Design and Analysis of Battery-Aware Automotive Climate Control for Electric Vehicles

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Electric Vehicles (EV) as a zero-emission mean of transportation encounter challenges in battery design which cause range anxiety for the drivers. It has been realized that Heating, Ventilation, and Air Conditioning (HVAC) system is another major contributor to the power consumption besides the electric motor that may influence the EV battery lifetime and driving range. In the state-of-the-art methodologies for battery management systems, the battery performance is monitored and improved. While in the automotive climate control, the passenger’s thermal comfort is the main objective. Hence, the influence of the HVAC power on the battery behavior for the purpose of jointly-optimized battery management and climate control has not been considered. In this paper, we propose an automotive climate control methodology which is aware of the battery behavior and performance while maintaining the passenger’s thermal comfort. In our methodology, battery parameters and cabin temperature are modeled and estimated, and the HVAC utilization is optimized and adjusted with respect to the electric motor and HVAC power requests. Therefore, the battery stress reduces while the cabin temperature is maintained by predicting and optimizing the system states in the near-future. We have implemented our methodology and compared its performance to the state-of-the-art in terms of battery lifetime improvement and energy consumption reduction. We have also conducted experiments and analyses to explore multiple control window sizes, drive profiles, ambient temperatures, and modeling error rates in the methodology. It is shown that our battery-aware climate control can extend the battery lifetime by up to 13.2% and reduce the energy consumption by up to 14.4%.

CCS Concepts: • Computer systems organization → Embedded and cyber-physical systems; • Hardware → Batteries: Power estimation and optimization; • Mathematics of computing → Continuous optimization; • Computing methodologies → Modeling and simulation;

Additional Key Words and Phrases: Electric vehicle, battery, climate control, HVAC, optimization, model predictive control, quadratic programming

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1 INTRODUCTION AND BACKGROUND

Electric Vehicles (EVs) have been accepted as a sustainable solution and a new paradigm of transportation for (non-)commercial purposes [8, 21, 24, 34, 46]. However, there are major design challenges with EVs which hinder their development and proliferation. Degrading battery capacity
(battery lifetime) and limited driving range are the major challenges of making the EVs economical for everyday usage [4, 24, 25].

The battery is the major component in the EV providing the power. The above-mentioned design challenges are mainly due to the specific battery characteristics and behavior [25, 35, 37]. Although researchers have succeeded to improve the battery energy density, the challenges still remain. Moreover, the design constraints on the size, weight, and cost of the battery packs restrict the stored energy for the EV. The restricted battery capacity limits the EV driving range [24, 34]. Furthermore, the recharging process of the EV battery is significantly slow compared to the refueling process of Internal Combustion Engine (ICE) vehicles. Both factors influence the EV usage for daily/long trips causing range anxiety for the drivers [18, 30, 31, 45, 49]. On the other hand, the available battery capacity degrades over time with every cycle of charging/discharging. The battery lifetime ends when the capacity reaches around 80% of its nominal value in the EVs [28]. This enforces more limitation on the driving range and a huge battery replacement cost for the drivers/manufacturers. For instance, the cost to replace a battery pack is more than 12,000$ for Tesla Model S 85 KWh [39] and 5,500$ for Nissan Leaf S [32]. Nevertheless, the battery pack itself costs significantly more than the above-mentioned cost.

The driving range and battery lifetime are the parameters affected by the power consumption of the EV. The power consumption is due to the power requests from the electric motor and the accessory systems [41, 52]. The influence of the power consumption on the battery becomes significant when considering the rate-capacity effect in the battery [34, 35]. In other words, the available battery capacity decreases when discharging the battery at higher rates.

