Geographical and temporal differences in electric vehicle range due to cabin conditioning energy consumption

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HIGHLIGHTS
- Dynamic electric vehicle thermal comfort model based on control volume approach.
- Impact of HVAC loads on electric vehicle range.
- Electric vehicle range variation across the geography of US and as a function of time of day.
- Benefits of cabin pre-conditioning.

ABSTRACT

Electric vehicles (EVs) are vehicles that are propelled by electric motors powered by rechargeable battery. They are generally asserted to have GHG emissions, driveability and life cycle cost benefits over conventional vehicles. Despite this, EVs face significant challenges due to their limited on-board energy storage capacity. In addition to providing energy for traction, the energy storage device operates HVAC systems for cabin conditioning. This results in reduced driving range. The factors such as local ambient temperature, local solar radiation, local humidity, duration and thermal soak have been identified to affect the cabin conditions. In this paper, the development of a detailed system-level approach to HVAC energy consumption in EVs as a function of transient environmental parameters is described. The resulting vehicle thermal comfort model is used to address several questions such as 1) How does day to day environmental conditions affect EV range? 2) How does frequency of EV range change geographically? 3) How does trip start time affect EV range? 4) Under what conditions does cabin preconditioning assist in increasing the EV range? 5) What percentage increase in EV range can be expected due to cabin preconditioning at a given location?

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1. Introduction

Electric vehicles (EVs) are a substantial and growing component of the US light duty passenger fleet compromising 5% of current light-duty vehicle sales [1]. As implemented in the mass-market EVs available today, the lower energy density of the onboard energy storage system limits their range to less than 160 km. Despite EVs’ lifecycle cost savings, lower environmental impacts and lower lifecycle energy consumption, their incremental purchase cost and reduced range is cited as reasons for their relatively small market share [2–4].

In EVs, the energy storage system must generally provide all of the energy to power the full function of the vehicle including traction loads, accessory loads, and cabin thermal comfort conditioning loads. Because of differences in driving behavior and climate conditions, the range of an EV varies regionally and temporally. Despite its importance in modeling the performance, robustness, and consumer acceptability of EVs, the role of thermal comfort conditioning loads in directly affecting the EV range has been relatively under-researched. A few studies have modeled the device-level function and energy consumption of vehicle heating, ventilation, and air-conditioning (HVAC) systems [6–9], but fewer have attempted to translate these device-level performance metrics into geographically- or temporally-realized EV energy consumption characteristics or range estimates [22,23].

Researchers at the National Renewable Energy Laboratory (NREL) have performed the most relevant recent work. These studies have found that the energy required to provide cabin cooling for thermal comfort can reduce the range of EVs from 35% to 50% depending on outside weather conditions [6] but, these...
models does not consider the role of cabin heating on EV energy consumption, [6,8,9] and uses a mean radiant temperature based on daily-integrated incident radiation for a given city. Although this simplification reduces the computational complexity of the model, this method of evaluating thermal behavior disregards the dynamic HVAC requirements that result from changing environmental conditions (i.e. hourly changes in irradiation and ambient temperature). In this previous work, the definition of passenger thermal comfort was based on Fanger’s description of person’s thermal sensation vote [10,11], wherein 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 PPD >0 is representative of a person likely to feel too hot. Under these assumptions, PPD was treated as a statistical representation of the fraction of time the air conditioning (AC) is turned on [8,9], whereas in real-world EVs heating loads (due to the lack of engine waste heat) and transient HVAC loading may be important contributors to overall energy consumption.

Various technologies have been developed with the objective of reducing the direct energy consumption of an EV’s HVAC system [5]. Thermal storage systems (which can reduce the electrical loads associated with HVAC), cabin preconditioning (which reduces HVAC transient loads) [13], and high efficiency HVAC systems all may have some role to play in reducing EV HVAC loads, but their effectiveness in achieving improvements in vehicle-level metrics has not been assessed to date. For this study, we concentrate on evaluating cabin preconditioning technology as it is the most near-term available and is optional equipment on various OEM PEVs [15].

