 6-5 Average monthly variation in electric miles through TOD in Phoenix, AZ

Month	EV Range without Pre-conditioning									
	8:00 AM		10:00 AM		12:00 AM		2:00 PM		4:00 PM	
	mi	Percent decrease	mi	Percent decrease	mi	Percent decrease	mi	Percent decrease	mi	Percent decrease
Jan	70.0	13%	67.8	15%	68.3	15%	72.3	10%	79.5	1%
Feb	68.2	15%	66.9	16%	67.9	15%	72.3	10%	78.9	1%
Mar	67.4	16%	66.6	17%	67.0	16%	69.3	13%	77.8	3%
Apr	63.7	20%	63.0	21%	63.7	20%	67.0	16%	75.6	6%
May	63.5	21%	62.5	22%	63.0	21%	65.8	18%	73.9	8%
Jun	62.1	22%	61.1	24%	61.5	23%	64.2	20%	71.7	10%
Jul	63.0	21%	61.5	23%	61.9	23%	65.2	19%	73.8	8%
Aug	63.4	21%	61.8	23%	62.7	22%	65.1	19%	73.8	8%
Sep	63.5	21%	62.2	22%	62.9	21%	67.1	16%	76.3	5%
Oct	64.8	19%	63.8	20%	65.2	19%	71.0	11%	78.9	1%
Nov	66.6	17%	65.5	18%	67.0	16%	74.3	7%	79.9	0%
Dec	69.1	14%	67.9	15%	68.5	14%	74.2	7%	78.9	1%

With respect to the ongoing discussions, the biggest challenge for the automakers is to mitigate the range variations so as to normalize the user experience irrespective of their location. This is currently partially achieved by over-sizing the battery. However, over-sizing the battery to compensate for the loss of range will not provide for a standardized user experience. Several other researchers [18, 19, 24, 69] have recommended pre-conditioning the cabin as a feasible solution. The benefit of cabin pre-conditioning is investigated and the result is presented in section 6.6.

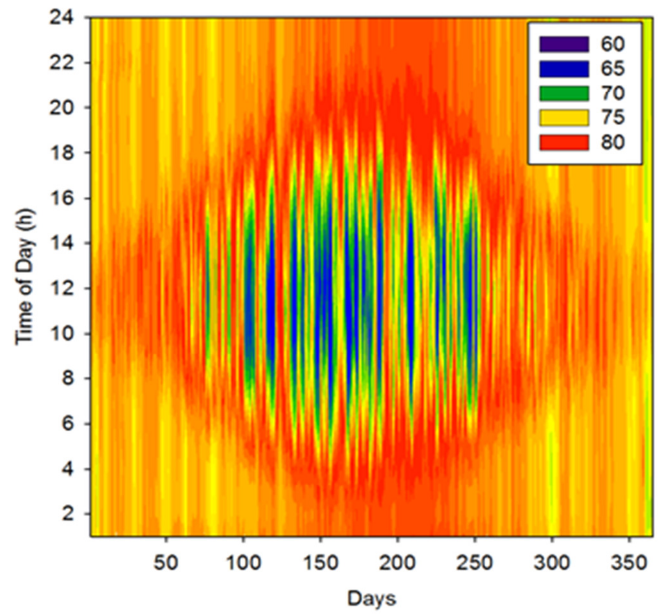


Figure 6-8: EV miles as a function of TOD and TOY in Anchorage, AK.

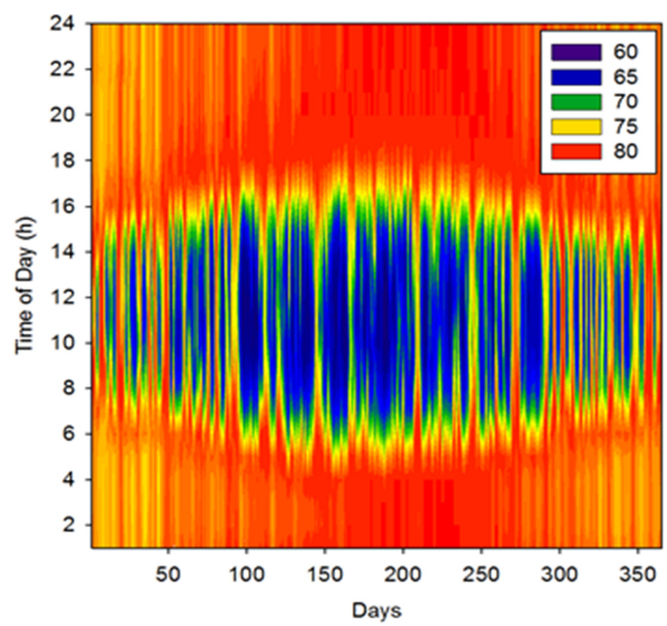


Figure 6-9: EV miles as a function of TOD and TOY in Atlanta, GA.

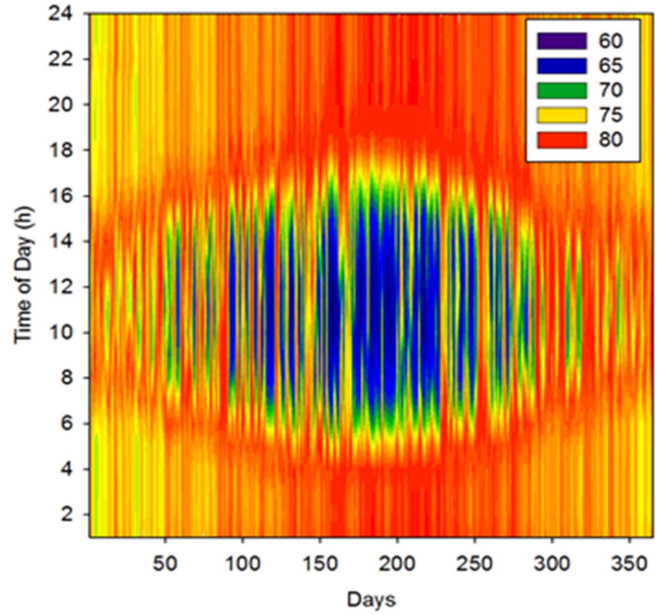


Figure 6-10: EV miles as a function of TOD and TOY in Detroit, MI.

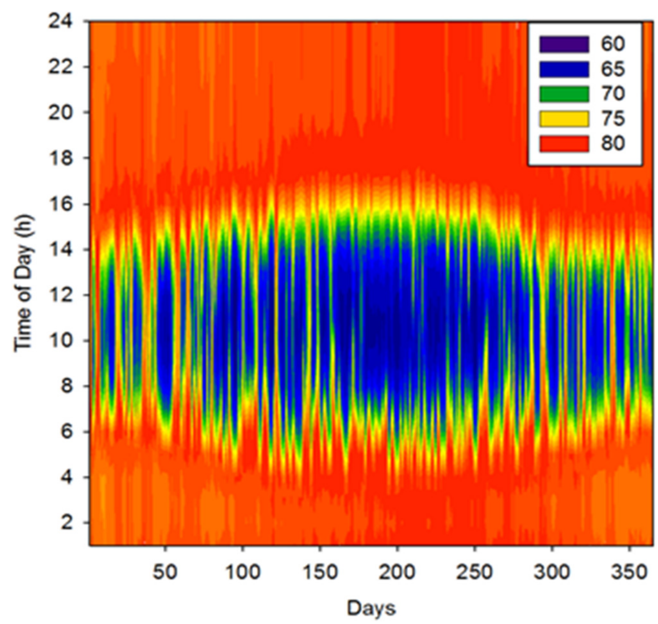


Figure 6-11: EV miles as a function of TOD and TOY in Los Angeles, CA.

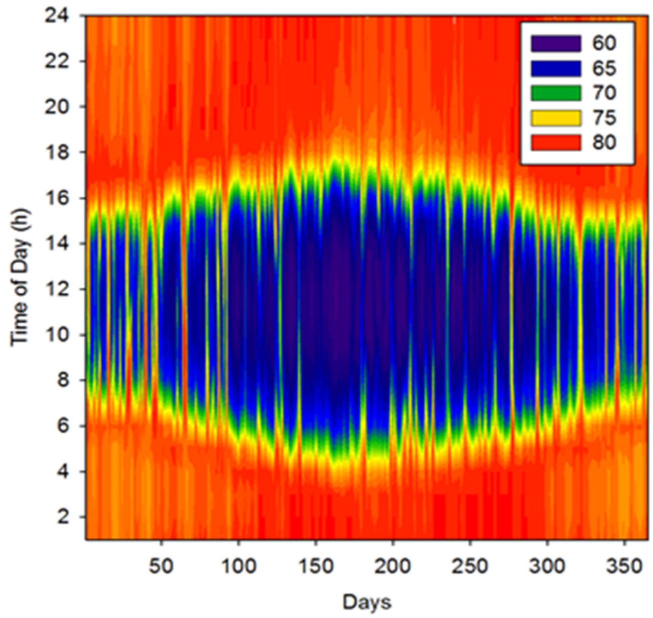


Figure 6-12: EV miles as a function of TOD and TOY in Phoenix, AZ.

6.5 Frequency distributions of EV Range

6.5.1 Frequency distribution of EV Range in Phoenix, AZ

Inability to consistently travel a predetermined distance using a fully charged electric vehicle is one of the main reasons for their slower adoption rate by the consumers. The reasons behind the lack of consistency have largely been associated with the degradation of active material in the battery and inadequately optimized cooling systems [23]. However, as seen in section 6.4, ambient conditions and the thermal comfort conditions strongly dictates the performance and contributes to wide fluctuations in the electric miles. The impact of daily local ambient conditions on the frequency of electric miles in Phoenix, AZ is represented Figure 6-13 to Figure 6-18 for trip start times 8AM, 10AM, 12noon, 2PM, 4PM and 6PM respectively. The electric miles in the distribution is sampled across 365 days of the year.

As the day progresses, it can be seen that the gap between the left most bar and the frequency axis is decreased indicating that the energy expended towards thermal comfort causes a reduction in the electric miles. This trend is reversed beginning 2PM and the gap widens significantly towards 6PM signaling lower requirements of thermal comfort and hence greater electric miles for travel.

The height of the bar represents the number of days of the year one can expect to achieve a certain electric miles. Large bar height is representative of consistent performance across a large number of days and also indicates smaller local weather fluctuations during that TOD. Ideally, in conventional vehicles, few large bars occur very close to the rated miles per gallon of the vehicle fleet assuming standard driving conditions. For EVs as clearly seen from Figure 6-13 though Figure 6-18, the distribution is stochastic. However, large bar heights spread across smaller range is desired even if the magnitude of the range across which the spread occurs may be small.

In summary, it can be seen that a user can expect between 60 to 65 miles consistently for 243 days of 8AM trips, 266 days for 10 AM trips, 220 days for 12 noon trips and 97 days for 2 PM trips. The minimum EV range for 4 PM trips is above 65 miles for 124 days of the year. The correlation between trip start time and expected electric miles distribution can be evaluated for any location in US for better estimation of the EV performance.

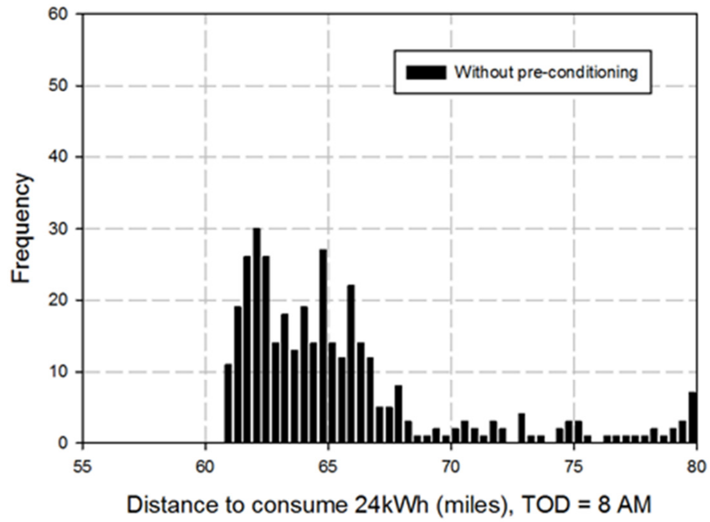


Figure 6-13: Frequency of miles distribution in Phoenix, AZ for trips starting at 8 AM of the day.

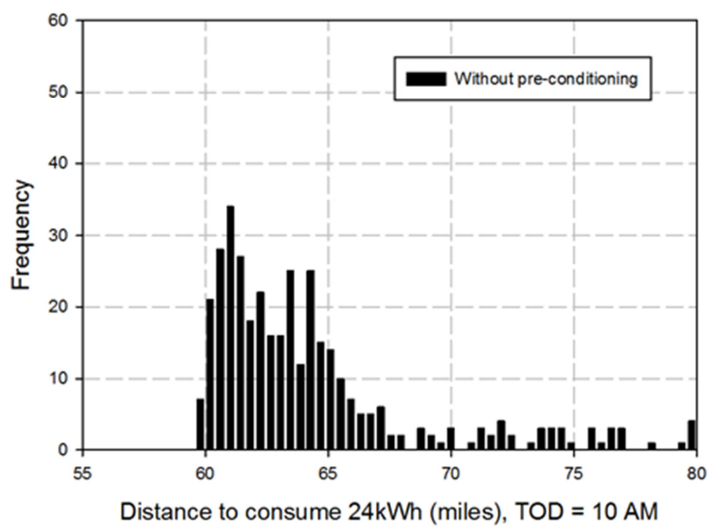


Figure 6-14: Frequency of miles distribution in Phoenix, AZ for trips starting at 10 AM of the day.

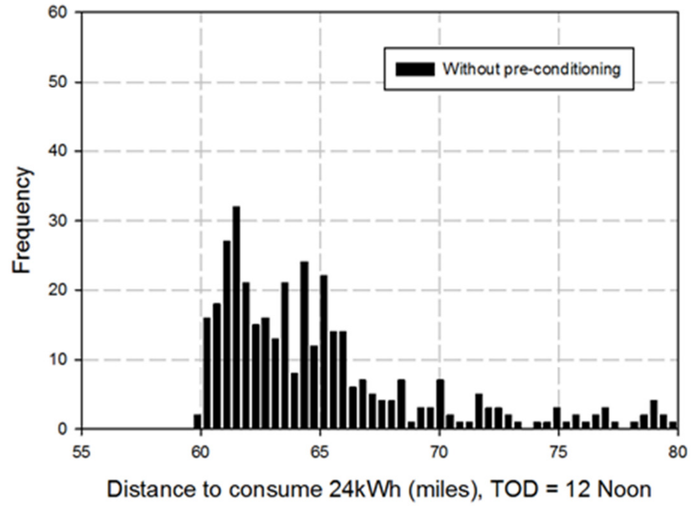


Figure 6-15: Frequency of miles distribution in Phoenix, AZ for trips starting at 12 Noon of the day.

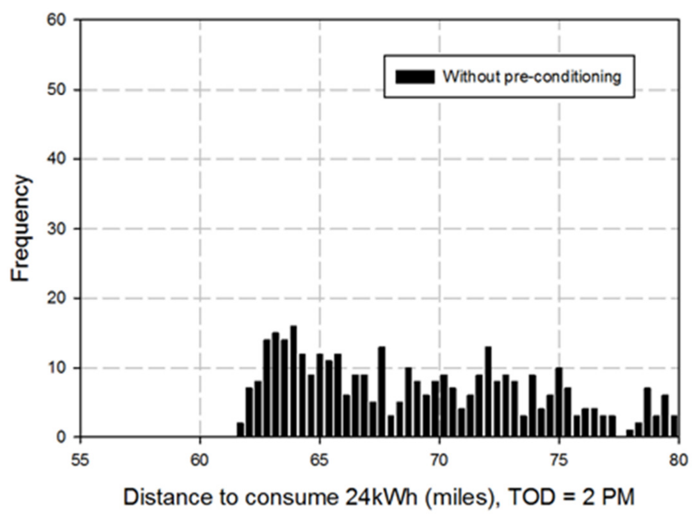


Figure 6-16: Frequency of miles distribution in Phoenix, AZ for trips starting at 2 PM of the day.

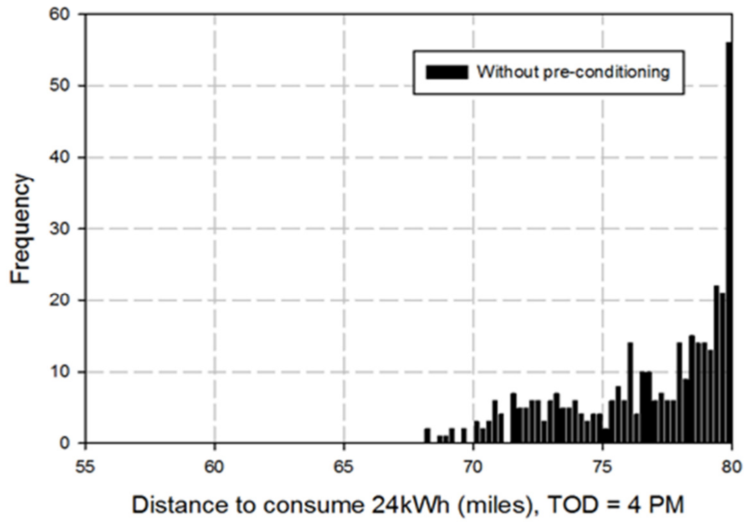


Figure 6-17: Frequency of miles distribution in Phoenix, AZ for trips starting at 2 PM of the day.

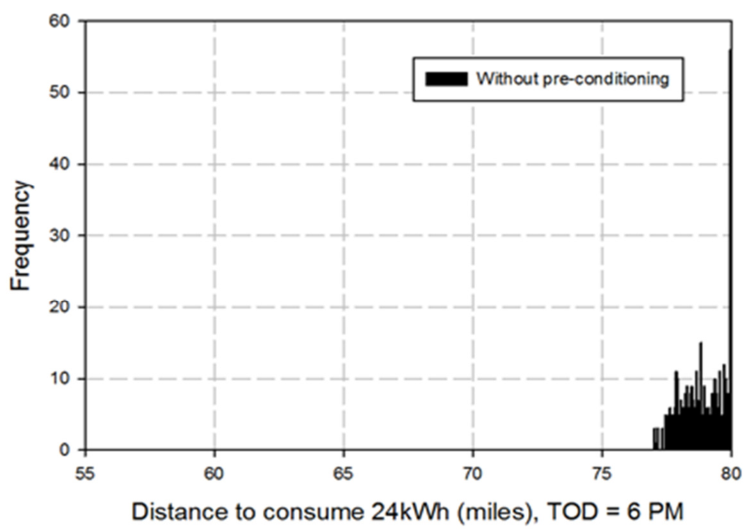


Figure 6-18: Frequency of miles distribution in Phoenix, AZ for trips starting at 6 PM of the day.

6.5.2 Frequency distribution of EV Range comparison across five US cities

In this section, the expected EV mile is sampled across 365 days of the year for peak hour travel (8 AM and 4 PM of the day). The results presented in Figure 6-19 gives an overview of the range consistency in Anchorage (AK), Atlanta (GA), Detroit (MI), Los Angeles (CA) and Phoenix (AZ). Comparing the histograms for Phoenix (AZ) and Anchorage (AK), it can be clearly seen that for similar sized EV, a user in Arizona experiences lowest mile (62 miles for highest number of days of the year (42 days of the year), while the user in Alaska can travel close to the maximum range of 80 miles for 46 days. Atlanta and Detroit exhibit bi-modal EV mile distribution spread out from 60 to 80 mile indicating a wide fluctuation in the EV range and hence poor user experience. For improving the user experience in terms of the EVs ability to consistently travel a specific range, the distribution similar to that of Arizona is preferred even though the reduction in EV miles is very significant.