![Fig. 1. Contribution of three types of power consumers in EV [39] and ICE vehicle [17] for different ambient temperatures [41].](image)

The electric motor is the major component that provides the required force for propelling the EV. The energy goes to overcoming the driving forces on the EV (for details see Section 3.2). Moreover, the electric motor may generate power in the regenerative mode while decelerating the EV [34]. On the other hand, the accessory systems comprise of the Heating, Ventilation, and Air Conditioning (HVAC) system and other computing, communication, and entertainment devices in the vehicle. The HVAC system is the major consumer among the accessories (see Figure 1). The heating coils, cooling coils, and fans in the HVAC system consume power according to their architecture design, control target, and the ambient temperature (for details see Section 3.3) [41]. For instance in ICE vehicles, the heat generated from the combustion engine is utilized to heat the supply air to the cabin. While in EVs, negligible heat is generated by the electric motor and is not sufficient enough to heat the supply air. Hence, electric heating coils are necessary as well for heating which increase the power consumption further (up to 21% of total power consumption), compared to the ICE vehicles (see Figure 1). As shown in the figure, the influence of the HVAC system on the battery in EV can be more significant than on the fuel consumption in ICE vehicles, especially in severe
weathers. This becomes more challenging considering the limited energy available in a battery of an EV. The amount of the power consumption by the HVAC system results in further driving range reduction by up to 13% in the cold weather as shown in Figure 2.

![Fig. 2. Range reduction resulted by HVAC power consumption [1].](image)

Typically, the electric motor power consumption is defined by the driving behavior and route. Although the electric motor power consumption can be optimized by adjusting the driving behavior and route, it is not flexible within the EV itself. However, the HVAC system has flexible and large power consumption; the power consumption can be controlled by adjusting the control parameters such as cooling/heating temperature, and fan speed [41]. These HVAC control parameters are mainly adjusted according to the cabin temperature.

The observations explained above illustrate that managing the limited energy in the battery of an EV is problematic. Moreover, the HVAC system is a major factor impacting the battery operation in terms of the driving range and battery lifetime in certain situations. Hence, it becomes the challenge of how to reduce the influence of the HVAC on the battery operation (battery lifetime and energy consumption) without losing the thermal comfort for the passengers. By looking into the relationships between HVAC, EV power, and battery characteristics, the flexibility of the HVAC system in terms of its power consumption can be beneficial in reducing these impacts by controlling its inputs while being aware of the battery behavior and the EV power consumption [41].

2 RELATED WORK AND OUR CONTRIBUTIONS

The major challenges of driving range and battery lifetime have been addressed by various approaches in different levels. Battery cell materials for electrodes and electrolytes have been researched on in order to provide more power density and energy density while diminishing the battery capacity degradation rate [25, 35]. Battery-level monitoring and controls are implemented by the Battery Management Systems (BMS). The BMS is responsible for monitoring the battery temperature, the State-of-Charge (SoC), etc. in order to manage the power requests to the battery pack and the cells inside [6, 16, 37, 42, 44, 46]. Hence, the battery is prevented from being over discharged, over charged, and over heated during charging and discharging process [24]. Moreover, the utilization of the battery cells may get balanced by evenly distributing the power requests by the BMS in order to improve the driving range and extend the battery lifetime. Furthermore, in higher levels in the system, the power requests to the battery pack are monitored and controlled according to the battery behavior and considering the battery energy efficiency [21, 41]. This has been applied in Hybrid Electrical Energy Storage (HEES) systems where the battery and ultracapacitor utilization is adjusted for better energy efficiency and lifetime [5, 34, 43, 53, 54]. Moreover, the driving route which influences the battery energy consumption can also be optimized for better driving range and battery lifetime [49, 51]. There exist multiple algorithms that are capable of predicting the driving route behavior with various performances for the purposes of navigation and safety [2, 3, 19, 20, 47, 48].
On the other hand, automotive climate controls are responsible for monitoring and controlling the HVAC system. The main objective of the automotive climate control has been to maintain the passenger thermal comfort\(^1\) \([1, 22, 41]\). There are various automotive climate control and HVAC system designs in the literature with different performances in terms of energy consumption and thermal comfort maintenance for the passengers. They may implement different control algorithms, e.g., on-off controller, feedback control, Proportional-Integrator-Derivative (PID), Linear-Quadratic Regulator (LQR), and Model Predictive Control (MPC) \([11, 21, 34]\). Some of the automotive climate controls attempt to provide uniform thermal environment for the passengers by maintaining the whole cabin temperature (single-zone). While, other methodologies maintain the temperature in multiple zones of the cabin separately providing higher thermal comfort for the passengers (multi-zone). In these methodologies, multiple variables, e.g., the cabin temperature, ambient temperature, and solar radiation, may be monitored and the HVAC system is controlled accordingly to cool/heat the cabin \([1]\). They only consider the behavior of the HVAC system (e.g., cabin and environment thermodynamics) during their operation. However, they may also be capable of rejecting the disturbance caused by the environment (e.g., solar radiation). Moreover, in these classical methodologies, the control parameters are set based on the design-time thermal loads and are not adaptive to the environmental factors.