In order to develop a more detailed and dynamic understanding of climate on the range of EVs, this paper presents a study of the regional and temporal differences in the energy requirements of EV cabin thermal conditioning. Both the energy consumed for thermal comfort and tractive energy is translated into the metric of EV range as a function of time of day (TOD) and time of year (TOY). The results and discussion section focuses on the temporal and climatic sensitivity of EV range in various key cities of the US, discusses the statistical distribution of EV range as a function of location, and assesses the effectiveness of cabin preconditioning in reducing the variability of EV range.

2. Methods

In this paper, we seek to understand the effects of thermal comfort conditioning (cabin heating and cabin cooling) on EVs range based on a bottom-up control volume approach including the dynamics of climatic conditions at various US locations as a function of time of day (TOD) and time of year (TOY).

This synthesis requires modeling of the local climate, the thermal response of the vehicle and its HVAC system, and energy consumption model of the vehicle. The relationship among these models is represented in Fig. 1 and described in the following sections.

2.1. Climate and solar irradiation modeling

The input database to the model characterizes the environmental conditions under which the vehicle will be simulated. The cabin space is subjected to changing environmental conditions including ambient temperature ($T_{amb}$), relative humidity (RH), solar irradiation ($Q_{solar}$). These input environmental conditions are derived from the National Solar Resource Database (NSRDB), which contains hourly averaged climatic data for 365 days of the year across 1019 locations within US [9]. The input to the model is based on the NSRDB typical meteorological year (TMY) 3 dataset.

2.2. Vehicle thermal comfort model

The transient inputs from the NSRDB database are fed into the dynamic vehicle thermal comfort model, which is built using the Matlab/Simulink simulation platform as shown in Fig. 1. The vehicle characteristics such as size of the vehicle, window configurations, and material properties are used to evaluate the conduction and

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Simulation parameters.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Vehicle model parameters</strong></td>
<td></td>
</tr>
<tr>
<td>Total cabin volume</td>
<td>3.29 m³</td>
</tr>
<tr>
<td>Total fenestration area</td>
<td>3.02 m²</td>
</tr>
<tr>
<td>Front wind shield area</td>
<td>0.80 m²</td>
</tr>
<tr>
<td>Rear wind shield area</td>
<td>0.68 m²</td>
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<tr>
<td>Side glass windows area</td>
<td>0.76 m²</td>
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<tr>
<td><strong>HVC power consumption model parameters</strong></td>
<td></td>
</tr>
<tr>
<td>AC COP</td>
<td>2.33 —</td>
</tr>
<tr>
<td>Heater COP</td>
<td>1 —</td>
</tr>
<tr>
<td><strong>Thermal comfort model parameters</strong></td>
<td></td>
</tr>
<tr>
<td>RH setpoint</td>
<td>&lt;50 % [22]</td>
</tr>
<tr>
<td>Temperature upper setpoint</td>
<td>27 °C [22]</td>
</tr>
<tr>
<td>Temperature lower setpoint</td>
<td>23 °C [22]</td>
</tr>
</tbody>
</table>

Fig. 1. Simulation architecture for cabin comfort conditioning thermal model.
convection losses. This control volume based approach, dynamically evaluates the power required by the AC and the heater to maintain the passenger’s thermal comfort for every hour in which the driver is driving. The associated parameters used in the models are presented in Table 1.

In the previous literature, thermal comfort predictions were based on experiments conducted in a climate chamber [12,13]. The physical (air temperature, mean radiant temperature, relative humidity and air velocity) and physiological variables (metabolic rates and clothing) were measured experimentally [14]. However, follow-up studies [18–20] have shown large measurement errors in predicting actual thermal comfort, resulting from uncertainties in controlling the effects of all 6 variables accurately.

In this study, the cabin space temperature is assumed to be regulated by the driver or the vehicle itself by operating the cabin heater and AC controls such that the temperature inside the cabin is controlled to be between 23 °C and 27 °C with <50% relative humidity [17,21]. For an example of the function of the dynamic thermal comfort model, two scenarios are simulated on January 1st (0 h–24 h) at 29 Palms, California. Fig. 2 presents the variations in ambient temperature ($T_{amb}$) and the corresponding cabin temperature ($T_{cabin}$) response as a function of TOD for the following three cases. The first case is one wherein no driving occurs and the