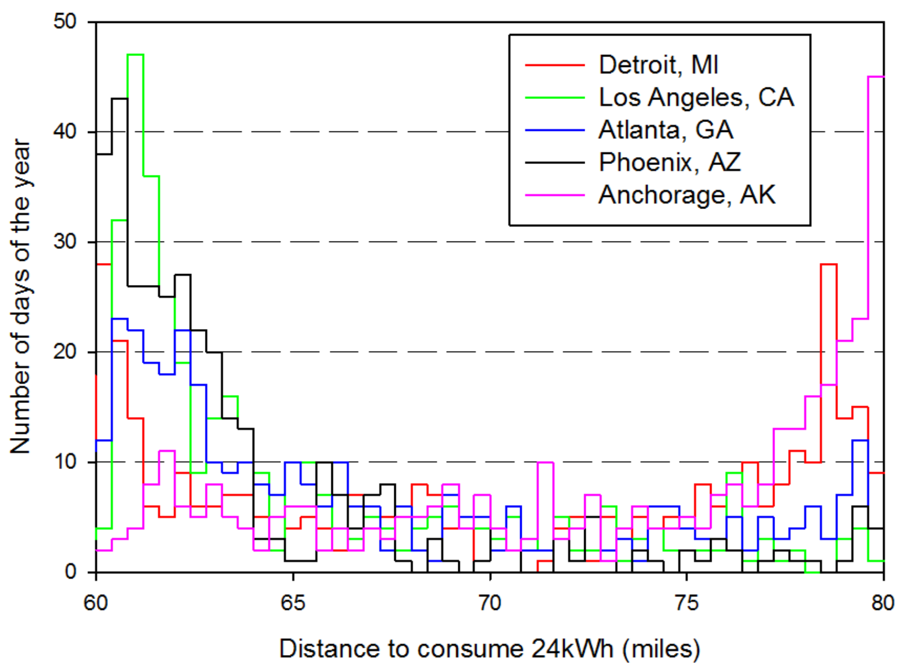


Figure 6-19: Frequency comparison of electric miles for peak hour travel in five cities

6.6 Cabin pre-conditioning

The thermal comfort load on the vehicle has two components, transient and steady state loads. The transient loads account for close to 30% of total HVAC energy consumption. Energy for both transient and steady loads is supplied by the on-board energy storage device. This significantly reduces the utility factor of the vehicle in terms of electric range that can be travelled on a single charge. The reduction in electric range can be mitigated by preconditioning the cabin space prior to the start of the trip. In this scenario, the onboard energy storage device needs to account only for the steady-state loads.

The outputs from the resulting simulations will be used to synthesize electric range as a performance metric of EVs for both scenarios, without pre-conditioning and with pre-conditioning. The modeling method is described in section 4.5.

6.6.1 Geographical and temporal variations

Figure 6-20 to Figure 6-24 represents a side by side comparison of EV range contours as a function of TOD and TOY for Anchorage (AK), Atlanta (GA), Detroit (MI), Los Angeles (CA) and Phoenix (AZ) respectively.

The range varies from a minimum of 68 miles to a maximum of 80 miles in the 5 cities. The reduction is more significant across all the seasons and cities during noon portion of the day. The Table 6-6 compares average miles through TOD in Phoenix (AZ). It can be seen that a maximum of 6% increase in the electric miles is achieved as a result of pre-conditioning the cabin.

Table 6-6: Average seasonal variation in electric miles without pre-conditioning and with pre-conditioning in Anchorage, AK.

	Time of Year							
	Spring		Summer		Fall		Winter	
Time of Day	Without Pre-conditioning	With Pre-conditioning	Without Pre-conditioning	With Pre-conditioning	Without Pre-conditioning	With Pre-conditioning	Without Pre-conditioning	With Pre-conditioning
8AM	73.9 mi (118.2 km)	76.3 mi (122.1 km)	72.3 mi (115.7 km)	75.3 mi (120.5 km)	76.6 mi (122.6 km)	77.9 mi (124.6 km)	76.3 mi (122.1 km)	77.8 mi (124.5 km)
10AM	73.1 mi (117 km)	75.8 mi (121.3 km)	71.1 mi (113.8 km)	74.6 mi (119.4 km)	76 mi (121.6 km)	77.6 mi (124.2 km)	77 mi (123.2 km)	78.2 mi (125.1 km)
12Noon	73.4 mi (117.4 km)	76 mi (121.6 km)	70.9 mi (113.4 km)	74.4 mi (119 km)	76.1 mi (121.8 km)	77.6 mi (124.2 km)	76.8 mi (122.9 km)	75.7 mi (121.1 km)
2PM	75.2 mi (120.3 km)	77.1 mi (123.4 km)	72.9 mi (116.6 km)	75.7 mi (121.1 km)	76.6 mi (122.6 km)	77.9 mi (124.6 km)	75.7 mi (121.1 km)	77.4 mi (123.8 km)
4PM	77 mi (123.2 km)	78.2 mi (125.1 km)	76.2 mi (121.9 km)	77.7 mi (124.3 km)	76.5 mi (122.4 km)	77.9 mi (124.6 km)	75.3 mi (120.5 km)	77.2 mi (123.5 km)

Table 6-7: Average seasonal variation in electric miles without pre-conditioning and with pre-conditioning in Atlanta, GA.

	Time of Year							
	Spring		Summer		Fall		Winter	
Time of Day	Without Pre-conditioning	With Pre-conditioning	Without Pre-conditioning	With Pre-conditioning	Without Pre-conditioning	With Pre-conditioning	Without Pre-conditioning	With Pre-conditioning
8AM	68.6 mi (109.8 km)	73 mi (116.8 km)	66.6 mi (106.6 km)	71.7 mi (114.7 km)	70.4 mi (112.6 km)	74.1 mi (118.6 km)	73.1 mi (117 km)	75.8 mi (121.3 km)
10AM	67.3 mi (107.7 km)	72.2 mi (115.5 km)	65.7 mi (105.1 km)	71.2 mi (113.9 km)	69.5 mi (111.2 km)	73.5 mi (117.6 km)	71.4 mi (114.2 km)	74.7 mi (119.5 km)
12Noon	68.1 mi (109 km)	72.6 mi (116.2 km)	66.5 mi (106.4 km)	71.7 mi (114.7 km)	70.2 mi (112.3 km)	74 mi (118.4 km)	72.5 mi (116 km)	76.6 mi (122.6 km)
2PM	71 mi (113.6 km)	74.5 mi (119.2 km)	69.5 mi (111.2 km)	73.6 mi (117.8 km)	74.3 mi (118.9 km)	76.5 mi (122.4 km)	76.6 mi (122.6 km)	77.9 mi (124.6 km)
4PM	77.8 mi (124.5 km)	78.7 mi (125.9 km)	76.3 mi (122.1 km)	77.7 mi (124.3 km)	78.9 mi (126.2 km)	79.4 mi (127 km)	78.2 mi (125.1 km)	78.9 mi (126.2 km)

Table 6-8: Average seasonal variation in electric miles without pre-conditioning and with pre-conditioning in Detroit, MI.

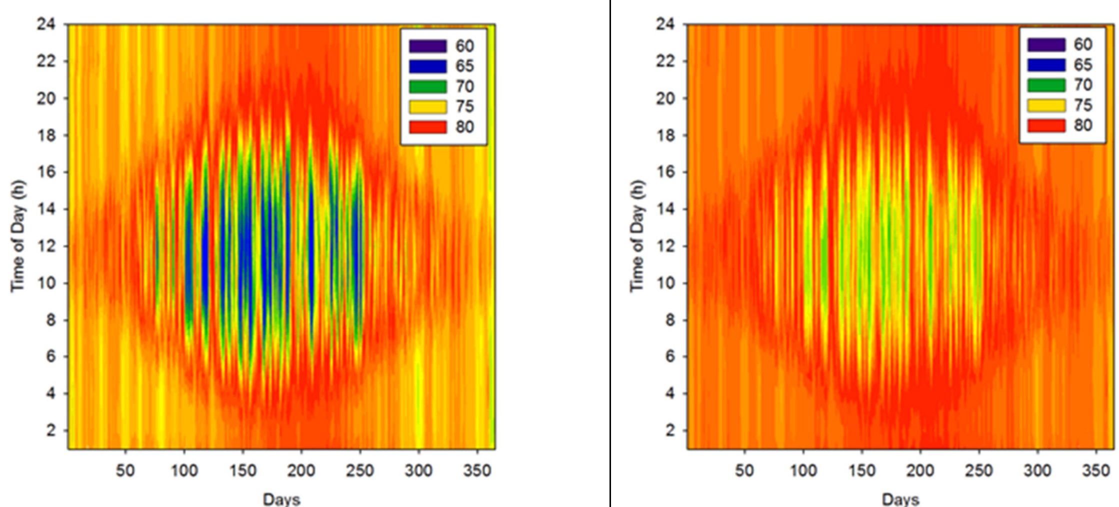
	Time of Year							
	Spring		Summer		Fall		Winter	
Time of Day	Without Pre-conditioning	With Pre-conditioning	Without Pre-conditioning	With Pre-conditioning	Without Pre-conditioning	With Pre-conditioning	Without Pre-conditioning	With Pre-conditioning
8AM	72.8 mi (116.5 km)	75.6 mi (121 km)	67.7 mi (108.3 km)	72.4 mi (115.8 km)	74.1 mi (118.6 km)	76.4 mi (122.2 km)	76.7 mi (122.7 km)	78 mi (124.8 km)
10AM	72 mi (115.2 km)	75.1 mi (120.2 km)	67.3 mi (107.7 km)	72.1 mi (115.4 km)	73.5 mi (117.6 km)	76 mi (121.6 km)	76 mi (121.6 km)	77.6 mi (124.2 km)
12Noon	72.3 mi (115.7 km)	75.3 mi (120.5 km)	68 mi (108.8 km)	72.6 mi (116.2 km)	74.4 mi (119 km)	76.6 mi (122.6 km)	77.1 mi (123.4 km)	77.6 mi (124.2 km)
2PM	74.8 mi (119.7 km)	76.8 mi (122.9 km)	70.4 mi (112.6 km)	74.1 mi (118.6 km)	76.6 mi (122.6 km)	77.9 mi (124.6 km)	77.6 mi (124.2 km)	78.6 mi (125.8 km)
4PM	77.9 mi (124.6 km)	78.8 mi (126.1 km)	76 mi (121.6 km)	77.6 mi (124.2 km)	77.9 mi (124.6 km)	78.8 mi (126.1 km)	75.8 mi (121.3 km)	77.5 mi (124 km)

Table 6-9: Average seasonal variation in electric miles without pre-conditioning and with pre-conditioning in Los Angeles, CA.

	Time of Year							
	Spring		Summer		Fall		Winter	
Time of Day	Without Pre-conditioning	With Pre-conditioning	Without Pre-conditioning	With Pre-conditioning	Without Pre-conditioning	With Pre-conditioning	Without Pre-conditioning	With Pre-conditioning
8AM	68 mi (108.8 km)	72.6 mi (116.2 km)	65.7 mi (105.1 km)	71.2 mi (113.9 km)	67.8 mi (108.5 km)	72.5 mi (116 km)	69.6 mi (111.4 km)	73.6 mi (117.8 km)
10AM	67 mi (107.2 km)	72 mi (115.2 km)	64.8 mi (103.7 km)	70.6 mi (113 km)	66.8 mi (106.9 km)	71.8 mi (114.9 km)	69.2 mi (110.7 km)	73.4 mi (117.4 km)
12Noon	68.6 mi (109.8 km)	73 mi (116.8 km)	65.9 mi (105.4 km)	71.3 mi (114.1 km)	69.1 mi (110.6 km)	73.3 mi (117.3 km)	71.9 mi (115 km)	78.5 mi (125.6 km)
2PM	73.8 mi (118.1 km)	76.2 mi (121.9 km)	70.9 mi (113.4 km)	74.4 mi (119 km)	76.2 mi (121.9 km)	77.7 mi (124.3 km)	78.5 mi (125.6 km)	79.1 mi (126.6 km)
4PM	79.3 mi (126.9 km)	79.6 mi (127.4 km)	79 mi (126.4 km)	79.4 mi (127 km)	79.5 mi (127.2 km)	79.7 mi (127.5 km)	78.9 mi (126.2 km)	79.3 mi (126.9 km)

Table 6-10: Average seasonal variation in electric miles without pre-conditioning and with pre-conditioning in Phoenix, AZ.

Time of Day	Time of Year							
	Spring		Summer		Fall		Winter	
	Without Pre-conditioning	With Pre-conditioning	Without Pre-conditioning	With Pre-conditioning	Without Pre-conditioning	With Pre-conditioning	Without Pre-conditioning	With Pre-conditioning
8AM	64.9 mi (103.8 km)	70.6 mi (113 km)	62.8 mi (100.5 km)	69.3 mi (110.6 km)	65.0 mi (104.0km)	70.7 mi (113.1 km)	68.6 mi (109.8 km)	73.0 mi (116.8 km)
10AM	64.0 mi (102.4 km)	70.1 mi (112.2 km)	61.5 mi (98.4 km)	68.5 mi (109.6 km)	63.8 mi (102.1km)	70.0 mi (112.0 km)	67.0 mi (107.2 km)	72.0 mi (115.2 km)
12Noon	64.5 mi (103.2 km)	70.4 mi (112.6 km)	62.0 mi (99.2 km)	68.8 mi (110.1 km)	65.0 mi (104.0km)	70.7 mi (113.1 km)	67.9 mi (108.6 km)	73.6 mi (117.8 km)
2PM	67.3 mi (107.7 km)	72.2 mi (115.5 km)	64.8 mi (103.7 km)	70.6 mi (113.0km)	70.8 mi (113.3 km)	74.3 mi (118.9 km)	73.6 mi (117.8 km)	76.1 mi (121.8 km)
4PM	75.8 mi (121.3 km)	77.4 mi (123.8 km)	73.1 mi (117.0 km)	75.8 mi (121.3 km)	78.4 mi (125.4 km)	79.0 mi (126.4 km)	79.4 mi (127.0 km)	79.7 mi (127.5 km)



(a)

(b)

Figure 6-20: EV miles as a function of TOD and TOY in Anchorage, AK (a) Without pre-conditioning (b) With preconditioning.

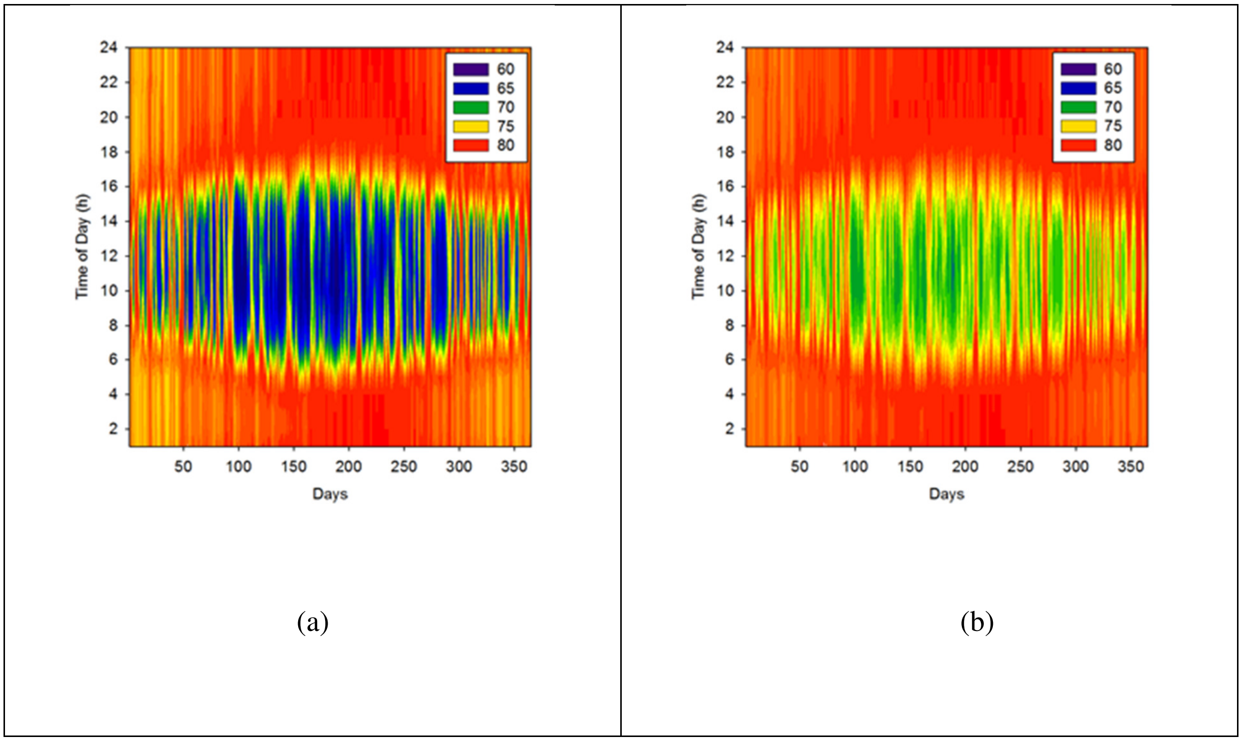


Figure 6-21: EV miles as a function of TOD and TOY in Atlanta, GA (a) Without pre-conditioning (b) With preconditioning.

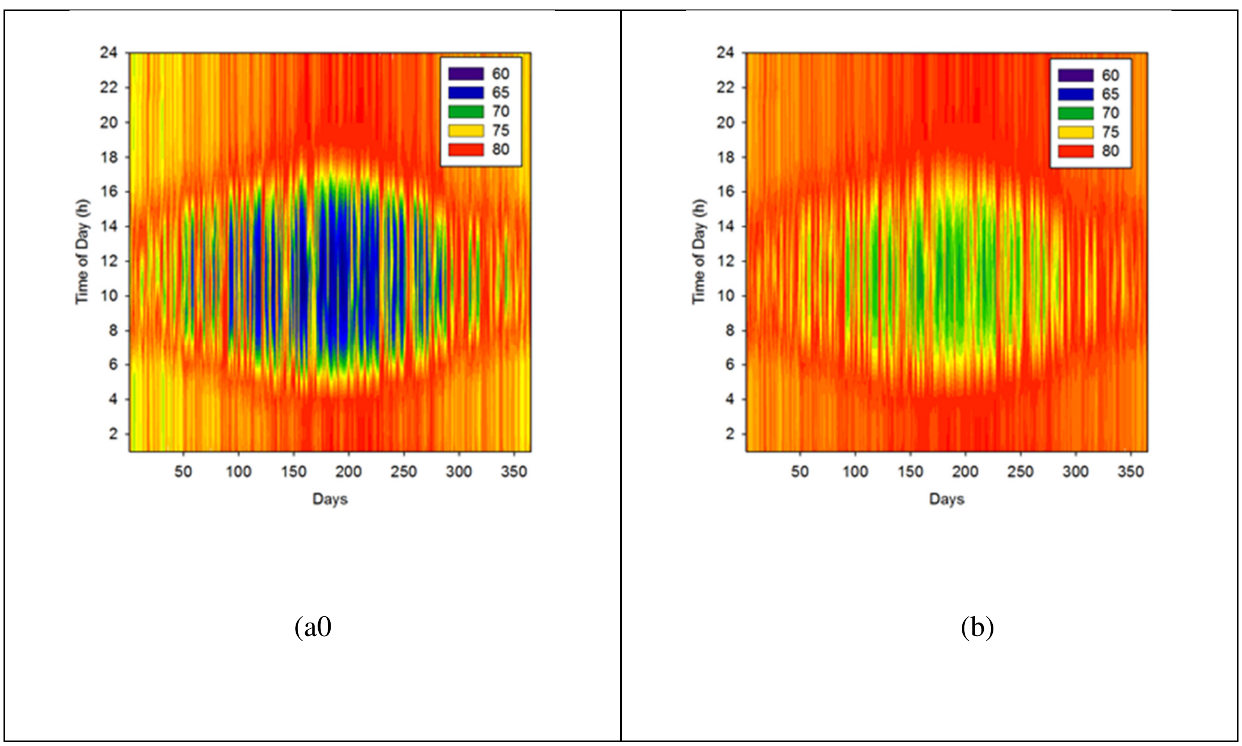
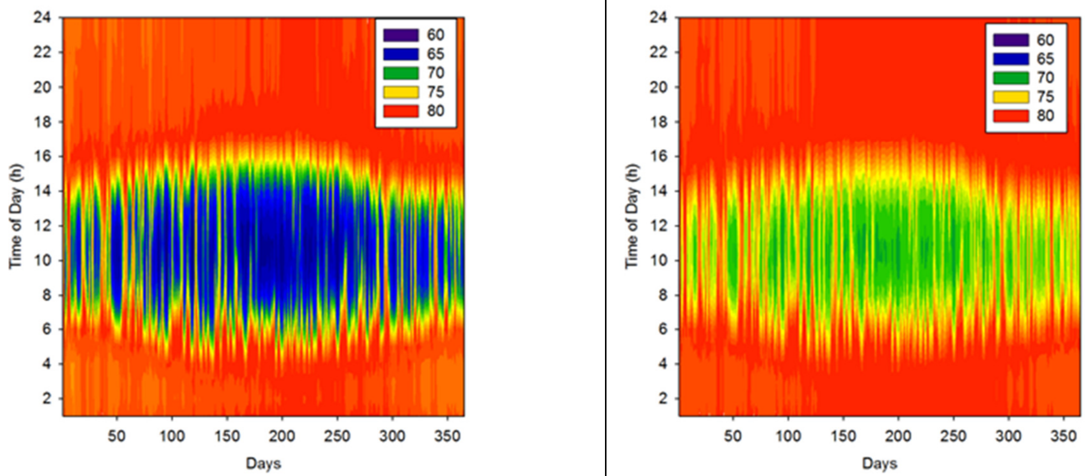
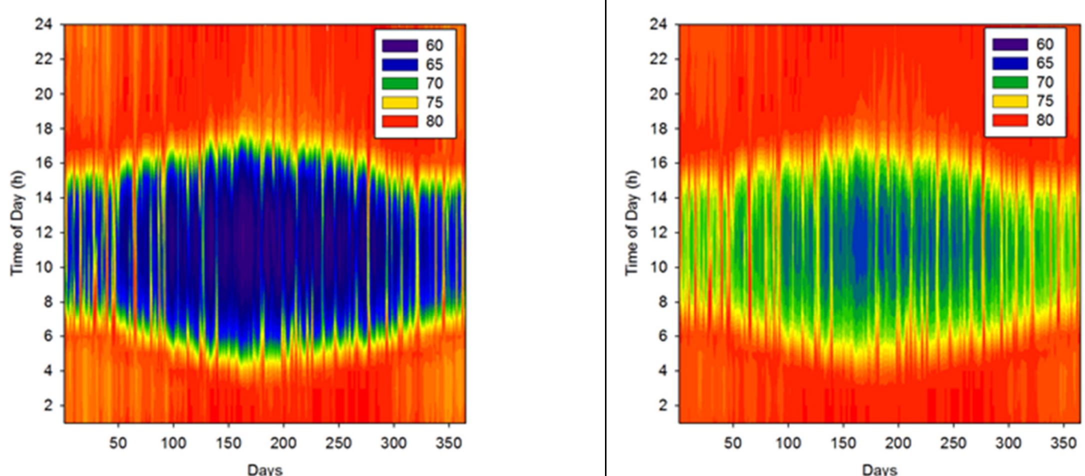


Figure 6-22: EV miles as a function of TOD and TOY in Detroit, MI (a) Without pre-conditioning (b) With preconditioning.