However, the BMSs do not consider the influence of the automotive climate control which controls the HVAC system - a flexible and large power consumer - on the battery behavior. Moreover, the automotive climate control does not account the battery operation behavior, e.g. driving range and battery lifetime, into the HVAC system control.

### 2.1 Problem and Research Challenges

In summary, the problem of designing an automotive climate control in an EV to improve the battery lifetime and driving range poses the following challenges:

- Accounting the influence of the detailed HVAC load besides the electric motor on the battery operation behavior, e.g. driving range and battery lifetime.
- Considering and integrating the battery behavior in the automotive climate control while managing the HVAC.
- Applicability and scalability of the battery-aware automotive climate control ensuring the passenger thermal comfort for any driving route and weather.

### 2.2 Our Novel Contributions and Concept Review

To address the above-mentioned challenges, we propose a novel methodology of battery-aware automotive climate control which employs:

- **EV Modeling and Estimation (Section 3)**: the dynamic behavior of the EV components is described, modeled, and estimated:
  - **Drive Profile (Section 3.1)**: the behavior of the EV driving route is described. The drive profile models the driving speed, acceleration, and route slope.
  - **Power Train (Section 3.2)**: the power consumption/generation of the electric motor which provides the propelling force for the EV or regenerate power is modeled and estimated by considering the driving forces.

\(^1\)The modeling of the passenger thermal comfort is important to the automotive climate control design, however, the details of the modeling is out of the scope of this paper. Moreover, the thermal comfort modeling approach is orthogonal to our methodology. Hence, temperature deviation from the target temperature is considered as a metric for thermal comfort (see Section 4.2).
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- HVAC System (Section 3.3): the thermodynamics and power consumption of the HVAC system and the automotive climate control are modeled and estimated.
- Battery (Section 3.4): the battery behavior such as rate-capacity effect and battery lifetime regarding the power request by the EV is modeled and estimated.

- Battery-Aware Automotive Climate Control (Section 4): our novel methodology estimates the battery behavior and takes it into consideration for controlling the HVAC system in order to improve the driving range and extend the battery lifetime while ensuring the passenger thermal comfort:
  - Predicting and optimizing the system state variables in the near-future control window (receding horizon) using a Model Predictive Control (MPC) algorithm.
  - Ensuring the passenger thermal comfort by predicting and maintaining the cabin temperature in a convenient range around a target temperature.

- Experiment, Exploration, and Analysis of Methodology (Section 5): the performance of the methodology in terms of execution time, memory usage, improvement on the battery lifetime, and energy consumption has been measured and analyzed for various conditions and has been compared to the state-of-the-art methodology:
  - Availability of the predicted data in the near-future in terms of the control window size, e.g. number of estimated states and time duration of the each predicted state.
  - Environment factors such as the driving route and ambient temperature.
  - Modeling and estimation error of the HVAC system as the physical plant.

As shown in Figure 3, our novel methodology of automotive climate control for EVs considers the battery behavior such as driving range and battery lifetime while monitoring and controlling the HVAC system. The drive profile is utilized to describe and model the driving route (Section 3.1). The power consumption of the EV power train is then modeled and predicted for the input drive profile (Section 3.2). Moreover, the HVAC system state variables such as cabin temperature and the power consumption are modeled and estimated (Section 3.3). Finally, the total EV power request is evaluated and used for battery energy consumption and battery lifetime estimation. These EV state variables are estimated and optimized for better driving range and battery lifetime. Eventually, the optimal control inputs are applied to the HVAC system.
3 ELECTRIC VEHICLE MODELING AND ESTIMATION

In our novel methodology of battery-aware automotive climate control, modeling of the EV components are required to estimate the dynamics of the power train, HVAC system, and battery operation. (Non-)linear and Ordinary Differential Equations (ODE) are utilized in order to describe the dynamic behavior of these components.