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**Fig. 2.** (a) Sample temperature profiles for a test location and date, (29 Palms CA, January 1 of TMY), over a period of 24 h (b) Sample electric power profiles for a test location and date, (29 Palms CA, January 1 of TMY), over a period of 24 h.
vehicle is soaked in the sunlight (labeled: $T_{\text{cabin}}$: Without pre-conditioning). The second case consists of one wherein no trip occurs and the vehicle is pre-conditioned to ensure thermal comfort as the occupant enters (labeled: $T_{\text{cabin}}$: With pre-conditioning). The third case is one wherein the vehicle is driven between 11 h and 13 h. In this case, the occupant enters the vehicle that is heat soaked and turns the AC on to pull the temperature down to the set temperature limits. After the completion of the trip, $T_{\text{cabin}}$ increases to attain thermal equilibrium with the environment ($T_{\text{cabin}}$ during and after trip).

As is visible in Fig. 2, without any pre-conditioning the vehicle cabin absorbs thermal energy and $T_{\text{cabin}}$ reaches a maximum of 45 C during the hottest time of day. For a trip starting at 11:00 h, $T_{\text{amb}}$ is 10 C and the $T_{\text{cabin}}$ is 35 C due to the solar heating. Turning the AC on, the $T_{\text{cabin}}$ is pulled down from soak temperature to the thermal comfort limits. In an EV, the transient and steady state power required to pull the cabin from soak to the comfort conditions must be sourced from stored electricity and therefore affects the EV range. In comparison, pre-conditioning the vehicle maintains the cabin conditions at set comfort limits prior to the starting of the trip, thereby eliminating the transient AC power requirements.

In this paper, this type of HVAC power consumption results are combined with models of the vehicle energy consumption to model the overall effect of HVAC energy consumption on EV range. The thermal and energy consumption characteristics of the EVs are chosen to be representative of a typical popular light-duty passenger vehicle. The energy consumed by the vehicle for traction is computed assuming a constant discharge rate (172 DCWh/km) and standard driving conditions over the 5-cycle EPA test for EVs. The transient and steady state HVAC energy consumption is evaluated using the dynamic thermal comfort model. The vehicle is assumed to start each trip fully-charged.

3. Results and discussion

The inability of EVs to consistently travel a predetermined distance is purported to be one of the main reasons for their slow adoption [22]. As illustrated by the vehicle level results shown in Fig. 2, ambient conditions and the thermal comfort conditions strongly affects the energy consumption of the HVAC system, and will therefore contribute to fluctuations in the available EV range. Based on the results of the cabin conditioning thermal simulation, we seek to understand the effect of climatic and environmental conditions, and preconditioning technology on the range performance of EVs.

3.1. The magnitude of the effect of geographically-realized climatic and environmental conditions on EV range

The energy consumption of the cabin thermal comfort conditioning system is a strong function of local ambient conditions, but the conditions of the ambient vary geographically, diurnally, and seasonally. In order to understand how EV range will change across various locations in the US, the range performance of a 24 kWh electric vehicle with a discharge rate of 172 DCWh/km is simulated across 1019 NSRDB locations in US. The simulation estimates the EV range of the vehicle for trips starting at various time of the day, and for all 365 days of the TMY.

Results are presented in Fig. 3. The Fig. 3(a1, b1, c1, d1, e1) presents the hourly averaged ambient temperature as a function of time of day (TOD) and time of year (TOY) for a few cities in the US: (a) Anchorage (AK), (b) Atlanta (GA), (c) Detroit (MI) (d) Los Angeles (CA) and (e) Phoenix (AZ) respectively. These five cities were chosen to represent contrasting weather patterns prevalent across US. The Fig. 3(a2, b2, c2, d2, e2) and Fig. 3(a3, b3, c3, d3, e3) shows electric range contours computed for trips starting in any of the 24 h and 365 days of the year without and with cabin pre-conditioning, respectively. These graphs demonstrate that simulated range varies from a minimum of 95 km (for midday trips in hot and sunny ambient conditions) to a maximum of 128 km (for early morning trips in moderate ambient conditions) in the 5 cities. The reduction in EV range is most pronounced across all the seasons and cities during middle portion of the day, when ambient temperatures are the highest and solar load is the highest.

Table 2 summarizes these results for the city of Phoenix (AZ). For each season, Table 2 presents the seasonally-averaged range of the EV for trips that depart at a given TOD. The maximum seasonally averaged loss in range is 23.1%. The vehicle range for trips that are cabin-preconditioned can be directly compared to the vehicle range for trips that have no preconditioning. A maximum of 8.75% increase in the EV range can be achieved as a result of pre-conditioning the cabin.