(a) (b)

Figure 6-23: EV miles as a function of TOD and TOY in Los Angeles, CA (a) Without pre-conditioning (b) With preconditioning.



(a) (b)

Figure 6-24: EV miles as a function of TOD and TOY in Phoenix, AZ (a) Without pre-conditioning (b) With preconditioning.

6.6.2 Frequency distribution of EV range without and with cabin pre-conditioning

Similar to the results presented in Section 6.5.1, the frequency of EV miles distribution without and with preconditioning is compared side by the side for EV use during different TOD in Phoenix, AZ. This is represented in Figure 6-25 to Figure 6-29. The distributions clearly shift towards higher miles. For ex, 8 AM trip with 75 miles bar occur for only 10 days, while it occurs for more than 35 days when the cabin is pre-conditioned. This percentage difference varies from 2.5% to approximately 10% for trips starting at 8 AM and 12 Noon respectively.

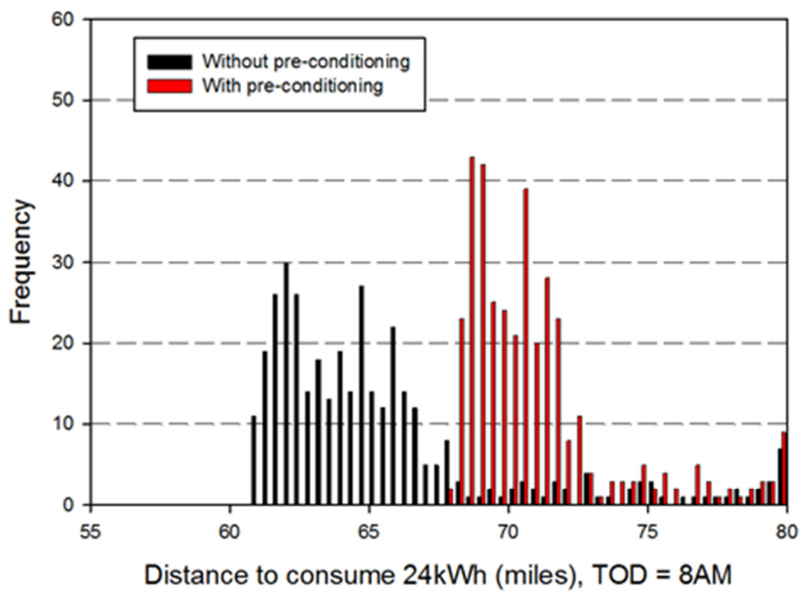


Figure 6-25: Side by side comparison of frequency of miles distribution in Phoenix, AZ for trips starting at 8 AM of the day.

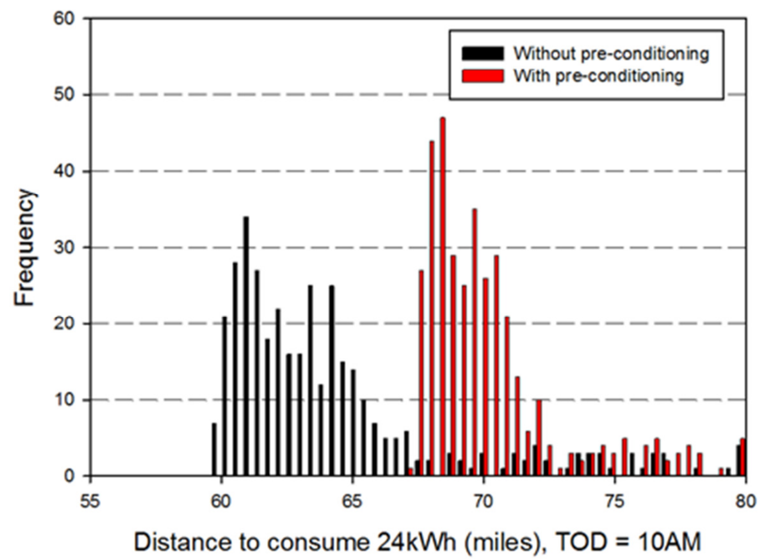


Figure 6-26: Side by side comparison of frequency of miles distribution in Phoenix, AZ for trips starting at10 AM of the day.

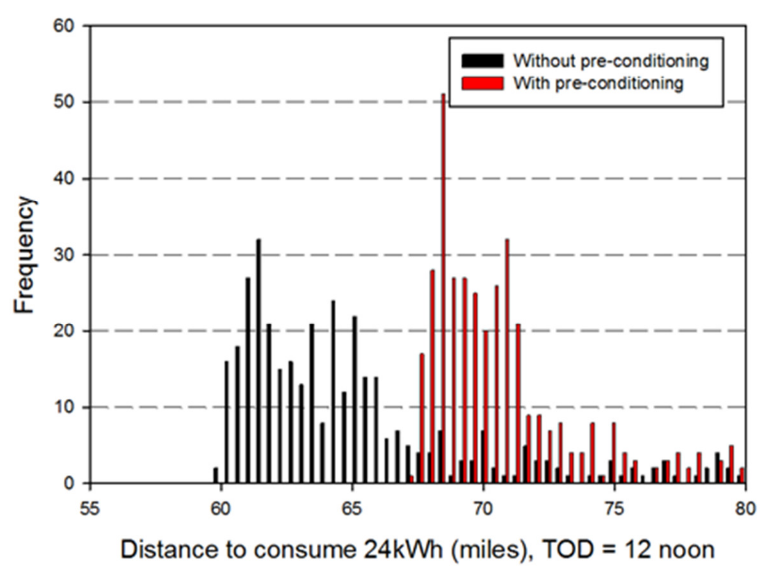


Figure 6-27: Side by side comparison of frequency of miles distribution in Phoenix, AZ for trips starting at 12 Noon of the day.

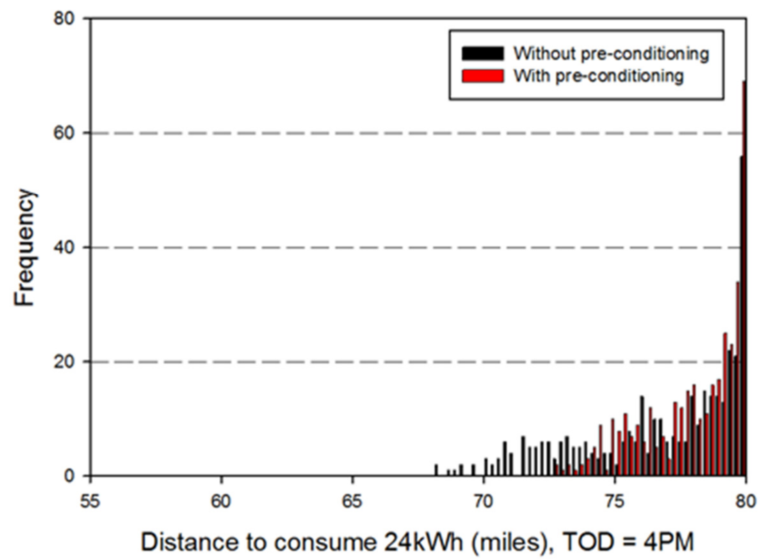


Figure 6-28: Side by side comparison of frequency of miles distribution in Phoenix, AZ for trips starting at 4 PM of the day.

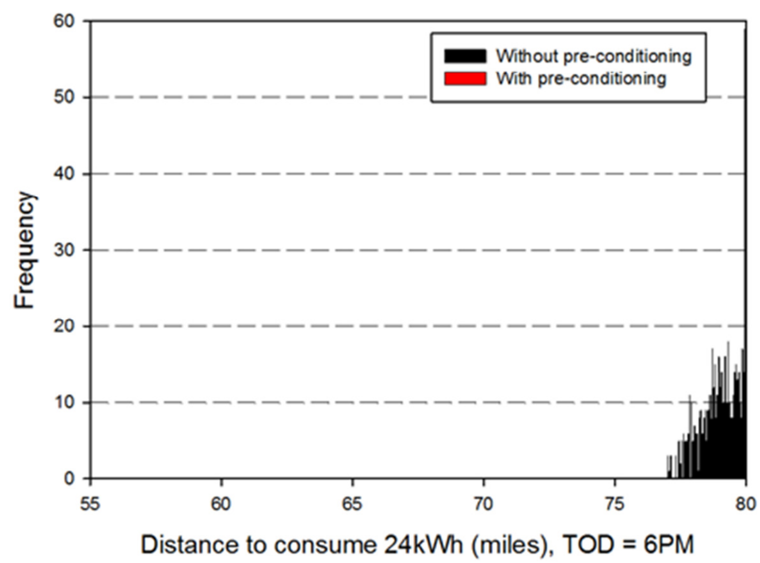


Figure 6-29: Side by side comparison of frequency of miles distribution in Phoenix, AZ for trips starting at 6 PM of the day.

6.6.3 EV Range as a function of trip start time

In order to understand the relation between time of use and increase in EV range due to cabin pre-conditioning, the yearly averaged EV range for a given trip time is evaluated and the results are presented for both without and with cabin preconditioning.

6.6.3.1 Without and with preconditioning, averaged across 365 days of the year

The **Figure 6-30** to Figure 6-34 shows the yearly averaged electric miles travelled (with thermal comfort) during different TODs in Anchorage (AK), Atlanta (GA), Detroit (MI), Los Angeles (CA) and Phoenix (AZ). During the early and later portion of the day, the curves with and without cabin pre-conditioning can be seen to be overlapping over each other.

Sparsely available charging infrastructure does not permit ubiquitous cabin pre-conditioning. Cabin pre-conditioning may be possible only during certain scenarios, ex. Trips originating from home. However, ambient conditions during the early part of the day may be such that the cabin is close to thermal comfort. The electric miles available for travel is reduced as the day progresses due to increase in the ambient temperature and solar irradiation and further increases towards the end of the day. Assuming the necessary infrastructure is in place permitting cabin preconditioning, the summary from Table 6-11 to Table 6-15 shows the percentage increase in the electric miles with cabin pre-conditioning. During the early portion of the day, the cabin conditions are close to required thermal comfort. As the day progresses, the thermal soak affects the cabin space increasing the need for using HVAC to reestablish thermal comfort. The percentage increase in electric miles is highest during the noon across all the cities.

Table 6-11: Percentage increase in EV range due to pre-conditioning the cabin in Anchorage, AK

Month	Percentage increase in EV range due to pre-conditioning				
	8:00 AM	10:00 AM	12:00 AM	2:00 PM	4:00 PM
Jan	1.4%	1.0%	1.0%	1.5%	2.2%
Feb	1.7%	2.2%	2.2%	1.6%	1.5%
Mar	3.8%	4.4%	4.0%	2.8%	1.4%
Apr	4.1%	4.4%	4.3%	3.2%	1.8%
May	5.5%	6.2%	6.1%	4.6%	2.6%
Jun	3.7%	4.4%	4.6%	3.7%	2.0%
Jul	3.3%	3.9%	4.3%	3.1%	1.3%
Aug	2.6%	3.4%	3.3%	2.2%	1.2%
Sep	1.3%	1.7%	1.5%	1.3%	2.1%
Oct	1.4%	1.2%	1.3%	1.8%	2.2%
Nov	2.3%	1.9%	2.1%	2.7%	2.7%
Dec	2.0%	1.5%	1.6%	2.3%	2.5%

Table 6-12: Percentage increase in EV range due to pre-conditioning the cabin in Atlanta, GA

Month	Percentage increase in EV range due to pre-conditioning				
	8:00 AM	10:00 AM	12:00 AM	2:00 PM	4:00 PM
Jan	3.1%	4.4%	3.7%	2.0%	1.2%
Feb	4.3%	5.0%	4.4%	2.7%	0.9%
Mar	5.1%	6.2%	6.2%	4.4%	0.8%
Apr	6.8%	7.6%	6.9%	5.3%	1.3%
May	7.5%	7.9%	7.0%	5.1%	1.3%
Jun	8.1%	8.7%	7.8%	5.9%	2.2%
Jul	7.6%	8.0%	7.7%	5.8%	2.0%
Aug	7.5%	8.3%	7.7%	5.7%	1.7%
Sep	6.0%	6.3%	5.9%	4.2%	0.7%
Oct	5.4%	6.0%	5.5%	3.0%	0.4%
Nov	4.4%	5.2%	4.8%	1.9%	0.5%
Dec	3.5%	4.3%	3.4%	1.3%	1.0%

Table 6-13: Percentage increase in EV range due to pre-conditioning the cabin in Detroit, MI

Month	Percentage increase in EV range due to pre-conditioning				
	8:00 AM	10:00 AM	12:00 AM	2:00 PM	4:00 PM
Jan	1.6%	2.3%	1.5%	1.5%	2.7%
Feb	3.1%	3.1%	3.0%	1.8%	1.9%
Mar	2.0%	2.5%	2.6%	1.8%	1.3%
Apr	5.1%	5.8%	5.5%	3.4%	1.0%
May	4.5%	4.7%	4.3%	3.0%	0.9%
Jun	6.8%	7.4%	6.4%	4.8%	2.2%
Jul	7.8%	7.8%	7.5%	6.0%	2.6%
Aug	6.4%	6.5%	6.4%	5.0%	1.4%
Sep	4.6%	5.2%	5.1%	3.2%	0.5%
Oct	2.8%	3.2%	2.4%	1.1%	1.0%
Nov	1.9%	2.0%	1.5%	0.9%	1.7%
Dec	1.6%	1.9%	1.5%	1.3%	2.2%

Table 6-14: Percentage increase in EV range due to pre-conditioning the cabin in Los Angeles, CA

Month	Percentage increase in EV range due to pre-conditioning				
	8:00 AM	10:00 AM	12:00 AM	2:00 PM	4:00 PM
Jan	4.8%	5.3%	4.0%	1.0%	0.6%
Feb	5.3%	5.6%	4.0%	1.3%	0.5%
Mar	6.2%	6.9%	5.7%	2.4%	0.3%
Apr	7.2%	8.1%	6.8%	3.5%	0.3%
May	6.9%	7.3%	6.7%	4.0%	0.4%
Jun	7.7%	8.7%	8.2%	5.1%	0.6%
Jul	9.1%	9.4%	8.3%	5.2%	0.5%
Aug	8.2%	8.8%	8.0%	4.7%	0.5%
Sep	7.7%	8.6%	7.6%	3.7%	0.2%
Oct	6.4%	7.4%	5.8%	1.5%	0.2%
Nov	6.8%	6.8%	4.9%	0.7%	0.4%
Dec	5.7%	5.9%	4.1%	0.6%	0.6%

Table 6-15: Percentage increase in EV range due to pre-conditioning the cabin in Phoenix, AZ

Month	Percentage increase in EV range due to pre-conditioning				
	8:00 AM	10:00 AM	12:00 AM	2:00 PM	4:00 PM
Jan	5.5%	6.9%	6.6%	4.1%	0.2%
Feb	6.6%	7.5%	6.8%	4.1%	0.5%
Mar	7.1%	7.6%	7.4%	6.0%	1.1%
Apr	9.7%	10.2%	9.7%	7.4%	2.3%
May	9.8%	10.6%	10.2%	8.2%	3.2%
Jun	10.9%	11.6%	11.3%	9.3%	4.5%
Jul	10.2%	11.3%	11.0%	8.6%	3.3%
Aug	9.9%	11.1%	10.4%	8.7%	3.3%
Sep	9.8%	10.8%	10.3%	7.4%	1.9%
Oct	8.9%	9.6%	8.6%	4.9%	0.5%
Nov	7.7%	8.4%	7.5%	3.0%	0.0%
Dec	6.1%	6.9%	6.4%	3.0%	0.6%

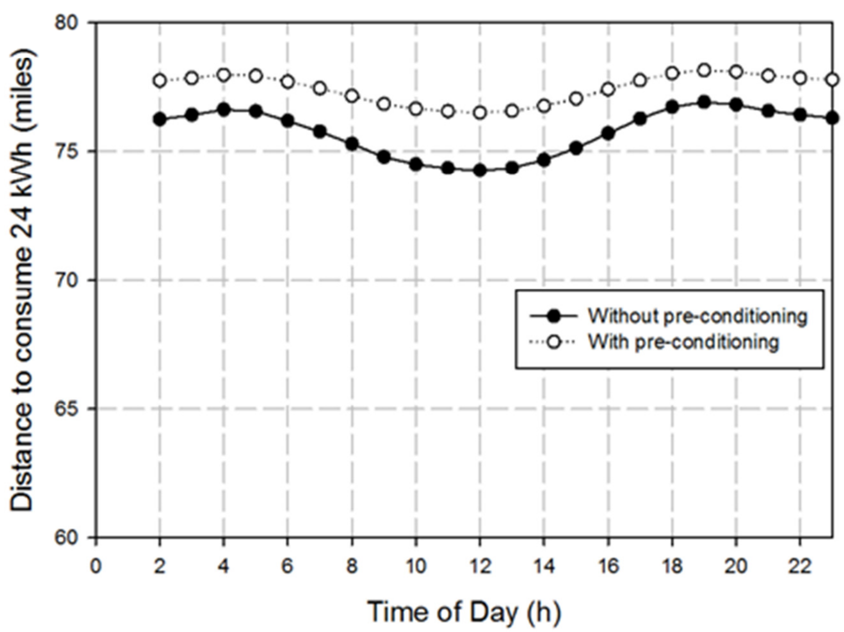


Figure 6-30: EV miles as a function of TOD, without and with cabin pre-conditioning in Anchorage, AK

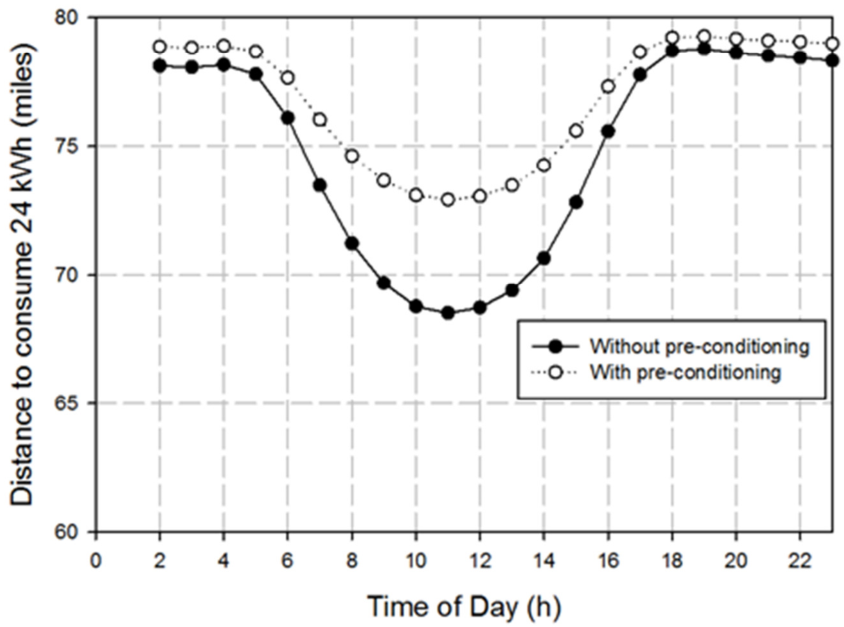


Figure 6-31: EV miles as a function of TOD, without and with cabin pre-conditioning in Atlanta, GA.