3.1 Drive Profile

The driving route is a factor influencing the power consumption of the electric motor in the power train\(^2\). The estimation of the driving route is required for predicting the power consumption and our automotive climate control near-future optimization.

A driving route is modeled and termed as a drive profile in this paper. A drive profile encapsulates the behavior of the driving route at each time instance. The drive profile contains the information about 1) velocity, 2) acceleration, 3) road slope, and 4) time step, for each route segment (see Figure 4). The route segments may have uniform or non-uniform time steps according to the abstracting and modeling level.

Nowadays, navigation systems are the common method of finding the route to the destination. The driving route may be estimated by utilizing the map databases of the navigation systems [10, 49]. The map databases may represent an abstracted version (model) of the geographical map of the surrounding area using graphs (see Figure 4). Hence, the selected route by the navigation system can be modeled and abstracted as a drive profile for our battery-aware automotive climate control using this graph. There also exist other algorithms that are capable of predicting the driving route behavior with various performances for the purposes of navigation and safety that can be utilized [19, 20, 45, 47–49].

Moreover, multiple standard drive cycles are created by United States Environmental Protection Agency (EPA) or United Nations Economic Commission for Europe (ECE) for experimenting and testing the performance of the vehicles in terms of fuel/energy consumption, air pollution, etc. Therefore, these standard drive cycles can also be used as the drive profiles for modeling the typical driving routes [9, 38, 49].

![Fig. 4. Modeling and abstracting the driving route as a drive profile.](image)

3.2 Power Train

The power train which contains the electric motor is the major power consumer in EVs. It is responsible for generating the required power and driving force using the electric motor and transferring it to the wheels.

\(^2\)The power consumption of the electric motor is dependent on the driving behavior. However, estimating the driver behavior on route is out of the scope of this paper. Hence, the driving route is only considered for estimating the power consumption which might be sufficient for adjusting the HVAC utilization.
The tractive force \( F_{tr} \) provided by the power train overcomes the road load force \( F_{rd} \) imposed on the vehicle. It propels the vehicle forward at a desired speed and acceleration \([36]\). \( F_{rd} \) consists of the aerodynamic drag, the gravitational force, and the rolling resistance (see Figure 5).

\[
F_{rd} = F_{gr} + F_{aero} + F_{roll}
\]  

(1)

The aerodynamic drag \( F_{aero} \) is the viscous resistance of the air working against the vehicle motion which is quadratically proportional to the vehicle speed \( v \).

\[
F_{aero} = \frac{1}{2} \rho_{air} C_x A (v + v_{wind})^2
\]

(2)

where \( \rho_{air} \) is the air density, \( C_x \) is the aerodynamic drag coefficient, \( A \) is the effective frontal area of the vehicle, and \( v_{wind} \) is the head-wind velocity.

\[
F_{gr} = m g \sin \left( \arctan \left( \frac{\alpha}{100} \right) \right)
\]

(3)

where \( m \) is the total mass of the vehicle, \( g \) is the gravitational acceleration constant, and \( \alpha \) is the percentage of the road slope; 100\% represents the slope of 45°.

The rolling resistance \( F_{roll} \) is produced by the flattening of the tire at the contact surface of the road.

\[
F_{roll} = m g \left( c_0 + c_1 v^2 \right)
\]

(4)

where \( c_0 \) and \( c_1 \) are the rolling resistance coefficients.