3.2. Assessment of the role of cabin preconditioning in EV range reduction

Cabin preconditioning is a near-term available technology for reducing the mean loss in EV range due to cabin comfort conditioning loads. Under the cabin preconditioning scenario, the vehicle maintains the cabin temperature within the comfort range when the vehicle is connected to the electric grid under charge. As implemented in modern EVs (including Nissan Leaf and others), cabin preconditioning operates by converting grid electricity to DC electricity through the conventional vehicle charger. The vehicle HVAC system is then powered by the conventional DC vehicle bus, and is controlled to condition the cabin prior to the driver entering the vehicle. When the driver unplugs the vehicle and begins his/her trip, the cabin is already at a condition of thermal comfort and the transient HVAC loads on the vehicle battery are eliminated [22]. The vehicle battery must still supply the energy to meet HVAC requirements for the remainder of the trip, but the displacement of the transient HVAC energy from the vehicle’s batteries to grid electricity may have substantial range benefits in terms of reduced range reduction.

To understand and quantify the effect of preconditioning on EV range reduction, we can exercise the simulation to estimate the EV range of our example EV for trips starting at various times of the day, for all 365 days of the TMY, and with and without cabin preconditioning. The electric range obtained without and with cabin pre-conditioning for trips originating at varying TOD and averaged over TMY is represented in Fig. 4(a–e) for Anchorage (AK), Atlanta (GA), Detroit (MI), Los Angeles (CA) and Phoenix (AZ) respectively. These EV ranges are averaged over the 365 days of the year.

The electric range 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. During the early portion of the day, the cabin conditions are close to required thermal comfort, and the effect of preconditioning is relatively minor. For trips starting later in the day, the “thermal soak” increases the transient power required for the non-preconditioned HVAC system to reestablish thermal comfort, thereby increasing the effectiveness of preconditioning. The maximum EV range benefit available from cabin preconditioning is the 9.86% increase in EV range for 12:00 noon trip in summer, in Phoenix (AZ).

3.3. Discussion of inter-day variability in EV range

An impartial assessment of the mean effect of thermal comfort conditioning energy consumption on the range of EVs might
Fig. 3. Inputs to and results of the cabin conditioning model showing the magnitude of the effect of geographically-realized climatic and environmental conditions on EV range (km) for 5 US cities: Anchorage (AK) (a1, a2, a3), Atlanta (GA) (b1, b2, b3), Detroit (MI) (c1, c2, c3), Los Angeles (CA) (d1, d2, d3), Phoenix (AZ) (e1, e2, e3). Left column shows hourly temperature for every hour of the year. Center column shows EV range (km) without cabin preconditioning for every hour of the year. Right column shows EV range (km) with cabin pre-conditioning for every hour of the year.
Table 2
Seasonally averaged electric vehicle range as a function of time of day in Phoenix, AZ, A) without pre-conditioning, and B) with pre-conditioning.

<table>
<thead>
<tr>
<th>Time of day</th>
<th>Time of year</th>
<th>Without pre-conditioning</th>
<th>With pre-conditioning</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Spring</td>
<td>103.8 km</td>
<td>113 km</td>
</tr>
<tr>
<td>8 AM</td>
<td>Summer</td>
<td>100.5 km</td>
<td>110.6 km</td>
</tr>
<tr>
<td></td>
<td>Fall</td>
<td>104.9 km</td>
<td>113.1 km</td>
</tr>
<tr>
<td></td>
<td>Winter</td>
<td>109.8 km</td>
<td>116.8 km</td>
</tr>
<tr>
<td>10 AM</td>
<td></td>
<td>102.4 km</td>
<td>112.2 km</td>
</tr>
<tr>
<td>12 noon</td>
<td></td>
<td>98.4 km</td>
<td>109.6 km</td>
</tr>
<tr>
<td>2 PM</td>
<td></td>
<td>104.0 km</td>
<td>111.1 km</td>
</tr>
<tr>
<td>4 PM</td>
<td></td>
<td>107.7 km</td>
<td>115.5 km</td>
</tr>
<tr>
<td></td>
<td></td>
<td>103.7 km</td>
<td>113.0 km</td>
</tr>
<tr>
<td></td>
<td></td>
<td>113.3 km</td>
<td>118.9 km</td>
</tr>
<tr>
<td></td>
<td></td>
<td>125.4 km</td>
<td>126.4 km</td>
</tr>
<tr>
<td></td>
<td></td>
<td>127.0 km</td>
<td>127.5 km</td>
</tr>
</tbody>
</table>