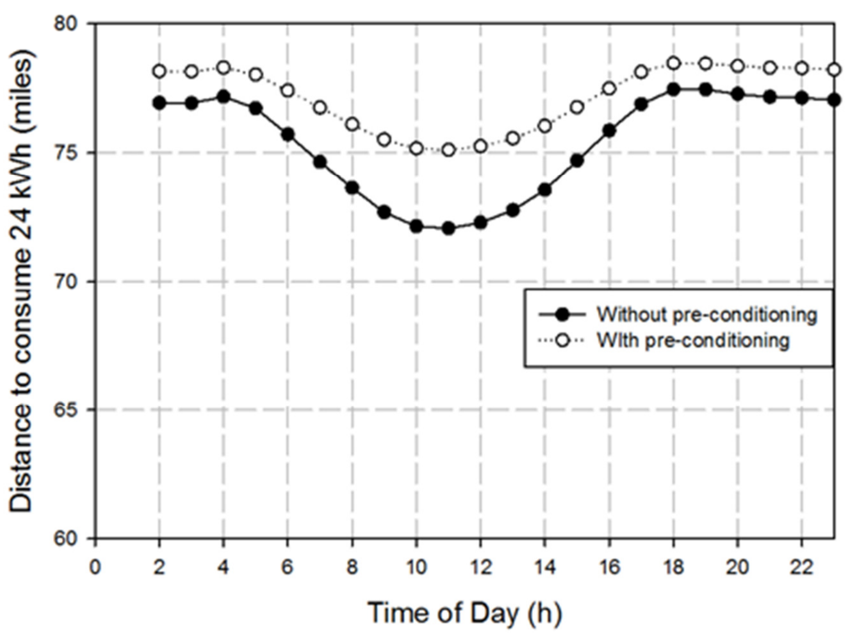


Figure 6-32: EV miles as a function of TOD, without and with cabin pre-conditioning in Detroit, MI.

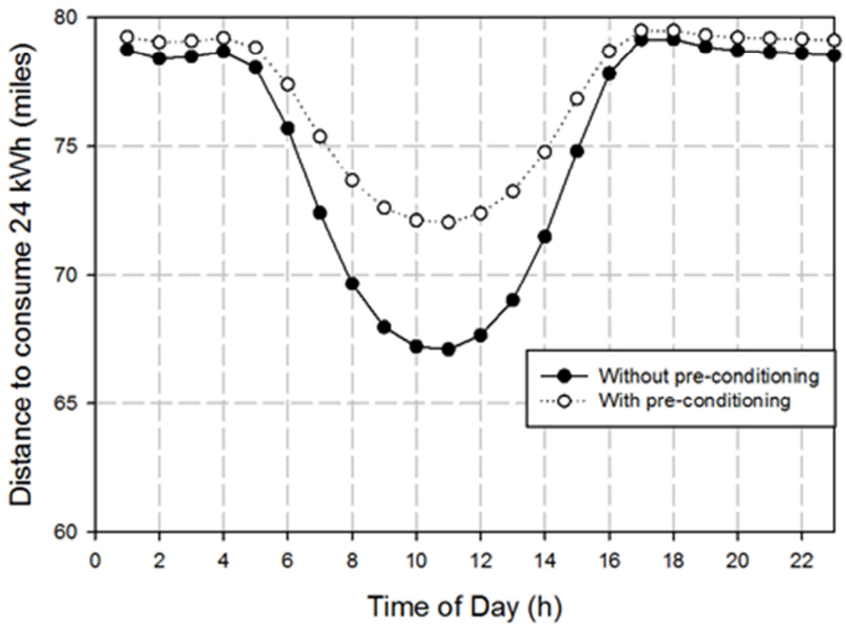


Figure 6-33: EV miles as a function of TOD, without and with cabin pre-conditioning in Los Angeles, CA.

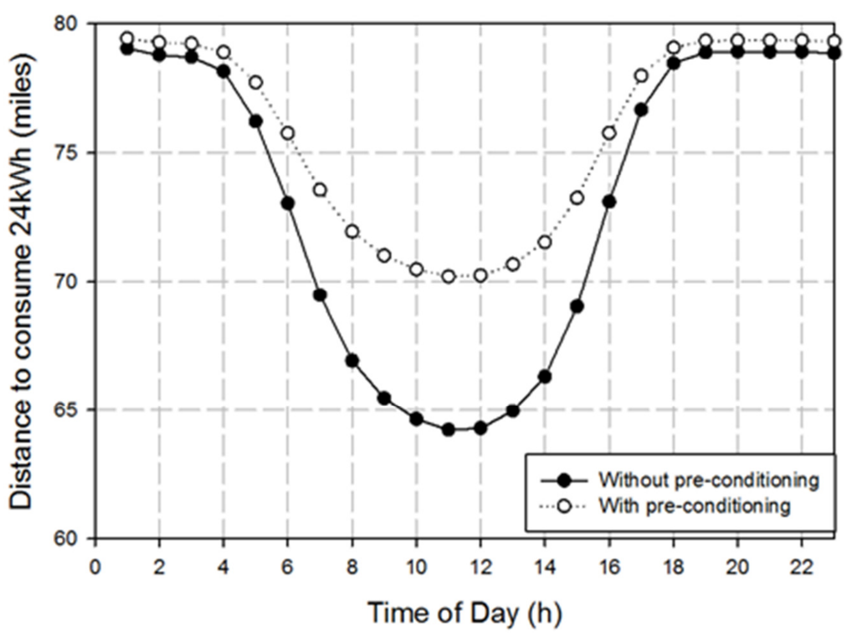


Figure 6-34: EV miles as a function of TOD, without and with cabin pre-conditioning in Phoenix, AZ.

6.6.3.2 Without and with preconditioning, averaged across 24 hour of the day

The Figure 6-39 represents the trace of EV range averaged across TOD and sampled for 365 days of the year. The trace with cabin-preconditioning clearly lies above that of the trace without any cabin preconditioning. The effect of cabin preconditioning is seen to be more significant during the summer and fall seasons of the year due to higher daily average temperature and solar irradiation. The number of days when both the traces overlap is less than 4%.

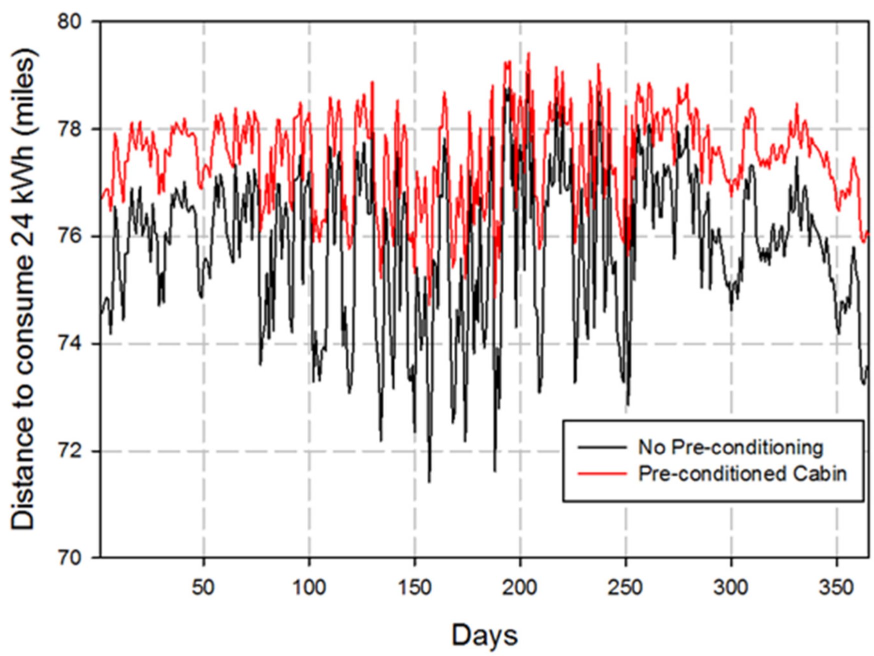


Figure 6-35: EV miles as a function of TOY, without and with cabin pre-conditioning in Anchorage, AK.

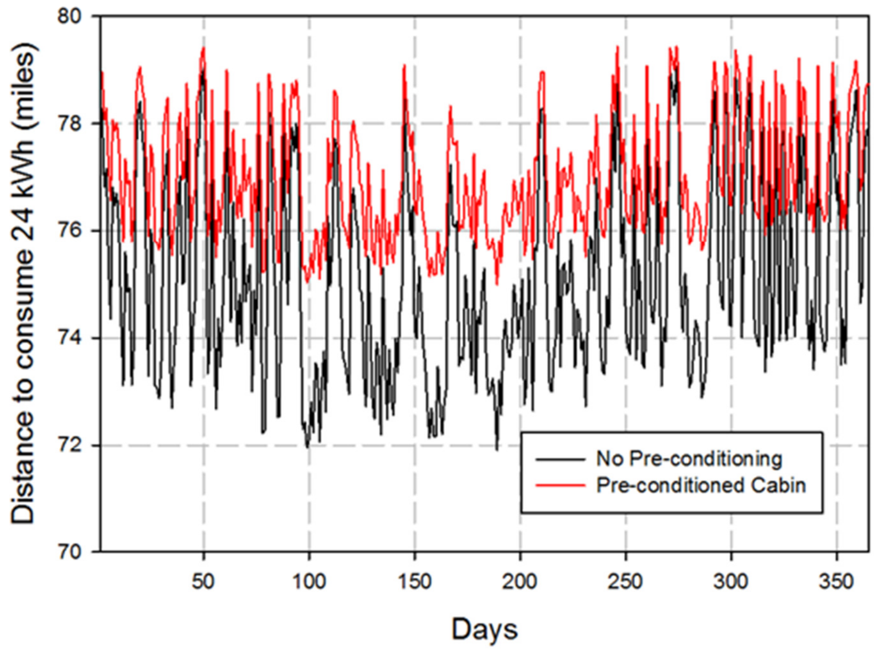


Figure 6-36: EV miles as a function of TOY, without and with cabin pre-conditioning in Atlanta, GA.

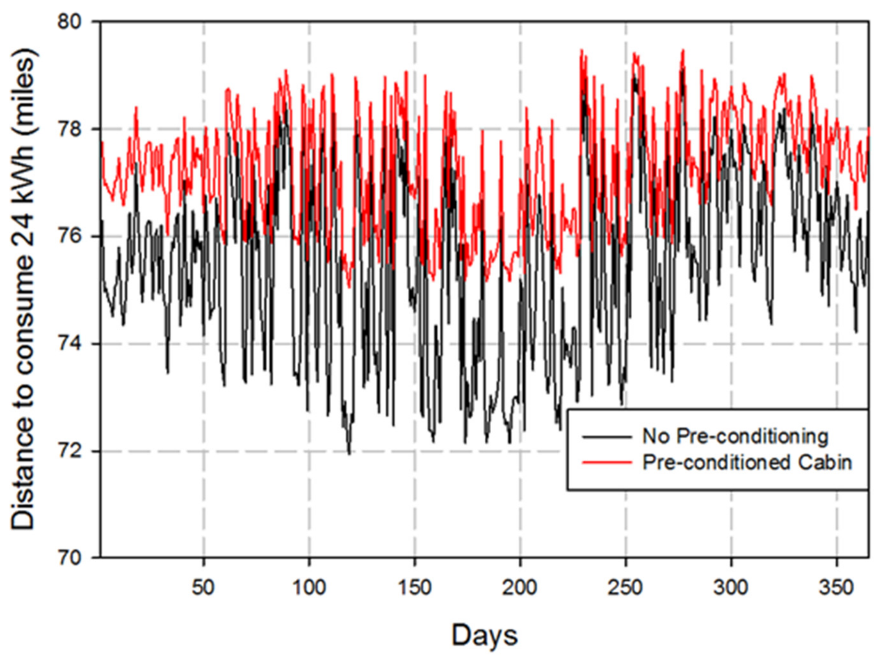


Figure 6-37: EV miles as a function of TOY, without and with cabin pre-conditioning in Detroit, MI.

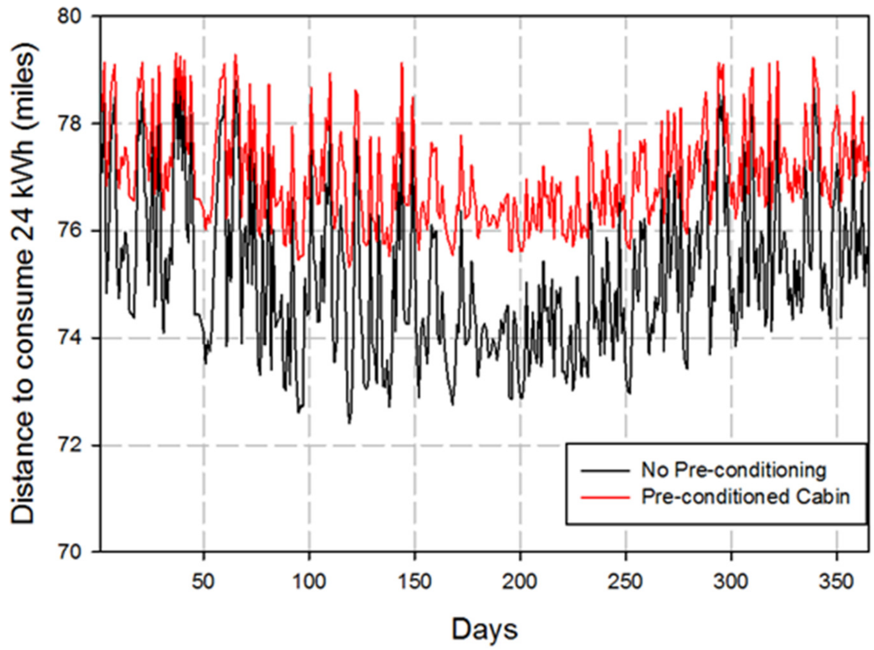


Figure 6-38: EV miles as a function of TOY, without and with cabin pre-conditioning in Los Angeles, CA.

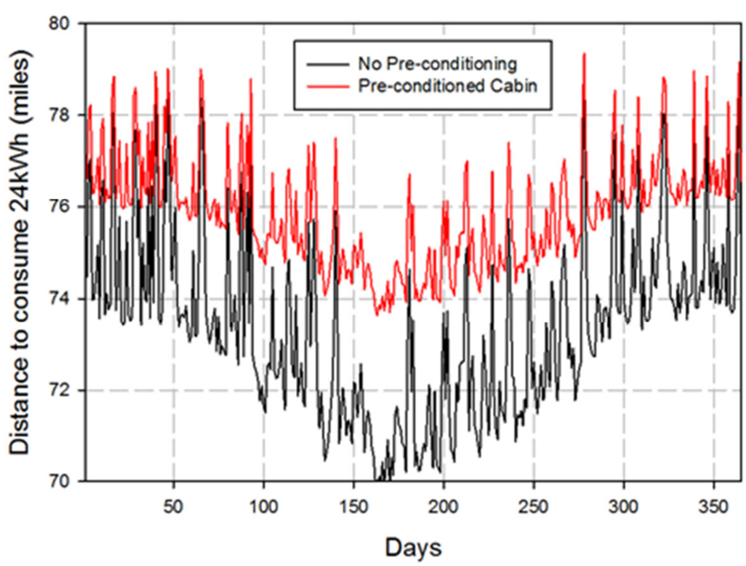


Figure 6-39: EV miles as a function of TOY, without and with cabin pre-conditioning in Phoenix, AZ.

6.7 Summary

This section of the research effort has allowed us to address research question 2, which is restated here:

Research Question 2: What is the geographical sensitivity of the accessory loads and vehicle fueling costs for HEVs, PHEVs and BEVs? Are there regions of the country that are most advantageous or that should be precluded from vehicle fleet electrification?

In this chapter, the impact of environment on the day to day range of EV was quantified across 5 cities that have widely varying weather characteristics. The geographical and temporal variation in the EV range was presented as a function of TOD and TOY. Further, several questions regarding the consistency with which an EV can travel during a predetermine time of the day was evaluated for Phoenix, AZ. It was clearly seen that the EV range was shortest for noon trips during the hottest portion of the day. The gain in EV range by means of pre-conditioning the cabin was discussed in detail. The maximum increase in the EV range via cabin preconditioning varied from 4% during early part of the day to 12.5% after noon. The result presented here highlights the need for increasing the charging infrastructure through private public partnerships so as to enable the users to pre-conditioning the cabin. Since the thermal soaking accounts for 30% of HVAC loads, a dedicated auxiliary storage device for HVAC systems may be considered. In the next chapter, the possibility of using combinations of various alternative accessory technologies for providing cabin thermal comfort is presented.

CHAPTER 7 ALTERNATIVE ACCESSORY TECHNOLOGY EVALUATION

7.1 Introduction

As with conventional vehicles, EVs have a number of accessory systems that require electric power. Some systems, such as the radio/tape player, lights, and horn, operate the same way as they do on a conventional vehicle. Other systems, such as the power steering and power brakes, require an additional small electric motor and have very less impact on the EV range. However, the air conditioning and heating systems on EV can have a dramatic impact on the range. Federal safety standards require all vehicles to have adequate HVAC systems.

The heater/defroster system is easily operated in a conventional gasoline-powered vehicle as the supply of heated water from the engine cooling system is readily available. An EV does not have this heat source and therefore must provide the heat with an auxiliary heating system. This power must come from the main battery pack with a corresponding decrease in vehicle range. Depending on the outside temperature and the desired temperature in the vehicle, the range reduction can approach 25% as seen in Chapter 6.

Air conditioning systems on EVs can also have a significant impact on a vehicle‘s range. These are usually standard automotive AC units that must be powered by an auxiliary electric motor instead of being powered by the engine. This additional motor consumes energy from the on-board battery pack, which reduces the range of the EV. The amount of energy needed for AC depends on the outside ambient temperature and the desired inside temperature. The EV has a 12-volt auxiliary battery just as in the conventional vehicle to operate the lights, radio, and other equipment. The 12-volt battery in a conventional vehicle is recharged with an alternator driven by the engine. In an EV, the auxiliary battery is recharged with the use of a DC-to-DC converter. This electrical device provides power to the 12-volt auxiliary battery from the high-voltage battery device used to power the vehicle. Heat pumps are being used on the latest electric vehicles to reduce the power requirements for heating and cooling such as in the GM EV1 and 2014 Nissan Leaf for climate control [64, 70].

In section 7.2, this chapter first presents an overview of the alternative HVAC technologies supported by ARPA-e's High Energy Advanced Thermal Storage systems (HEATS) towards designing and developing low cost environmentally friendly cabin climate control systems for EVs. Further, a sample system sizing analysis is presented in terms of the mass of PCM material required to meet heating and cooling requirements in 5 cities, Anchorage (AK), Atlanta (GA), Detroit (MI), Los Angeles (CA) and Phoenix (AZ) respectively. On the basis of these analyses, we can construct a multi-objective comparison of the performance characteristics of these PCM and other advanced HVAC technologies so as to assess their effectiveness relative to conventional HVAC technologies.