\( F_{tr} \) is generated by the electric motor to overcome \( F_{rd} \) so that the vehicle maintains the desired acceleration \( a \) and speed.

\[
F_{tr} = F_{rd} + ma
\]

(5)

When \( F_{rd} \) is positive and the speed needs to be maintained, the vehicle should provide enough forward force to prevent deceleration. In this case, the force is generated only by the electric motor \( (F_{tr}) \). On the other hand, when \( F_{rd} \) is negative and the speed needs to be maintained, the vehicle needs to provide backward force to prevent acceleration. In this case, the force may be generated by the electric motor and the braking system. The later force generated by the electric motor is due to the regenerative mode \( (F_{tr} < 0) \), is limited to \( F_{min} \), and may not provide enough backward force.
to neutralize the resistive force (Equation 6). Therefore, the rest of the backward force is generated by the braking pads (Equation 7).

\[
F_{tr} = \max(F_{min}, F_{tot}) \quad (N) \tag{6}
\]

\[
F_{brake} = F_{tr} - F_{tot} \quad (N) \tag{7}
\]

The electric motor power \( (P_e) \) is calculated based on the tractive force and speed.

\[
P_e = \frac{F_{tr} \cdot v}{\eta_m} \quad (8)
\]

where \( \eta_m \) represents the electric motor efficiency when converting electrical to mechanical energy in the motor mode and converting mechanical to electrical energy in the regenerative mode (regenerative brake). \( \eta_m \) is dependent on the motor rotational speed and the generated torque [21, 26, 55, 55].

In this paper, the specifications for the EV Nissan Leaf S have been used to validate the power train model and to demonstrate the EV power consumption behavior while driving [41]. The parameters regarding the specifications are extracted from the manufacturers’ forums and experimental data provided by the third-parties testing the vehicles [12, 32].

3.3 HVAC

The HVAC in modern vehicles mainly uses the Variable Air Volume (VAV) system [14]. The advantage of this system is the precise control of the temperature and humidity in multi-zone or single-zone with lower energy consumption [14]. The HVAC structure [29, 40] in an EV is depicted in Figure 6. The system contains a variable-speed fan to provide the supply air to the zone(s). A valve damper is used to control the mix of the outside air and the recirculated air back into the system. The cooler and the heater will control the air temperature by exchanging heat. In this paper, we assume a single-zone HVAC and model the corresponding behavior and dynamics in different parts of the system using low-order ODEs. Despite the simplicity (compared to higher-order thermodynamic equations), the model provides sufficient information for analyzing the transient behavior of the system. The humidity can be an important factor affecting the HVAC power consumption, but it is not typically directly measured or controlled [15]. Therefore, in this paper, the temperature
represents an equivalent dry air temperature at which the dry air has the same specific enthalpy as the actual moist air mixture.

As shown in Figure 7, the state-of-the-art automotive climate control methodologies monitor the cabin (zone) temperature and adjust the controlling inputs of the system such as heating coils, cooling coils, fan, and damper valves. Moreover, the temperature inside the cabin \((T_z)\) is influenced by the supply air \((T_s)\) to the cabin, the heat exchange with outside, and the solar radiation. The energy balance in the cabin model is described as:

\[
M_c \frac{dT_z}{dt} = \dot{Q} + \dot{m}_z c_p (T_s - T_z)
\]  

(9)

where \(M_c\) is the thermal capacitance of the air, wall, and the seats inside the cabin and \(c_p\) is the heat capacity of the air. The cabin temperature changing rate \(\left(\frac{dT_z}{dt}\right)\) is also controlled by the air flow rate into the cabin \((\dot{m}_z)\).

The exchanged heat with outside and the solar radiation are modeled as thermal loads \(\dot{Q}\):

\[
\dot{Q} = \dot{Q}_{solar} + c_x A_x (T_o - T_z)
\]  

(10)

where the solar radiation \(\dot{Q}_{solar}\) and outside temperature \((T_o)\) are time-varying factors. The values of \(T_o\) and \(\dot{Q}_{solar}\) are assumed to be constant during driving (ambient temperature and thermal load offset). The heat exchange through the walls with outside is proportional to the difference between \(T_z\) and \(T_o\), the heat exchange coefficient \(c_x\), and the area separating the cabin and outside \((A_x)\).