Fig. 4. Results of the cabin conditioning model showing the role of cabin preconditioning in EV range improvement (averaged across all days of the year) in 5 US cities (a) Anchorage, AK, (b) Atlanta, GA, (c) Detroit, MI, (d) Los Angeles, CA, (e) Phoenix, AZ and (f) Phoenix, AZ (averaged across all trip start times).
suggest that the effect is relatively minor. The lowest simulated range (occurring for vehicles starting trips at 12:00 on the hottest day of the year in Phoenix, AZ, see Fig. 3(e2)) is 95.1 km, and it is less than 3% of vehicle day trip chains that travel between 96 km and 128 km and would have launched on a vehicle trip anticipating full range, only to actually experience EV range limitation as “running out of range”. The fraction of trips that would have been rescued by the -6.4 additional km of EV range available from cabin preconditioning is even smaller [24].

Instead of dismissing the effect of cabin comfort conditioning loads on EV range, we hypothesize the primary source of driver discomfort with EV range is due to the day-to-day variability in EV range. In order to test this hypothesis, we present the results of the simulation of the energy consumption of the vehicle and cabin thermal comfort conditioning system in a histogram form. The

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Fig. 5. Results of the cabin conditioning model showing the inter-day variability in EV range, with and without preconditioning, in Phoenix, AZ, during different times of the day (TOD) (a): TOD = 8 AM, (b): TOD = 10 AM, (c): TOD = 12 noon, (d): TOD = 2 PM, (e): TOD = 4 PM, (f): TOD = 6 PM.
effect of daily local ambient conditions on the frequency of day—day EV range in Phoenix, AZ, without and with cabin preconditioning is represented in Fig. 5(a–e) for trip start times of 8 AM, 10 AM, 12 noon, 2 PM, 4 PM and 6 PM. These results demonstrate that the expected value and variability in the EV range available to a driver is a strong function of time of day. As the morning progresses, the increasing energy required for cabin thermal comfort conditioning causes a reduction in EV range, and an increase in range variance. The variance in EV Range is at a maximum at 4 PM.

Under this hypothesis, cabin preconditioning has an important role to play in improving the consumer acceptability of EVs by reducing the day-to-day variability in EV range. In all cases presented in Fig. 5, cabin preconditioning serves to reduce the range lost to cabin conditioning loads, but more importantly serves to reduce the day-to-day variability in EV range, thereby reducing the uncertainty in the driver’s and Range-to-Go meter’s prediction of EV range.

4. Conclusions

This study demonstrates the degree to which the range of EVs is dependent on the cabin comfort conditioning loads and therefore on prevailing local ambient conditions. EV range is shown to vary widely across the geography of the US, and as a function of the time of day.

Several studies [15,16] have qualitatively listed the benefits of cabin preconditioning as a means of improving the electric range. In this paper, the benefits of cabin preconditioning have been evaluated quantitatively. Cabin preconditioning serves to improve the range of EVs, but the benefits available from cabin preconditioning are a strong function of time of day. Pre-conditioning the cabin for trips after noon have much greater benefits compared to those starting during the early part of the day. Perhaps more importantly, cabin preconditioning also serves to reduce the variation in range that will be experienced by EVs. This may lead to reduced variability of EV range, which is a cited source of consumer concern with adoption of EVs.

Overall this study provides a framework for evaluating the effect of cabin conditioning loads and technologies on the system level metrics of performance of EVs. The results from the study can be integrated with the system level design of electric vehicles such that they meet the range of performance requirements that exist across US. This will allow for increase in market acceptance of electric vehicles and reduce greenhouse gas emissions at the wheels. Future work will seek to understand the effect that various cabin conditioning technologies can have on the range and performance of EVs.

Acknowledgments

This work was supported by the Electric Power Research Institute (EPRI) under grant EP-P40407/C17926.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jpowsour.2014.10.142.

References