7.2 ARPA-e HEATS

In an effort to leverage recent advances in materials and manufacturing science, the US DOE launched the ARPA-e HEATS program in Fall-2011. HEATS is aimed towards using thermal energy storage to provide heating and cooling for EV passenger compartments so as to achieve improvements in EV range. The HEATs research initiatives can be broadly categorized into the technologies of a) adsorption based HVAC systems b) thermo-electric based HVAC systems c) phase-change materials based HVAC systems.

7.2.1 Adsorption based system

Traditionally, refrigerant-based vapor compression systems have been in use for cooling smaller spaces (including automotive applications), while vapor absorption based systems are used in large industrial and commercial applications. In the adsorption-based system, the surface of adsorbents is tailored to achieve an increased affinity to the heat transfer fluid. The nature of adsorption process can be exothermic or endothermic based on the combination of material and heat transfer fluid. The heat transferred into and out of adsorbent surfaces can be exchanged with the cabin air to provide thermal comfort as desired. Over repeated cycles, the adsorbent surface will get saturated with the heat transfer fluid. The system can be reused by releasing the adsorbed fluid molecules. This process of discharging requires additional grid energy. Also with this technique, it is assumed that the EV is pre-conditioned prior to the trip so that the EV HVAC system can maintain the thermal comfort during the course of the trip. Due to the lack of harmful refrigerants that are requirements of the traditional vapor compression system, this technology has the potential to improve the EV range while being environmentally friendly. The proposed technologies are envisioned to be able to create an adsorption-based HVAC system, weigh less than 35kg while occupying less than 1.5ft 3 providing 2kWh and 4.5kWh of cooling and heating thermal energy respectively [71].

7.2.2 Thermo-electric based system

This system is based on solid-state thermo-electric convertors. The P and N type semi-conductor material sandwiched between 2 dissimilar metals convert the metal surfaces into a hot plate and a cold plate when current is passed through them. The extra electrons and holes in the N and P type semiconductors act as heat energy carriers. In addition to pre-conditioning the cabin, this system requires that the potential difference be maintained between hot and cold junctions needing the EV to be plugged in to the grid while parked. In general, even long-term thermo-electric systems operating at near-ambient conditions have COPs of less than 0.5.

7.3 PCM based HVAC system

Phase change materials (PCM) such as water and paraffin wax have high specific energy and are successfully used both as heat transfer fluid and also to store energy in various applications such as molten salt based concentrated solar power plants and ice based chiller system for commercial facilities. The main advantage of PCM is due to its ability to store energy in the form of latent heat. The depletion of energy occurs under isothermal conditions. However, insulating the energy storage device to minimize the loss is a major challenge that needs to be overcome. In automobile industries, specifically for EVs, a PCM based storage device can provide thermal comfort requirements for the passenger cabin without the need to use conventional HVAC system. All though no such technology exists in current generation commercial EVs, several university-industrial research programs sponsored by ARPAe are underway to successfully implement a PCM based climate control system (at Pacific North West National Laboratory: Metal Hydride Thermal Storage, University of Utah: Advanced Metal Hydrides based Thermal Battery, University of Texas at Austin: Thermal Batteries for Electric Vehicles).

7.4 Synthesis and Sizing of Advanced Technology HVAC Systems

The energy requirements of any HVAC system have been shown to vary geographically and temporally. By defining the stochastic HVAC energy requirement for these HVAC systems, study can allow for the development of HVAC system design that is robust to varying climatic and geographical conditions. Using the thermal comfort model, the maximum heat and AC energy requirements of a geographical location can be determined for trips as a function of time of day and time of year. As an example, will size and synthesize a heating and cooling HVAC system using PCMs. By choosing ice and paraffin wax based climate control system, a sample sizing exercise is presented in the following sections.

7.4.1 Cabin Heating using PCM

The widely available paraffin wax (latent heat = 195kJ/kg) is chosen as a PCM material to provide for cabin heating during winter conditions. It is assumed that the system will be charged from the grid and stored with 85% effectiveness. From Figure 4-7b it was seen that a peak power of 7.8 kW was required to bring the cabin temperature from the thermal soak condition to the desired comfort level. Steady state power helped maintain the thermal comfort. Due to the low power density of the PCM based systems that are proposed in HEATs or that have been developed to date, the cabin is assumed to be preconditioned prior to the beginning of the trip. Figure 7-1 to Figure 7-5 present the daily maximum

PCM mass requirement for cabin heating for 5 cities, Anchorage (AK), Atlanta (GA), Detroit (MI), Los Angeles (CA) and Phoenix (AZ).

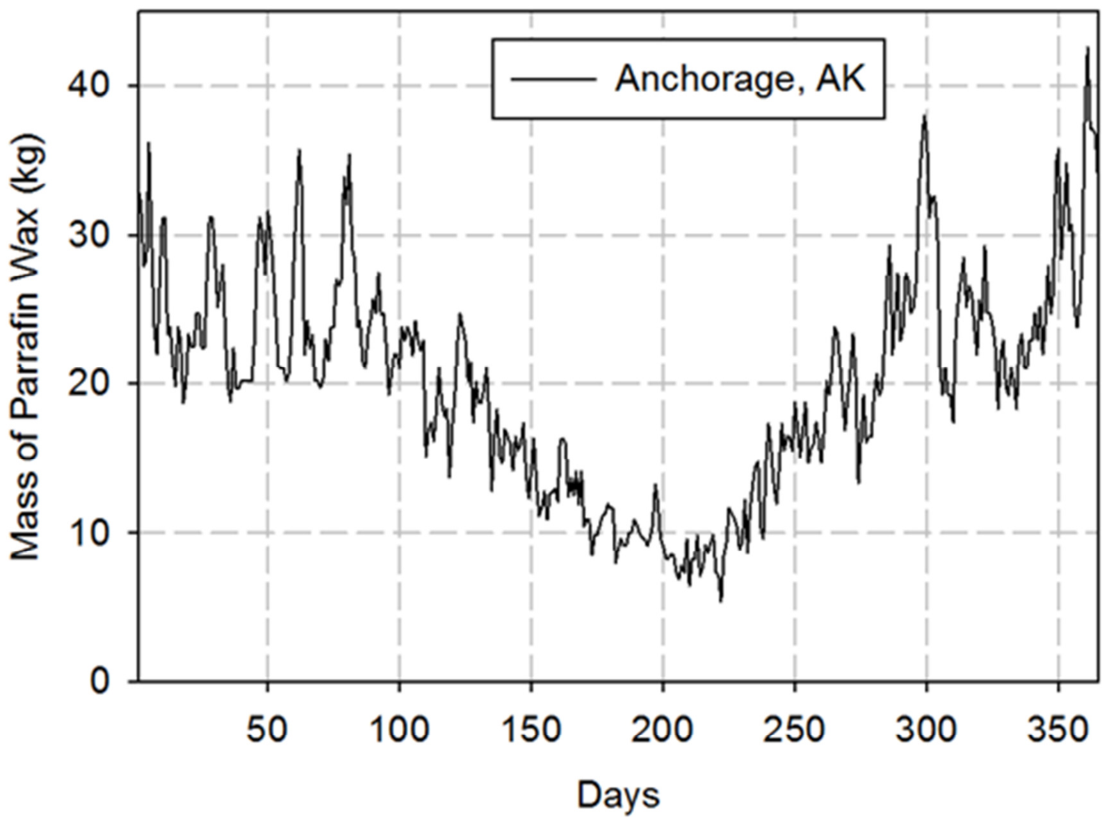


Figure 7-1: Calculated paraffin wax storage mass in Anchorage, AK

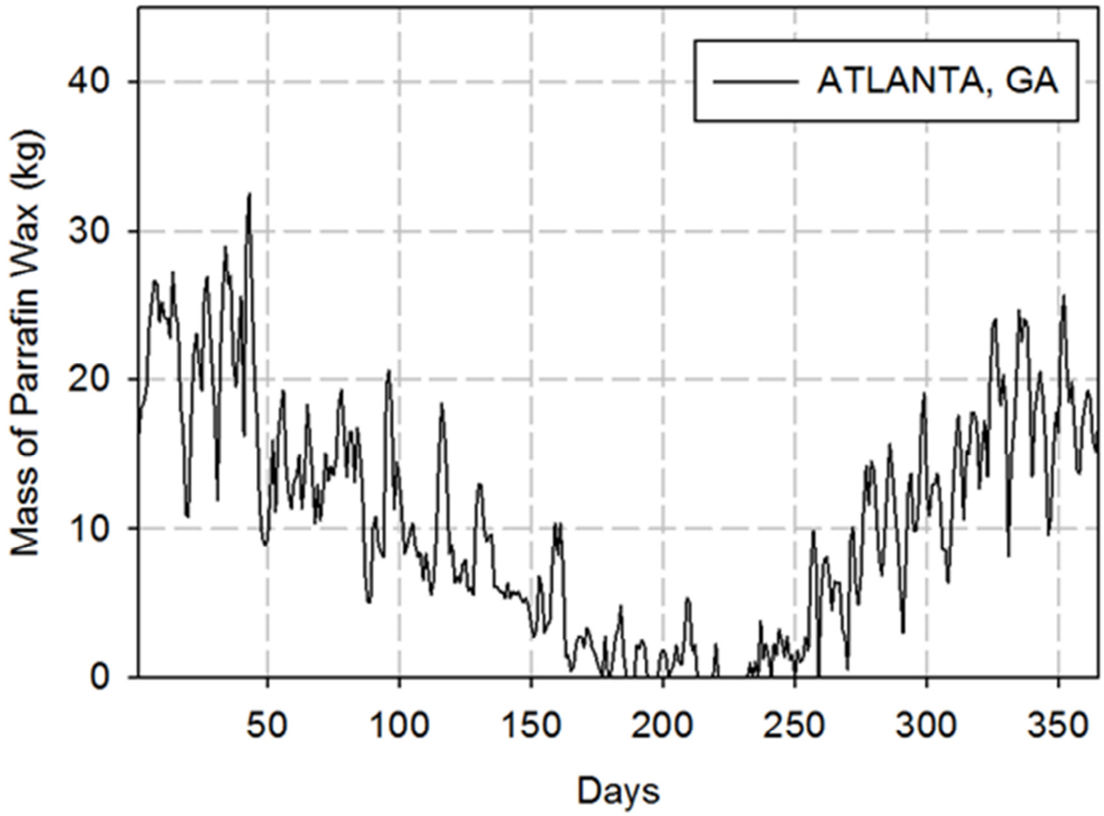


Figure 7-2: Calculated paraffin wax storage mass in Atlanta, GA

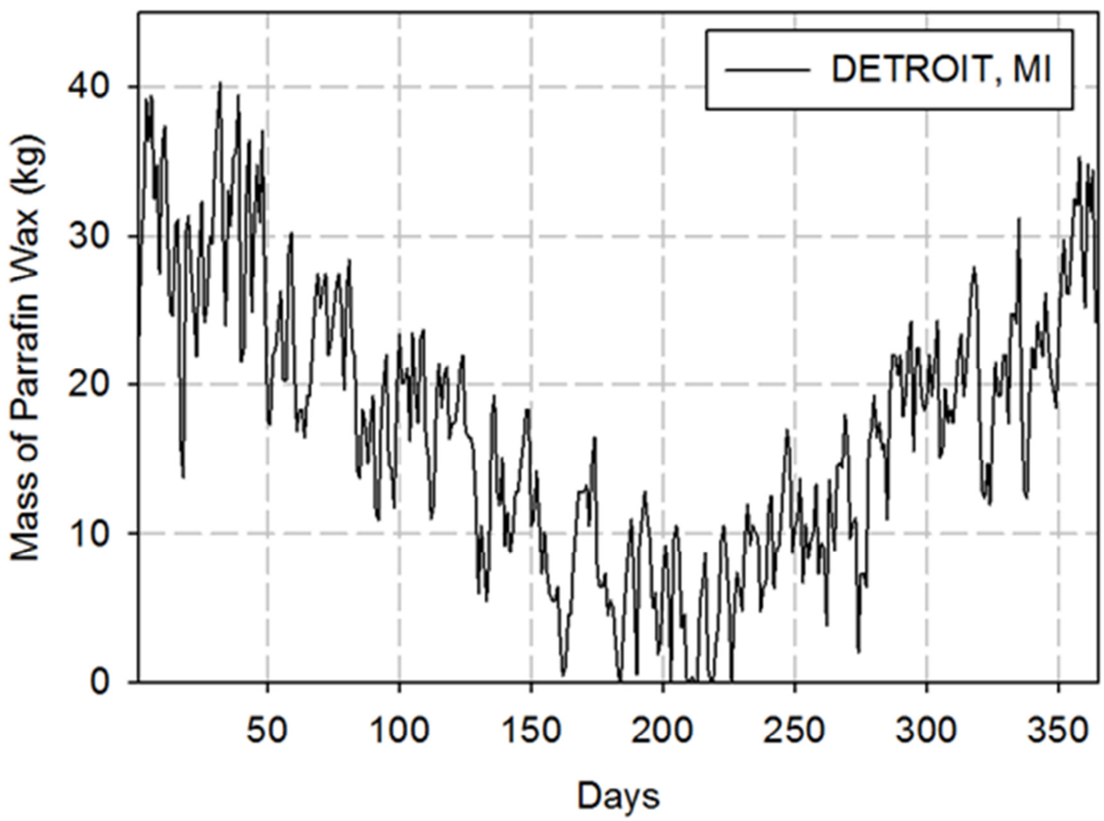


Figure 7-3: Calculated paraffin wax storage mass in Detroit, MI

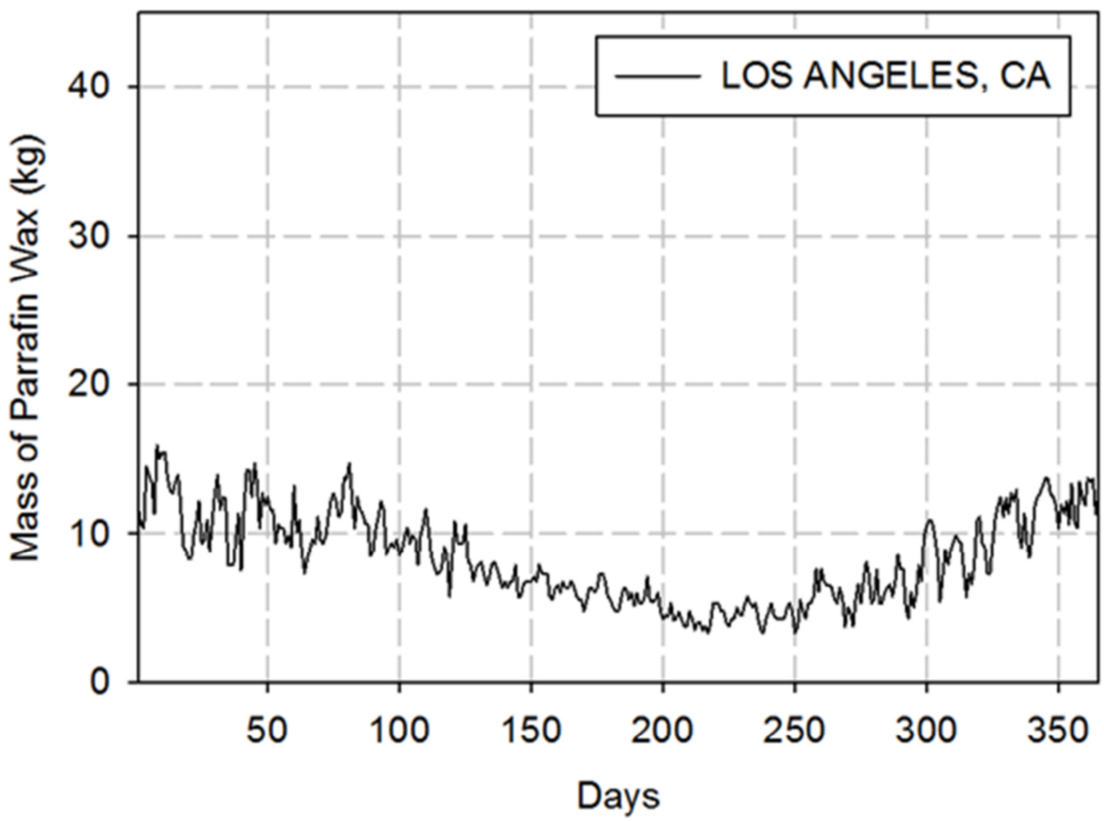


Figure 7-4: Calculated paraffin wax storage mass in Los Angeles, CA

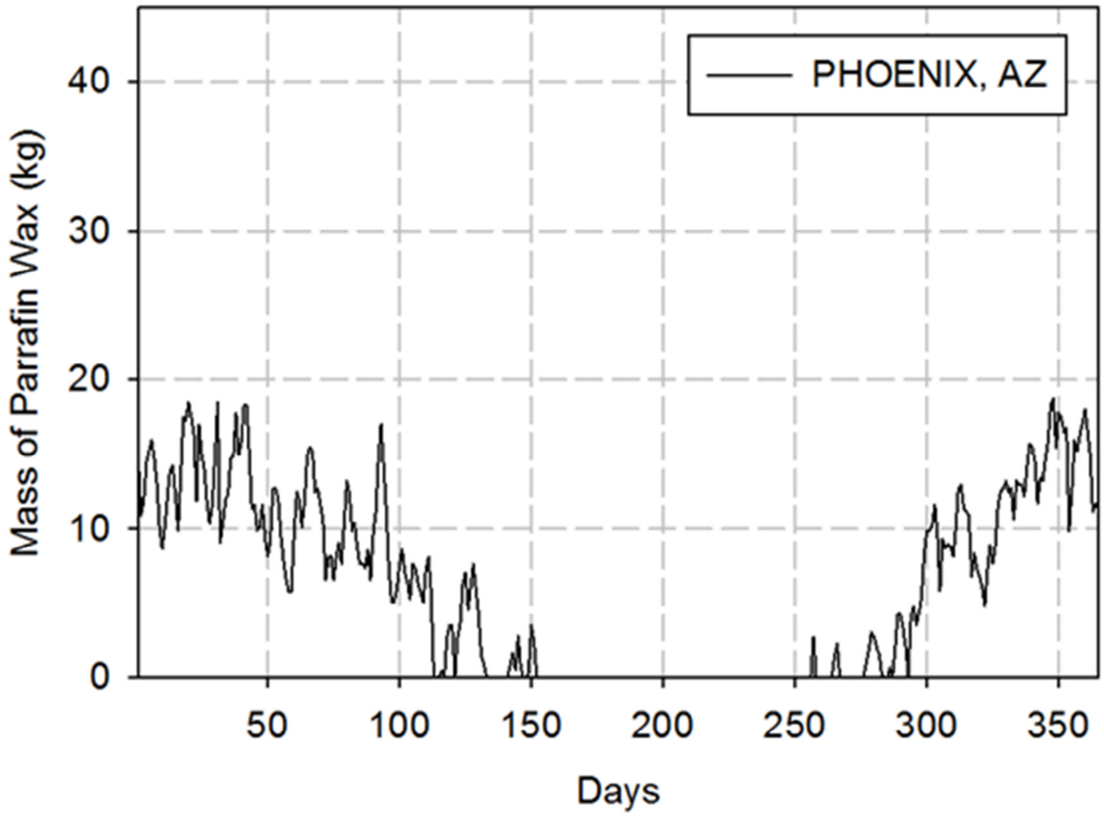


Figure 7-5: Calculated paraffin wax storage mass in Phoenix, AZ

7.4.2 Cabin Cooling using PCM

For providing required thermal comfort under summer climatic conditions, water ice (latent heat of fusion = 334 kJ/kg) is chosen as the PCM material. It is assumed that the ice made using the energy from the grid prior to the trip and is stored inside the EV with an 85% effective insulation system. Due to the poor power density of the PCM system, the peak power required to pull the cabin temperatures down to the required thermal comfort levels is again achieved by preconditioning the cabin using the energy from the grid. The Figure 7-6 to Figure 7-10 presents the daily maximum mass of ice required for cooling the cabin for 5 cities, Anchorage (AK), Atlanta (GA), Detroit (MI), Los Angeles (CA) and Phoenix (AZ).