The air returned from the cabin is mixed with the outside air and recirculated back to the system. The fraction of the returned air from the cabin is \(d_r\), which is controlled by a damper. Then, the energy balance in the air mixer gives the temperature of the system inlet air \((T_m)\) as following:

\[
T_m = (1 - d_r)T_o + d_rT_r
\]  

(11)

where \(T_r\) is the returned air temperature which is as same as the cabin temperature \((T_z)\) in a single-zone HVAC.

We consider the cooling and heating coil power consumption in terms of the energy difference between their inlet and outlet air flow. Moreover, the heat exchange between the coolant/evaporator and air is modeled as efficiency parameters:

\[
P_h = \frac{c_p}{\eta_h} \dot{m}_z (T_s - T_c)
\]  

(12)

\[
P_c = \frac{c_p}{\eta_c} \dot{m}_z (T_m - T_c)
\]  

(13)

where \(P_c\) and \(P_h\) are cooling coil and heating coil power consumption, respectively. \(\eta_h\) and \(\eta_c\) are the efficiency parameters describing the operating characteristics of the heating and cooling processes. \(T_c\) is the temperature of the cooling coil outlet air.

The fan power consumption \((P_f)\) is quadratically related to \(\dot{m}_z\).

\[
P_f = k_f (\dot{m}_z)^2
\]  

(14)

where \(k_f\) is a parameter that captures the fan efficiency and the duct pressure losses.

The parameters for the HVAC model have been extracted from the HVAC specifications provided in the literature [29, 40, 41] and to accurately match the thermodynamic behavior of an HVAC system similar to the Nissan Leaf in different conditions [13, 17].
3.4 Battery

Lithium-ion batteries are widely used as the primary electrical energy storage [23, 25, 37] in the EVs. Despite their high energy density, they have specific characteristics. They demonstrate less usable capacity in higher discharge rates (rate-capacity effect). This characteristic is described using the Peukert’s Law [6, 7, 34, 50]. Therefore, the battery SoC which shows the available charge in the battery can be estimated by having the battery current [33].

\[
\text{SoC}^t = \text{SoC}^0 - 100 \times \int_0^t \frac{I_{\text{eff}}}{C_n} dt
\]

\[
I_{\text{eff}} = I \left( \frac{I}{I_n} \right)^{p_c - 1}
\]

where \(C_n\) is the nominal capacity of the battery measured at the nominal current \(I_n\) predefined by the battery manufacturer. \(I_{\text{eff}}\) represents the effective current draining the chemical energy. \(p_c\) is the Peukert’s constant typically measured empirically for the type of the battery cell [7, 50]. \(\text{SoC}^t\) represents the SoC at time \(t\).

Fig. 8. Battery SoC behavior in terms of SoC average (horizontal line) and deviation (vertical arrows).

Moreover, the battery lifetime in other words, State-of-Health (SoH) - the ratio of the current capacity to the nominal capacity - degrades over time in Lithium-ion battery cells (capacity fade effect). The SoH degradation (\(\nabla\text{SoH}\)) is mainly influenced by the stress on the battery cell which may be modeled as SoC deviation (\(\text{SoC}_{\text{dev}}\)) and the SoC average (\(\text{SoC}_{\text{avg}}\)) [28]. \(\nabla\text{SoH}\) is measured based on the SoC pattern over a time period:

\[
\nabla\text{SoH} = f \left( \text{SoC}_{\text{dev}}, \text{SoC}_{\text{avg}} \right) = (a_1 e^{\alpha \text{SoC}_{\text{dev}}} + a_2)(a_3 e^{\beta \text{SoC}_{\text{avg}}})
\]

where \(\alpha, \beta, a_1, a_2, \) and \(a_3\) are the parameters empirically evaluated at design time for estimating \(\nabla\text{SoH}\) accurately based on the battery type. Consideration of the battery temperature for estimating \(\nabla\text{SoH}\) is out of the scope of the paper and is modeled as a constant in Equation 17. \(\text{SoC}_{\text{dev}}\) and \(\text{SoC}_{\text{avg}}\) are calculated based on a discharging/charging cycle (see Figure 8).