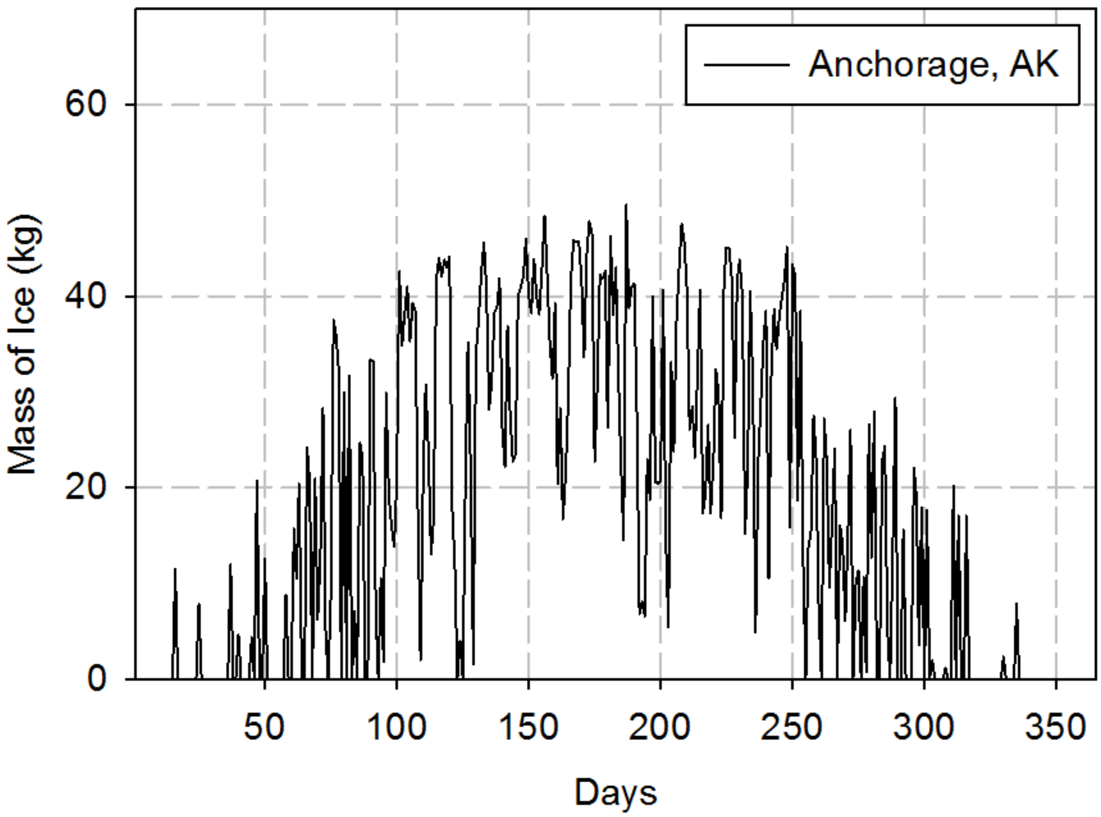


Figure 7-6: Calculated Ice storage mass in Anchorage, AK

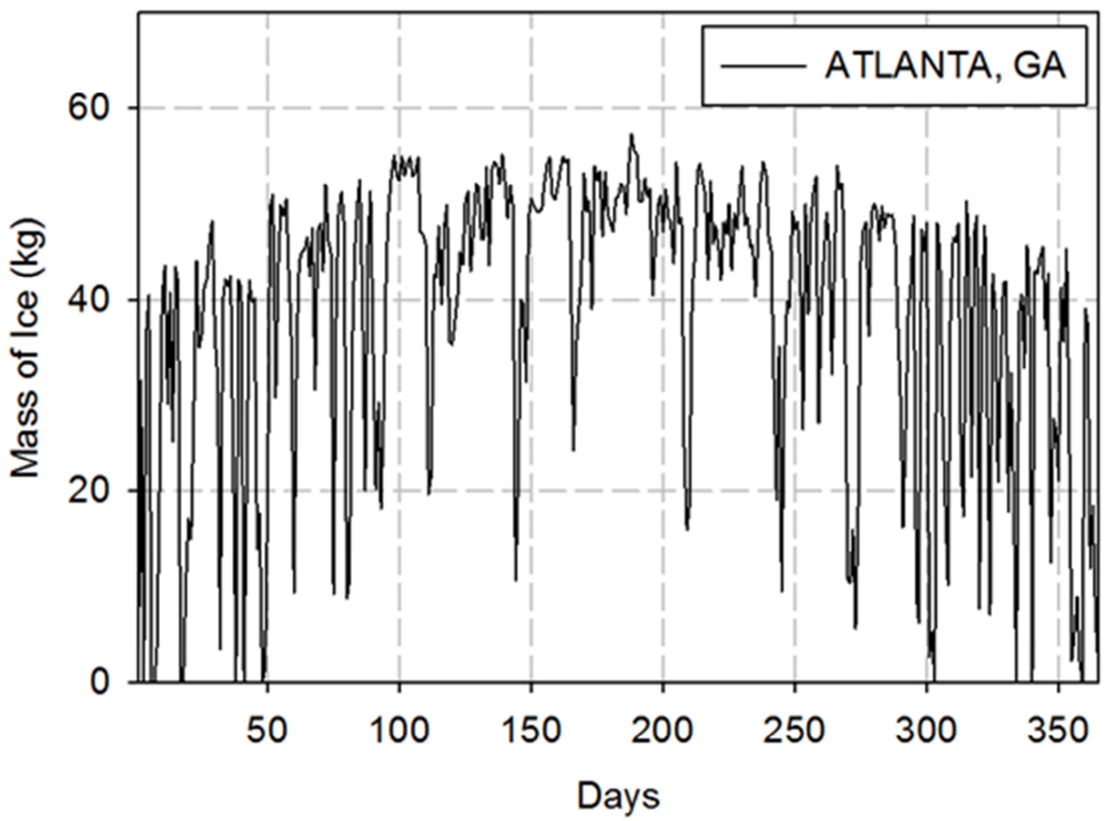


Figure 7-7: Calculated Ice storage mass in Atlanta, GA

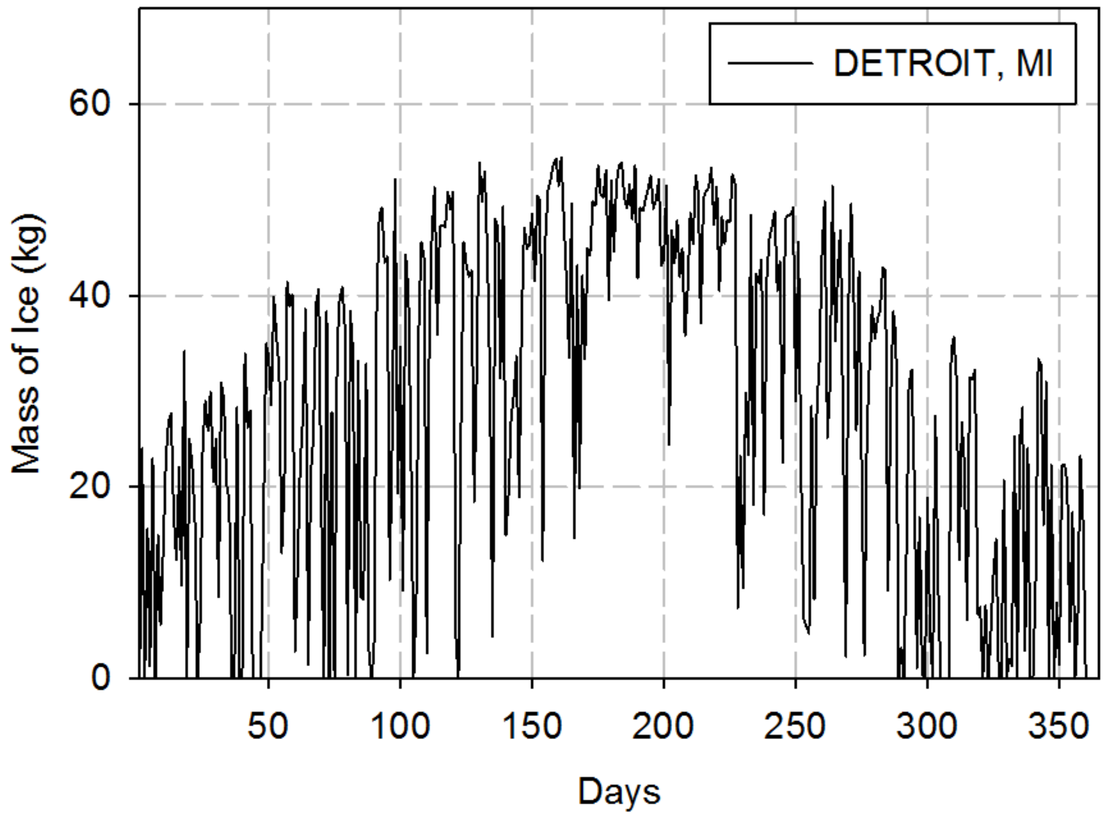


Figure 7-8: Calculated Ice storage mass in Detroit, MI

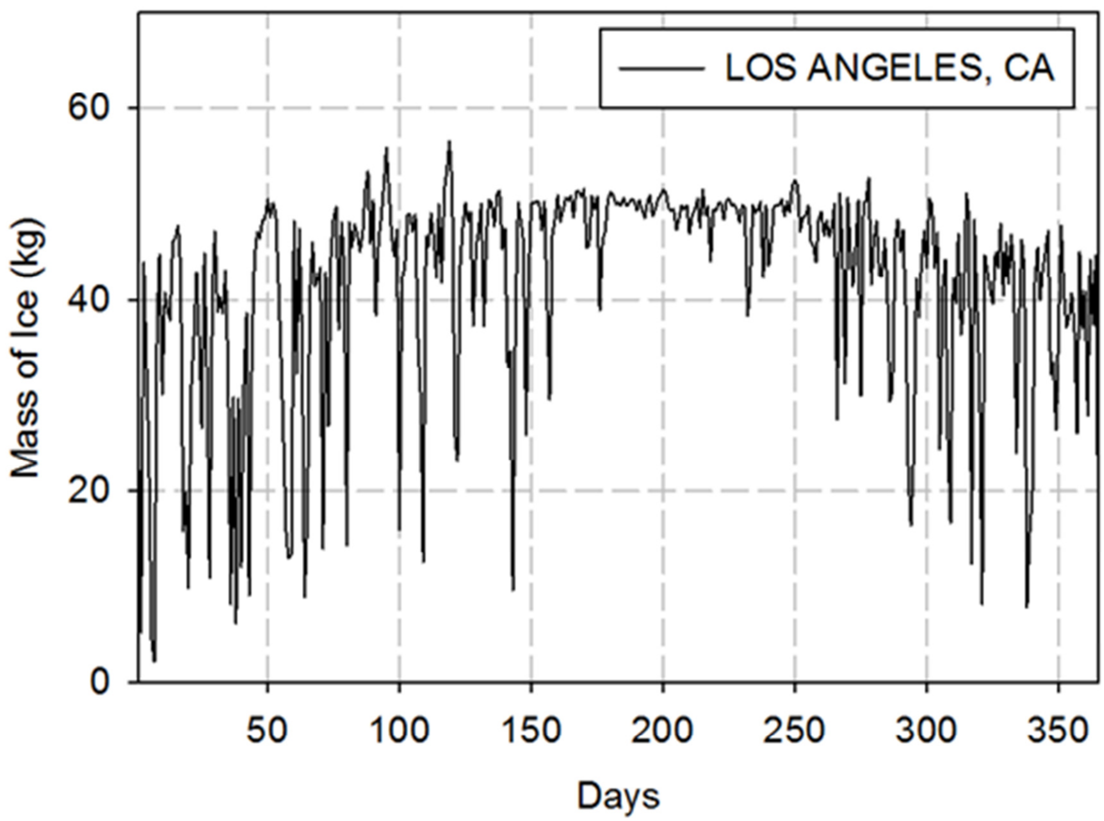


Figure 7-9: Calculated Ice storage mass in Los Angeles, CA

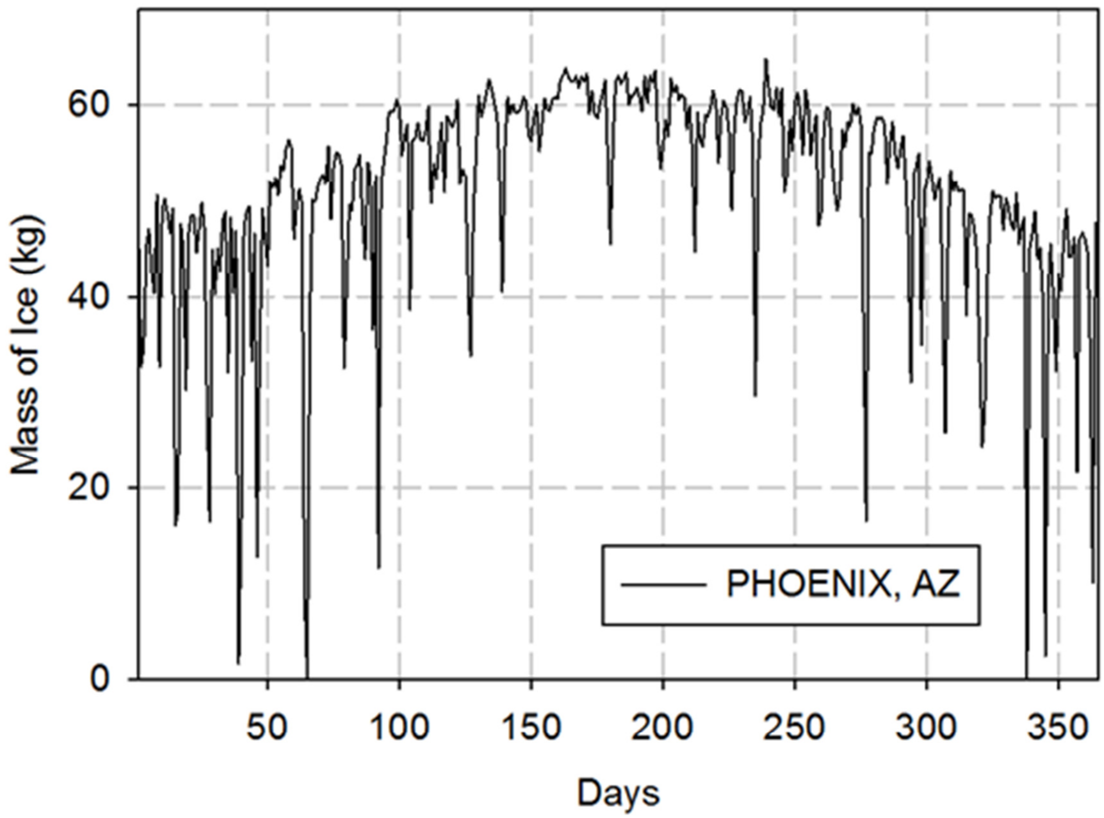


Figure 7-10: Calculated Ice storage mass in Phoenix, AZ

7.4.3 Integrated PCM system

With an integrated PCM based HVAC system in EVs for providing thermal comfort, from Figure 7-1to Figure 7-10, it is clearly seen that the requirement of PCM mass varies with time of day and time of year. The Table 7-1 summarizes the maximum PCM mass required for providing both cabin heating and cabin cooling in 5 cities. The paraffin wax mass required in Anchorage (AK) is 167% more than that required in Los Angeles (CA). This difference will further increase when all the associated heat exchange components are taken into consideration. Also, for PCM based system, it is important to ensure that prior to system discharge, a single phase exists (liquid wax for heating and ice for cooling so as to prevent the initiation of heat transfer via conduction in material matrix. This results in loss of energy due to melting of unused wax mass during every charging process. A common heating system designed based on requirements for Anchorage (AK) for all the other cities will also result in increase of vehicle curb weight and inefficient use of grid energy during the charging process.

Table 7-1: Maximum PCM mass requirements for cabin heating and cabin cooling in 5 cities

Cities	Maximum paraffin wax mass, kg	Maximum ice mass, kg	Total PCM mass, kg
Anchorage, AK	42.6	49.5	92.1
Atlanta, GA	32.5	57.3	89.8
Detroit, MI	40.3	54.4	94.7
Los Angeles, CA	15.9	56.5	72.4
Phoenix, AZ	18.8	64.9	83.7

7.5 Multi-objective Comparison of Technologies

Based on the results of this PCM sizing and HVAC system synthesis exercise, we can define the characteristics of PCM-based HVAC systems in terms of key metrics of interest including: EV range, AC energy consumption, and vehicle mass. To evaluate the performance of these PCM technologies, we can evaluate them in terms of the metrics of vehicle mass, vehicle energy consumption, and vehicle range. The technologies that can be evaluated using the toolset constructed for this research effort include:

- Vapor compression air conditioning system with resistive heater. This is the default HVAC system that has been the focus of evaluation for this research.

- Vapor compression air conditioning system with resistive heater and the ability to precondition the cabin while attached to the grid before driving. This is the preconditioning HVAC system that has been the focus of evaluation in the previous sections of this dissertation.
- The PCM system made up of paraffin wax undergoing a phase change to provide heating energy, and water ice undergoing a phase change to provide cooling energy. This option assumes 100kg of PCM is stored on board, as would meet the HVAC needs of 100% of vehicles in the 5 US city sample, as shown in Table 7-1. A 50kg mass is used to represent the system of containment and heat transfer that allows the PCM to function. This model assumes that the PCM is recharged using an off board cold and hot source whose weight is not allocated to the vehicle.
- A system is composed that meets all ARPAe HEATS goals. Its mass is equivalent to the conventional HVAC system, and carries enough energy to meet the steady state HVAC needs of the vehicle. Because the HEATS program goals do not include consideration of the energy requirements for transient pull-down or pull-up of the cabin temperature, this system model assumes that the vehicle is preconditioned when attached to the electric grid for charging

In each case, we can evaluate the stochastic performance of vehicles equipped with these technologies across a variety of US geographical locations, TOY, and TOD.

Using the metrics of comparison of AC energy consumption, vehicle mass, and EV range we can see that each technology addition (preconditioning, PCM, and advanced HVAC technology) improves the energy efficiency and EV range of the vehicle fleet. This improvement is not made through strict domination, as every technology is able to achieve very low energy consumption and high EV range in times and at locations where the HVAC accessory load is low. Instead, the advanced technologies realize their benefits through reducing the variability in energy consumption and EV range across geography and time. In comparing the vehicle masses, it is only the PCM system that adds appreciably to the vehicle mass, although the increase in vehicle mass does not have an appreciable impact on the vehicle energy efficiency or range.

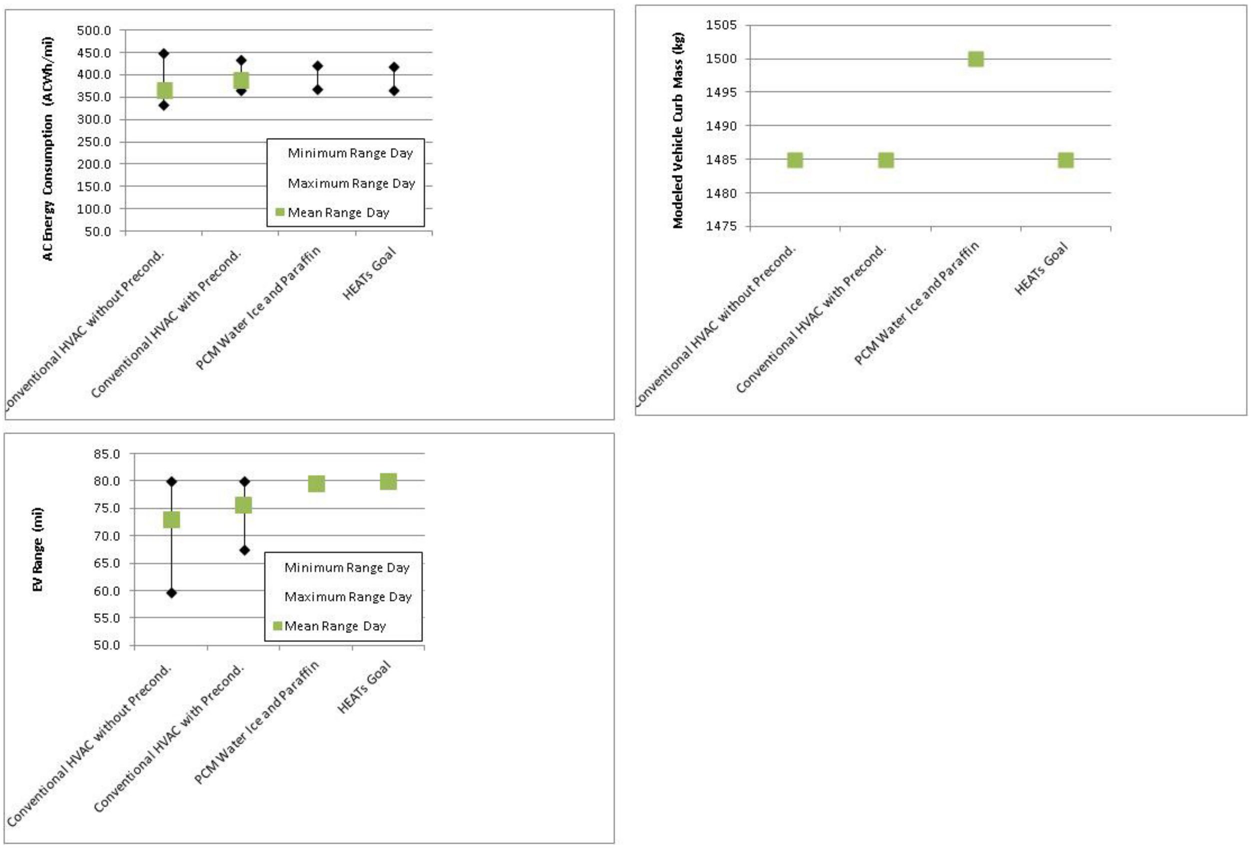


Figure 7-11 Graphical comparison of HVAC technologies across the proposed multi-objective trade space

Table 7-2 Comparison of HVAC technologies across the proposed multi-objective trade space

				AC Energy Consumption for a Full Range Trip (ACWh/mi)			Modeled Vehicle Range (mi) on 5 City Sample		
Air Conditioning Technology	Heating Technology	Preconditioning	Modeled Vehicle Curb Mass (kg)	Minimum Range Day	Maximum Range Day	Mean Range Day	Minimum Range Day	Maximum Range Day	Mean Range Day
Vapor Compression	Resistive Heating	No	1485	447.4	333.3	365.3	59.6	80.0	73.0
Vapor Compression	Resistive Heating	Yes	1485	434.1	366.3	387.1	67.5	80.0	75.7
PCM - Water Ice	PCM - Parrafin	Yes	1500	420.5	368.1		79.6	79.6	79.6
HEATs Goal	HEATs Goal	Yes	1485	418.3	366.3		80.0	80.0	80.0

Overall, these results point to a new understanding of the role that HVAC technologies may play in improving the consumer acceptability of EVs. In the previous understanding of the field, the conventional wisdom is that EV range is too low and that HVAC loads are making the EV range lower still. Based on the results of this study, we can understand that although HVAC accessory loads decrease the mean range available from the EV, the number of drivers who will launch on an 80 mile trip only to "run out of range" after 70+ miles is low, and the probability of an EV driver encountering such a trip and having it color their EV experience is quite low. Instead, the primary way that advanced HVAC systems improve the consumer acceptability of EVs is by improving the robustness of their performance.

7.6 Summary

This section of the research effort has allowed us to address research question 3 which is restated here:

Research Question 3: What accessory systems or technologies can improve the environmental performance and utility of HEVs, PHEVs and BEVs? What metrics or methods can be used to evaluate the economic, environmental and energy life cycle of the proposed technologies?

This study has shown that any of the suites of proposed technologies (heat pump system, preconditioning, PCM thermal storage, and advanced technologies) have the capability to improve the performance of EV HVAC systems. The primary metrics of interest that have been quantified in this study are vehicle mass, EV range, and AC energy consumption per unit of distance travelled.

The most result of this study has been to show that the advanced technology systems that have been proposed dominate presently available technologies for the objective of EV range, but they achieve their dominance primarily through a reduction in variability. Range variability and energy consumption variability are significantly reduced through the application of advanced HVAC technology, but the difference in utility that is achieved between "conventional" PCM systems (i.e. the proposed water/paraffin) and the advanced HVAC systems is relatively minor.

In fact, advanced HVAC technologies do not dominate the conventional HVAC technologies in the multi-objective tradespace among the primary metrics of interest. The advanced technology HVAC systems use more energy to travel a given distance primarily because of their reliance on cabin preconditioning to reduce the mobile thermal comfort conditioning load that must be served by the HVAC system.

CHAPTER 8 SUMMARY AND CONCLUSIONS

With the world's population reaching 8.5 billion by 2025 [72], the energy required for personal transportation sector will continue to place an increasing and irreversible burden on global oil reserves and the planet's capacity for CO_2 and criteria pollutants [73]. EVs are a near-term and technologically available means to reduce the environmental and social impacts of personal transportation, but many aspects of a more electric personal transportation system's energy consumption are unknown. A primary component of interest is the HVAC system as it is the second most energy intensive system onboard the vehicle.

In response to these research questions, this dissertation has defined and completed a series of tasks to address the primary research challenges associated with the modeling, analysis and assessment of HVAC systems for EVs. New subsystem models of the vehicle thermal behavior are integrated with models of climate, geography, personal driving habits, and the vehicle population so as to connect the performance of the EV HVAC system to the characteristics of the electrified personal transportation system. The multidisciplinary analysis process allows for the definition of system-level characteristics associated with the current state of the art in HVAC technologies, it allows for the definition of single vehicle performance metrics as a function of climactic and geographical information, and it allows for the development of design criteria for advanced HVAC system technologies. The scope of the modeling and analysis tools are US National, but are extensible to other regions of the world where similar data is available.

In Chapter 1, the benefits of EV over conventional gasoline and diesel powered vehicle were reviewed in terms of well to wheel, well to tank and overall well to wheel efficiencies. The significant gasoline consumption by the transportation sector was highlighted. The HVAC energy consumption in EV and its impact on the range reduction and negative user experience was discussed. The motivation, objective and organization for the current research work were presented.

Chapter 2 provides an extensive literature review on the past thermal comfort modeling methodologies, their limitations and subsequent error propagation, thermal comfort studies performed at NREL on conventional vehicles, limitations of current generation vehicle simulation software's and alternative accessory technologies.

Chapter 3 describes the research questions and scope of research that define this dissertation research effort.

In Chapter 4, the gaps existing within the past thermal comfort modeling methodology was identified. The control volume based thermal comfort modeling methods were discussed in detail. The data parsing from the databases containing the environmental data and passenger survey data from NSRDB and NHTS was discussed. The overall architecture of the model was highlighted by clearly identifying the flow of inputs and outputs. The outputs from the sample thermal comfort simulation of an EV at 29 Palms, California for 1'st day of January was presented. The process to evaluate HVAC energy consumption from the power curves based on the vehicle TOU from the NHTS survey data resulted in estimating the energy required for operating HVAC systems. By repeating the simulations for 1019 locations across US, a massive database consisting of heater and AC loads based on real world conditions was obtained. The resulting database was further used to investigate the potential benefits of replacing internal combustion based conventional vehicles with EVs in terms of national energy savings, environmental benefits, performance of EVs across all the states in US, additional accessory loading on the national grid due to EV charging and overall reduction of US gasoline imports and increase in energy generation at the source.

In Chapter 5, the real world HVAC energy consumption data base generated for 1019 locations across US was used to synthesize the state-wise HVAC energy consumption patterns for peak hour travel, annual average HVAC energy consumption at vehicle and fleet level. The real concern with the EV has always been the shorter travel range and longer charging times.

In Chapter 6, the dynamic energy depletion in EV during travel is translated into metrics of vehicle range to understand varying user experiences across different locations in US. Cabin preconditioning as a potential solution to increase EV range was presented. Since conventional AC powered compressor and resistance heating systems in EV can reduces range by almost 25%, a PCM-based alternative accessory technology is discussed in Chapter 7.

8.1 Research Contributions of this Dissertation

The unique contribution towards understanding the EV technology and their limitations from the consumers perspective were addressed in this dissertation. The following sections describe the specific contributions in greater detail.

8.1.1 Development of a vehicle specific thermal comfort and conditioning model

As detailed in Chapter 2, the limitations of the previous climate comfort models based on Fanger's description of thermal comfort have propagated uncertainty into many of its applications including previous estimations of HVAC energy consumption in conventional vehicles and EVs. In the present work, a control volume based dynamic thermal comfort model was built based on models of the energy interactions of the control volume with environment. Extensive use of existing databases such as NSRD and NHTS were used to build a comprehensive dynamic thermal comfort model based on widely varying weather patterns across US. The thermal comfort model developed for this dissertation is more generic, more amenable to sensitivity analysis, and can be extended to further evaluate HVAC energy requirements for other applications with minimal modifications in the simulation architecture.

8.1.2 A definition of vehicle and fleet-level HVAC energy consumption

The thermal comfort model presented in this dissertation was used to evaluate the annual average energy for providing thermal comfort both at the vehicle and fleet level. The energy of the displaced gasoline can now be added into the grid by integrating renewable technologies. The overall reduction of the gasoline consumption by passenger transportation fleet decreases the US dependence on foreign oil and increases the nation's energy security.

8.1.3 A definition of geographical and temporal variations in EV range

Several disjointed efforts by earlier researchers [7, 10, 19, 23, 37] have helped in vaguely understanding the reduction in EV range as a result of energy storage material deterioration, but very few studies have characterized the EV range deduction for day to day travel all through the year. In the current work, the variations in EV range have been presented comprehensively as a function of time and geography and inclusive of climactic effects, driving habits, the full suite of available and proposed HVAC technologies.

8.1.4 A evaluation of the multi-objective utility of cabin pre-conditioning technology

Cabin pre-conditioning has been proposed as a means to improve EV range by early investigators. However, the work performed to date has not quantitatively evaluated the benefits and costs of pre-conditioning of the vehicle cabin under time-varying and stochastic conditions. In the present work, a side by side comparison of two scenarios 1) without cabin pre-conditioning and 2) with cabin preconditioning were presented to understand the specific conditions of climate, geography and driving behavior under which they can be beneficial for improving the EV range, and energy consumption.

8.1.5 An evaluation and comparison of PCM based HVAC system performance in EVs

The compressor based AC cooling system and resistive elements based heating systems employed in current generation EVs have been demonstrated to reduce the EV range by up to 25%. Many technologists have proposed alternative accessory technologies including thermal storage, high efficiency HVAC systems, and other technologies. These systems are designed to meet the same thermal comfort conditioning requirements as conventional HVAC systems but operate without direct energy supply from the main on-board energy storage device. The multi-objective utility of a PCM-based HVAC system for EV applications was calculated and the limitations of such technologies were discussed.

8.2 Future Work

As discussed in Chapter 1, conventional vehicles have been under continuous technological and system-level development for more than a century. With depleting oil resources and irreversible threats to environment in terms of greenhouse gas emissions are setting an unprecedented push towards zero tail pipe emissions. EV technology is very promising in cutting down the tail pipe emissions at the fleet level. However, the specific energy density of fossil fuels is 40 times that of state of the art advanced electro-chemical materials used to store electrical energy in EVs. In addition to the storage capacity, there are additional concerns such as deterioration of battery materials over time of use, thermal runaway, and availability of rare earth materials that constitute the material composition for battery packs, cost of ownership, new infrastructure for vehicle charging, cheap accessibility to these charging stations, socio-economic issues, additional power generation requirements at the generating stations and depreciation of already existing investments in oil and gas industry to name a few.

However complex the dynamics between all the above discussed factors are, a positive consumer experience will certainly drive the success of EV technology in replacing the conventional vehicle fleet. There have been disjointed efforts among researchers in understanding the importance of various parameters in relation with EV. The lack of comprehensive models that takes into account all the above mentioned factors has led to incoherent appreciation of the EV technology among average consumers. Hence, a multithreaded approach is required to educate the consumer regarding the potential benefits of EVs while assisting them to create a pathway for intelligent use of EV. This can be achieved by constructing and connecting models at the component level to interact dynamically with each other to truly understand the obstacles and concerns from various stakeholders' perspective. For example, in a scenario where the local government initiates favorable policies to promote the EVs, the lack of knowledge among the average vehicle owner acting upon their prejudiced premise may not be able to truly appreciate the government initiatives.

The results presented in the current dissertation have considered the impact of real world environmental variables in adversely affecting the EV range. The real world environmental variables also affect the performance of storage device itself over its time of use. Several researchers have investigated this phenomenon in terms of life cycle analysis of storage devices. As an immediate extension of the current work, the thermal comfort model presented in chapter 3 can be combined with the energy storage life cycle model to more accurately predict the EV range for their use in any location of the country. The net reduction in EV range can help the early adopter of EV technology in planning their day to day trips based on real world estimations.

REFERENCES

1. *BP Statistical Review of World Energy June 2011*. 2011, British Petroluem.
2. Haubrich, J.G. and B. Meyer, *Peak Oil*. 2007, Federal Reserve Bank of Cleveland: Cleveland.
3. *Electric Vehicle Market Forecast*. 2011; Available from: www.pikeresearch.com/research.
4. Bradley, T.H. and A.A. Frank, *Design, demonstrations and sustainability impact assessments for plug-in hybrid electric vehicles.* Renewable and Sustainable Energy Reviews, 2009. **13**(1): p. 115-128.
5. Farrington, R. and J. Rugh, *Impact of Vehicle Air Conditioning on Fuel Economy,Tailpipe Emissions, and Electric Vehicle Range*, in *Earth Technologies Forum*. 2000: Washington DC.
6. Hendricks, T.J., *Vehicle Transient Air Conditioning Analysis: Model Development & System Optimization Investigations*. 2001: Golden.
7. Johnson, V.H., *Fuel Used for Vehicle Air Conditioning: A State-by-State Thermal Comfort-Based Approach.* Society of Automotive Engineers,, 2002(2002-01-1957).
8. Rugh, J., *Integrated Numerical Modeling Process for Evaluating Automobile Climate Control Systems.* Society of Automotive Engineers,, 2002.
9. Rugh, J., V.H. Johnson, and S.O. Andersen, *Significant Fuel Savings and Emission Reductions by Improving Vehicle Air Conditioning*. 2004, NREL.
10. Bingham, C., C. Walsh, and S. Carroll, *Impact of driving characteristics on electric vehicle energy consumption and range.* IET Intelligent Transport Systems, 2012. **6**(1): p. 29-35.
11. Global, B.P., *BP statistical review of world energy*. 2010.
12. Tate, E., M.O. Harpster, and P.J. Savagian, *The electrification of the automobile: from conventional hybrid, to plug-in hybrids, to extended-range electric vehicles*. 2008: SAE International.
13. Chan, C. and Y. Wong, *Electric vehicles charge forward.* Power and Energy Magazine, IEEE, 2004. **2**(6): p. 24-33.

14. Demirdöven, N. and J. Deutch, *Hybrid cars now, fuel cell cars later.* Science, 2004. **305**(5686): p. 974-976.

15. Burnham, A., M. Wang, and Y. Wu, *Development and applications of GREET 2.7--The Transportation Vehicle-CycleModel*. 2006, ANL.

16. Bharathan, D., et al., *An Overview of Vehicle Test and Analysis from NREL's A/C Fuel Use Reduction Research*. 2007, National Renewable Energy Laboratory.

17. Kaynakli, O. and I. Horuz, *An Experimental Analysis of Automotive Air Conditioning System.* Int. Comm. Heat Mass Transfer, 2003. **30**: p. 273-284.

18. Rugh, J. and R. Farrington, *Vehicle Ancillary Load Reduction Project Close-Out Report*. 2008, National Renewable Energy Laboratory: Golden.

19. Barnitt, R.A., et al., *Analysis of Off-Board Powered Thermal Preconditioning in Electric Drive Vehicles*, in *25th World Battery, Hybrid and Fuel Cell Electric Vehicle Symposium & Exhibition*. 2010: Shenzhen, China.

20. Duvall, M., *Advanced batteries for electric drive vehicles. A technology and cost-effectiveness assessment for battery electric vehicles, power assist hybrid electric vehicles, and plug-in hybrid electric vehicles.* Electric Power Research Institute, Palo Alto, CA, 2004.

21. Connolly, D., *A Review of Energy Storage Technologies.* University of Limerick, Limerick, 2009: p. 6-13.

22. Pesaran, A.A., et al., *Battery Requirements for Plug-in Hybrid Electric Vehicles--analysis and Rationale*. 2009: National Renewable Energy Laboratory.

23. Wood, E., M. Alexander, and T.H. Bradley, *Investigation of battery end-of-life conditions for plug-in hybrid electric vehicles.* Journal of Power Sources, 2011. **196**(11): p. 5147-5154.

24. Maitra, A., et al. *Grid impacts of plug-in electric vehicles on Hydro Quebec's distribution system*. in *Transmission and Distribution Conference and Exposition, 2010 IEEE PES*. 2010. IEEE.

25. Williams, T. and C. Crawford. *Probabilistic Power Flow Modeling: Renewable Energy and PEV Grid interactions*. in *Proceedings of The Canadian Society for Mechanical Engineering Forum*. 2010.

26. Perkins, D.E., et al. *An assessment of accessory loads in a hybrid electric vehicle*. in *Vehicle Power and Propulsion Conference (VPPC), 2011 IEEE*. 2011. IEEE.

27. Austin, D. and T. Dinan, *Clearing the air: The costs and consequences of higher CAFE standards and increased gasoline taxes.* Journal of Environmental Economics and Management, 2005. **50**(3): p. 562-582.

28. Fanger, P.O., *Thermal Comfort*. 1982, Malabar, FL: Kreiger Publishing Company.

29. Charles, K.E., *Fanger's thermal comfort and draught models.* 2003.

30. Van Hoof, J., *Forty years of Fanger's model of thermal comfort: comfort for all?* Indoor Air, 2008. **18**(3): p. 182-201.

31. Thom, E.C., *The discomfort index.* Weatherwise, 1959. **12**(2): p. 57-61.

32. Gagge, A.P., A. Fobelets, and L. Berglund, *A standard predictive index of human response to the thermal environment.* ASHRAE Trans.;(United States), 1986. **92**(CONF-8606125-).

33. Auliciems, A. and S.V. Szokolay. *Thermal comfort*. 1997. PLEA.

34. Humphreys, M.A., *Field studies of thermal comfort compared and applied*. 1975: Building Research Establishment.

35. Humphreys, M.A. and J. Fergus Nicol, *The validity of ISO-PMV for predicting comfort votes in every-day thermal environments.* Energy and buildings, 2002. **34**(6): p. 667-684.

36. Farrington, R.B., et al., *Challenges and potential solutions for reducing climate control loads in conventional and hybrid electric vehicles.* National Renewable Energy Laboratory, Golden, CO, USA, Download from: www. ott. doe. gov/coolcar/pubs. html, 1999.

37. Benouali, J., et al. *Fuel Consumption of Mobile Air Conditioning, Method of Testing and Results*. in *Proceedings of the 14th Annual Earth Technologies Forum*. 2003.

38. Rugh, J., *Proposal for a Vehicle Level Test Procedure to Measure Air Conditioning Fuel Use*. 2010: Retrieved from the National Renewable Energy Laboratory: http://www. nrel. gov/docs/fy10osti/47273. pdf.

39. Wipke, K.B., M.R. Cuddy, and S.D. Burch, *ADVISOR 2.1: a user-friendly advanced powertrain simulation using a combined backward/forward approach.* Vehicular Technology, IEEE Transactions on, 1999. **48**(6): p. 1751-1761.

40. Markel, T., et al., *ADVISOR: a systems analysis tool for advanced vehicle modeling.* Journal of power sources, 2002. **110**(2): p. 255-266.

41. Jaber, K., et al. *Modeling and Simulation of electrical vehicle in VHDL-AMS*. in *Electronics, Circuits, and Systems, 2009. ICECS 2009. 16th IEEE International Conference on*. 2009. IEEE.

42. Halbach, S., et al., *Model architecture, methods, and interfaces for efficient math-based design and simulation of automotive control systems.* Society of Automotive Engineers (SAE), 2010: p. 01-0241.

43. Olesen, B.W. and K. Parsons, *Introduction to thermal comfort standards and to the proposed new version of EN ISO 7730.* Energy and buildings, 2002. **34**(6): p. 537-548.

44. van Hoof, J. and J.L. Hensen, *Quantifying the relevance of adaptive thermal comfort models in moderate thermal climate zones.* Building and Environment, 2007. **42**(1): p. 156-170.

45. Brager, G.S. and R.J. de Dear, *Thermal adaptation in the built environment: a literature review.* Energy and buildings, 1998. **27**(1): p. 83-96.

46. Djongyang, N., R. Tchinda, and D. Njomo, *Thermal comfort: A review paper.* Renewable and Sustainable Energy Reviews, 2010. **14**(9): p. 2626-2640.

47. Hensen, J., *Literature review on thermal comfort in transient conditions.* Building and Environment, 1990. **25**(4): p. 309-316.

48. Oseland, N. and M. Humphreys, *Trends in Thermal Comfort Research*. 1994: Building Research Establishment.

49. Dear, R., J. Ring, and P. Fanger, *Thermal sensations resulting from sudden ambient temperature changes.* Indoor air, 1993. **3**(3): p. 181-192.

50. Croome, D., G. Gan, and H. Awbi, *Evaluation of thermal comfort and indoor air quality in offices: Thermal models based on laboratory tests at steady state conditions cannot accurately predict the real thermal environment where the conditions are transient and where occupants change their activities.* Building research and information, 1992. **20**(4): p. 211-225.

51. Wyczalek, F.A., *Heating and cooling battery electric vehicles-the final barrier.* Aerospace and Electronic Systems Magazine, IEEE, 1993. **8**(11): p. 9-14.

52. Bulusu, A. and D. Walker, *Review of electronic transport models for thermoelectric materials.* Superlattices and Microstructures, 2008. **44**(1): p. 1-36.

53. Burke, A. and H. Zhao, *Simulations of plug-in hybrid vehicles using advanced lithium batteries and ultracapacitors on various driving cycles.* 2010.

54. Hamut, H.S., I. Dincer, and G.F. Naterer, *Exergy analysis of a TMS (thermal management system) for range-extended EVs (electric vehicles).* Energy, 2012. **46**(1): p. 117-125.

55. Chan, C.C., *The State of Art of Electric and Hybrid Vehicles*. 2002.

56. Santos, A., et al., *Summary of travel trends: 2009 national household travel survey*. 2011.

57. DeNavas-Walt, C., B.D. Proctor, and J.C. Smith, *US Census Bureau, Current Population Reports, P60-238.* Income, poverty, and health insurance coverage in the United States: 2009, 2010.

58. Wilcox, S., *National Solar Radiation Database 1991-2005 Update: User's Manual*. 2007, National Renewable Energy Laboratory (NREL), Golden, CO.

59. Incropera, F.P., A.S. Lavine, and D.P. DeWitt, *Fundamentals of heat and mass transfer*. 2011: John Wiley & Sons Incorporated.

60. Handbook, A., *Fundamentals.* American Society of Heating, Refrigerating and Air Conditioning Engineers, Atlanta, 2001.

61. Reindl, D.T., W.A. Beckman, and J.A. Duffie, *Evaluation of hourly tilted surface radiation models.* Solar Energy, 1990. **45**(1): p. 9-17.

62. Roy, S., et al., *An experimental and numerical study of heat transfer off an inclined surface subject to an impinging airflow.* International Journal of Heat and Mass Transfer, 2002. **45**(8): p. 1615-1629.

63. Polking, J.C., *MATLAB Manual, Ordinary Differential Equations*. 1995: Prentice Hall PTR.

64. Leaf, N., *Nissan Leaf.* EPS. **10**(58.01): p. 104.37.

65. Ratts, E.B. and J.S. Brown, *An experimental analysis of cycling in an automotive air conditioning system.* Applied Thermal Engineering, 2000. **20**(11): p. 1039-1058.

66. Wang, S.J. and J.J. Gu, *Experimental Analysis of an Automotive Air Conditioning System With Two-Phase Flow Measurements*, in *International Refrigeration and Air Conditioning*. 2004: Purdue.

67. Eisele, M., *TRANSIENT PERFORMANCE EVALUATION OF AUTOMOTIVE SECONDARY LOOP SYSTEMS.* 2012.

68. Gärling, A. and J. Thøgersen, *Marketing of electric vehicles.* Business Strategy and the Environment, 2001. **10**(1): p. 53-65.

69. Nemry, F., G. Leduc, and A. Muñoz, *Plug-in Hybrid and Battery-Electric Vehicles: State of the research and development and comparative analysis of energy and cost efficiency*. 2009, Institute for Prospective and Technological Studies, Joint Research Centre.

70. Eberhard, M. and M. Tarpenning, *The 21st century electric car.* Retrieved July, 2006. **2**: p. 2012.

71. STORAGE, T.E., *HEATS.*

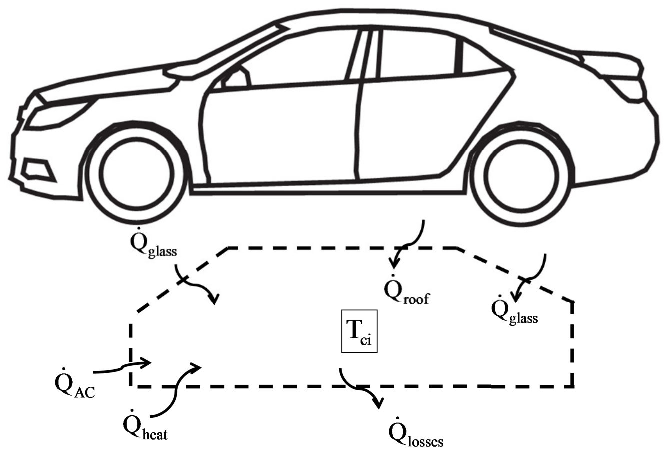
72. Woytinsky, W.S. and E.S. Woytinsky, *World population and production trends and outlook.* 2010.

73. Davis, S.C., S.W. Diegel, and R.G. Boundy, *Transportation energy data book: Edition 25*. 2003, United States. Department of Energy.

APPENDIX

Governing Equations

Over all energy balance for the cabin control volume



$$\dot{Q}_{roof} + 2\dot{Q}_{glass} + \dot{Q}_{conv,i} + \dot{Q}_{AC} + \dot{Q}_{heat} - \dot{Q}_{losses} = MCp\frac{dT_{ci}}{dt} \qquad \text{Eqn 1}$$

$$\dot{Q}_{conv,i,} = \dot{Q}_{conv,roof,i} + \dot{Q}_{conv,glass,i} \qquad \text{Eqn 2}$$

$$\dot{Q}_{conv,roof,i,} = \tilde{h}_{i,roof}\left(T_{ci} - T_{roof}\right) \qquad \text{Eqn 3}$$

$$\dot{Q}_{conv,glass,i} = \tilde{h}_{i,glass}\left(T_{ci} - T_{glass}\right) \qquad \text{Eqn 4}$$

The convection coefficient for internal horizontal surfaces are evaluated from,

$$Nu_{i,roof,avg} = \begin{bmatrix} 0.54Ra^{1/4}, & 10^4 \le Ra \le 10^7 \\ 0.15Ra^{1/4}, & 10^7 \le Ra \le 10^{11} \end{bmatrix} = \frac{\tilde{h}_{i,roof}L_{roof}}{k_{air}}, \text{ when } T_{roof} > T_{amb} \qquad \text{Eqn 5}$$

$$Nu_{i,roof,avg} = \left[0.27Ra^{1/4}, \quad 10^5 \le Ra \le 10^{11}\right] = \frac{\tilde{h}_{i,roof}L_{roof}}{k_{air}}, \text{ when } T_{roof} \le T_{amb} \qquad \text{Eqn 6}$$

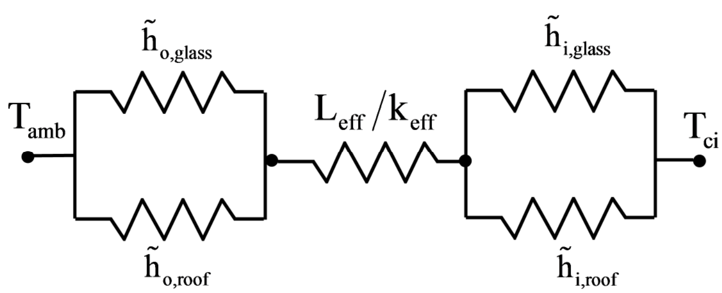
The convection coefficient for inclined glass surfaces are evaluated from,

$$Nu_{i,glass,avg} = \begin{bmatrix} 0.59Ra_L^{1/4}, & 10^4 \le Ra \le 10^9 \\ 0.1Ra_L^{1/4}, & 10^9 \le Ra \le 10^{13} \end{bmatrix} = \frac{\tilde{h}_{i,glass} L_{glass}}{k_{air}}, \text{when } T_{roof} > T_{amb} \qquad \text{Eqn 7}$$

$$Nu_{i,glass,avg} = \begin{bmatrix} 0.68 + \dfrac{0.67Ra_L^{1/4}}{\left[1+\left(0.492/Pr\right)^{9/16}\right]^{4/9}}, & Ra \le 10^9 \\ \left\{0.825 + \dfrac{0.387Ra_L^{1/6}}{\left[1+\left(0.492/Pr\right)^{9/16}\right]^{8/27}}\right\}^2, & Ra > 10^9 \end{bmatrix} = \frac{\tilde{h}_{i,glass} L_{glass}}{k_{air}}, \text{when } T_{roof} \le T_{amb}$$

Eqn 8

$\dot{Q}_{losses}$ is evaluated based on following thermal resistance network diagram,



Where,

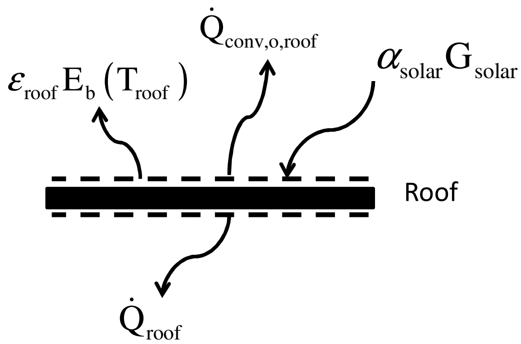
$$R_{eff} = \left(\frac{1}{1/\tilde{h}_{o,roof} + 1/\tilde{h}_{o,glass}}\right)^{-1} + \frac{L_{eff}}{k_{eff}} + \left(\frac{1}{1/\tilde{h}_{i,roof} + 1/\tilde{h}_{i,glass}}\right)^{-1} \qquad \text{Eqn 9}$$

$$\dot{Q}_{losses} = \frac{(T_{amb} - T_{ci})}{R_{eff}}$$ Eqn 10

$$\dot{Q}_{AC} = \dot{m}_{air}\left(\tilde{T}_{evap} - T_{ci}\right)$$ Eqn 11

$$\dot{Q}_{heater} = \dot{m}_{air}\left(\tilde{T}_{heater} - T_{ci}\right)$$ Eqn 12

Energy balance across the cabin roof as control surface



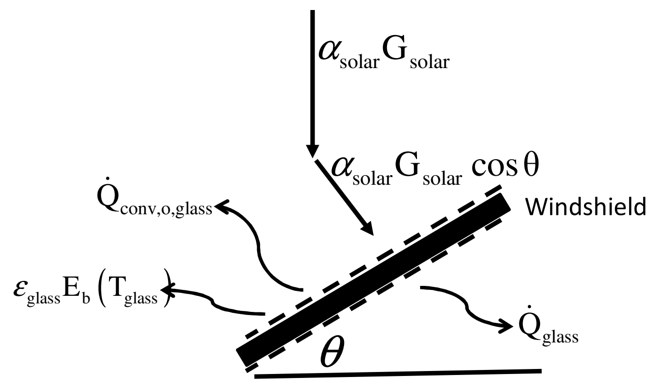
$$\alpha_{solar} G_{solar} - \varepsilon_{roof} E_b (T_{roof}) - \dot{Q}_{conv,o,roof} - \dot{Q}_{roof} = M_{roof} C_{p,\, roof} \frac{dT_{roof}}{dt}$$ Eqn 13

$$\dot{Q}_{conv,o,roof} = \tilde{h}_{o,roof}\left(\tilde{T}_{roof} - T_{amb}\right)$$ Eqn 14

The outside air forced heat transfer coefficient $\tilde{h}_{o,\, roof}$, for horizontal exterior surface was estimated from the following empirical correlation,

$$Nu_{o,avg} = \left[0.037 Re_L^{\frac{4}{5}} - 871\right] Pr^{\frac{1}{3}} = \frac{\tilde{h}_{o,\, roof} L_C}{k_{air}}, \qquad 0.6 < Pr < 60$$ Eqn 15

Energy balance across windshield as control surface



$$\alpha_{solar} G_{solar} \cos\theta - \varepsilon_{glass} E_b \left(T_{glass}\right) - \dot{Q}_{conv,o,glass} - \dot{Q}_{glass} = M_{glass} C_{p,\ glass} \frac{dT_{glass}}{dt} \qquad \text{Eqn 16}$$

$$\dot{Q}_{conv,o,glass} = \tilde{h}_{o,glass} \left(\tilde{T}_{glass} - T_{amb}\right) \qquad \text{Eqn 17}$$

The outside air forced heat transfer coefficient $\tilde{h}_{o,\ glass}$, for horizontal exterior surface is evaluated from $Nu_{o,avg} = \left[0.037 Re_L^{\frac{4}{5}} - 871\right] Pr^{\frac{1}{3}} = \frac{\tilde{h}_{o,\ roof} L_C}{k_{air}}, \qquad 0.6 < Pr < 60$ Eqn 15.

Table of parameters

Materials properties used in the simulation

	Air	Windows	Plastics	Aluminum
Density (kg/m^3)	1.23	2500		
Specific heat (J/kg-K)	1006.43	750		
Thermal Conductivity (W/m-K)	0.024	0.96	0.03	250
Viscosity (Pa-s)	1.7894e-5			

Surface radiation properties

Aluminum: Total emissivity = 0.8

Window Material: $0.2 \leq \lambda \leq 4$ µm, $\tau_\lambda = 0.9$, $\rho_\lambda = 0$,

$\lambda > 4$ µm, $\tau_\lambda = 0$, $\alpha = \varepsilon = 0.95$, diffuse-gray, opaque

Car dimensions

Cabin Size (m^3)	2.3m X 1.3m X 1.19m
Number of Windows	6

Sensitivity Analysis

Varying Thermal comfort domain:

Initial Cabin Temperature = 10C

Trip Time: 11h to 13 h

Trip Location: 29 Palms, CA

Trip Day: January 1, Average Ambient Temperature: 12C

Temperature Limits	Heater Energy (DC kWh)	AC Energy (DC kWh)	HVAC Energy (DC kWh)
15C-20 C	0.23	2.20	2.53
20C-25C	0.47	1.93	2.40
23C-27C	0.62	1.74	2.36
25C-30C	0.72	1.35	2.07
30C-35C	0.95	0.76	1.71

Varying Cabin Size:

Initial Cabin Temperature = 10C

Trip Time: 11h to 13 h

Trip Location: 29 Palms, CA

Trip Day: January 1, Average Ambient Temperature: 12C

Cabin Size	Heater Energy (DC kWh)	AC Energy (DC kWh)	HVAC Energy (DC kWh)
1.5 (m^3)	0.61	1.73	2.35
2 (m^3)	0.62	1.73	2.36
3.5 (m^3)	0.62	1.73	2.36
4 (m^3)	0.63	1.73	2.37

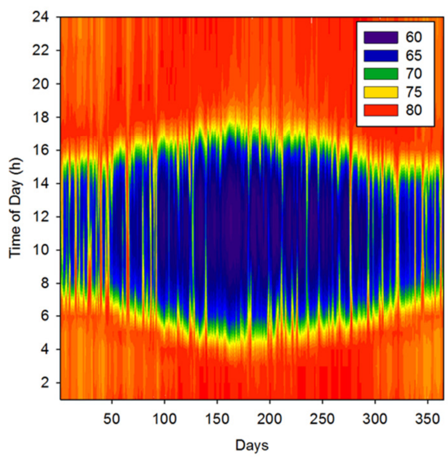
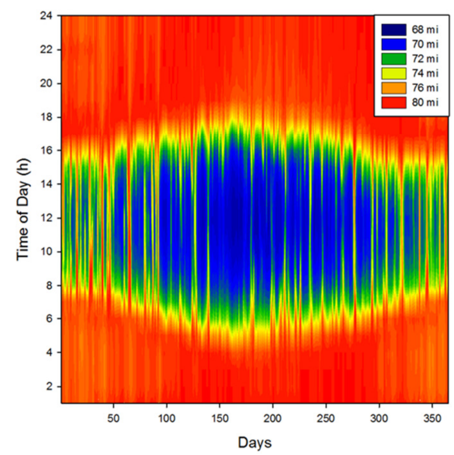
Varying Vehicle Speed:

<table>
<tr>
<td>Average Vehicle Speed: 28 mph,

Location: Phoenix, AZ

24kWh, 0.3 DC kWh/mi</td>
<td>Average Vehicle Speed: 60mph

Location Phoenix, AZ

24kWh, 0.3 DC kWh/mi</td>
</tr>
<tr>
<td>
</td>
<td>
</td>
</tr>
</table>

Mean Radiant Temperature

Mean radiant temperature (MRT) is a measure of average net heat gain or heat loss from all the surfaces inside a control volume. This varies from the ambient air temperature when the surfaces from which heat is gained or lost are at significantly different temperatures. For example, in cold conditions, human body when exposed to direct sun light is subjected to heat gain and experience thermal discomfort, while on a hot summer day, opening a freezer door results in radiant heat loss to the ambient. This is due to high emissivity and absorptivity of human skin. The rate at which the surface temperature increases or decreases depends on the thermal and irradiative capacity of the surfaces.

In the case of an automobile, under normal operating conditions, contribution to the thermal discomfort via solar irradiation transmitted through windshield is higher compared to that from other surfaces and the mean radiant temperature is closer to the average cabin temperature. In a scenario when the automobile is stationary while being exposed under direct sunlight, the mean radiant temperature will be closer to that of surfaces with high thermal capacity. The previous thermal comfort models [5, 6, 7, 8, 9] estimated MRT using two discrete conditions (ambient temperature, peak soak temperature) as the main input to the PMV equation defined by Fanger.

Accordingly, if there are 'n' surfaces with non-uniform temperatures forming a control volume, then the mean radiant temperature is given by.

$$MRT = \sum_{i=1}^{n} \propto_i T_i$$

where, $\sum \propto_i = 1$, $0 < \propto_i < 1$,

To estimate the MRT for cabin control volume, the primary heat transfer surfaces are windshield (ws) and car-body (cb). The car-body further comprises several conjoined surfaces. The MRT equation is now reduced to,

$$MRT = \propto_{ws} T_{ws} + \propto_{cb} T_{cb} \,,$$

Where, T_{ws} and T_{cb} represents an effective windshield and car body temperature. $\propto$ is the constant surface view factor for stationary applications.

In the case of automobiles, $\propto_{ws}$ varies dynamically between 0 and 1 for thermal soak and steady state operating conditions respectively, as the balance between conductive, convective and irradiative exchange at the surfaces change with TOD. Also it can be seen that evaluating $\propto_{ws}$ to subsequently estimate MRT requires information on parking conditions, tracking geographical trip direction in addition to trip times and directional-hemispherical irradiation.

The lack of availability of this data limits the use of PMV equation to predict thermal comfort for fewer cases. Hence in the current work, a method based on dynamic energy exchanges at the boundary of control volume to evaluate thermal comfort is developed.

Subscripts

amb	Ambient
c	Cabin
eff	Effective
i	Inside
L	Characteristic length
o	Outside
conv	Convection
s	Surface

Index

A	Area (m^2)
Cp	Specific heat capacity (kJ/kgK)
G	Solar irradiation (W)
h	Heat transfer coefficient (W/mK)
k	Thermal conductivity (W/m^2K)

Lc	Characteristic Length (m)
M	Mass (kg)
$\dot{m}$	mass flow rate (kgs^{-1})
Nu	Nusselt number
Pr	Prandtl number
$\dot{Q}$	Heat transfer rate (W)
Ra	Raleigh number
R	Resistance (K/W)
t	Time (s)

Greek symbols

ε	emissivity
α	absorptivity
ρ	density
Ө	Windshield angle (deg)
~	average value

Abbreviations

NSRDB	National Solar Resource Database
NHTS	National Highway Transportation Survey