\[
\text{SoC}_{\text{avg}} = \frac{1}{T} \int_0^T \text{SoC}(t)dt
\]

\[
\text{SoC}_{\text{dev}}^2 = \frac{1}{T} \int_0^T (\text{SoC}(t) - \text{SoC}_{\text{avg}})^2 dt
\]
where $T$ is the period of the discharging/charging cycle. However, in this paper, the charging part of the cycle is assumed to have a fixed pattern and duration. Hence, the effect of the charging part on $\text{SoC}_\text{dev}$ and $\text{SoC}_\text{avg}$ are modeled as constants. The battery cell capacity decreases with the rate of $\nabla \text{SoH}$. When the battery capacity reaches 80% of its nominal capacity, it will be useless. Therefore the number of discharging/charging cycles, the battery can be used (the battery lifetime), is dependent on battery lifetime degradation ($\nabla \text{SoH}$). Although, the battery lifetime degradation is effected by both $\text{SoC}_\text{dev}$ and $\text{SoC}_\text{avg}$, the influence and flexibility of $\text{SoC}_\text{dev}$ is more significant on the battery lifetime [28]. Hence, in this paper, we further focus on the battery SoC deviation for reducing the battery stress.

The parameters for modeling the battery cell is empirically evaluated using the data for a family of lithium-ion cells which are commonly used in EVs like Nissan Leaf. Moreover, the structure of the battery package is defined according to the Nissan Leaf specifications [12, 32, 50].

4 Battery-Aware Automotive Climate Control

4.1 Methodology Description

The HVAC system in the automotive has multiple actuators and sensors for monitoring and controlling the operating parameters such as air speed, temperature set points, and valve damper ratio. The automotive climate control is responsible for sensing these values and making decision on the control inputs. Figure 9 illustrates the control inputs and variables in the system from the controller’s perspective.

In our battery-aware automotive climate control methodology, the goal is to improve the driving range and extend the battery lifetime while maintaining the thermal comfort for the passengers. In abstract, the methodology predicts the EV electric motor power consumption regarding the route behavior and attempts to adjust the HVAC system power consumption by deciding on the operating parameters such that the stress on the battery is reduced. The route behavior is predicted and modeled using a drive profile (Section 3.1). The power consumption of the electric motor is modeled and estimated by knowing the driving forces on the EV (Section 3.2). The HVAC system thermodynamics and power consumption regarding the operating parameters and control inputs are modeled and estimated (Section 3.3). Therefore, our automotive climate control enables us to adjust the HVAC system variables while knowing the EV electric motor power consumption in order to reduce the SoH degradation and energy consumption of the battery predicted according to its power request (Section 3.4).

The operation state of the HVAC can be defined by multiple state variables $x = \{T_z, \text{SoC}\}$, control inputs $i = \{T_s, T_c, d_r, m_z\}$, and auxiliary variables $u = \{T_m, P_h, P_c, P_f, P_e\}$ for each time step.

MPC is an advanced method of control that relies on dynamic models of the process or physical plant (HVAC). The main advantage of MPC is the fact that it allows the current time step to be optimized, while keeping future time steps in account (EV states). This is achieved by optimizing a finite time horizon (control window), but only implementing the current time step. MPC has the ability to anticipate future events and can take control actions accordingly. PID and LQR controllers do not have this predictive ability [15].

Our battery-aware climate control is implemented based on a MPC algorithm (Figure 10). For each time step of the control \(t\), the current system state is monitored. Then, the state variables, control inputs, and auxiliary variables are predicted in the near-future control window. \(x^k|t\), \(i^k|t\), and \(u^k|t\) are the values of the state variables, control inputs, and auxiliary variables at time \(t + k \cdot \Delta T\), respectively predicted at time step \(t\). The estimation of the variables in the control window enables the controller to optimize the variables of the system such that it minimizes a cost function. Moreover, in the MPC, the variables can be explicitly constrained which is important and beneficial to defining the temperature range limits for thermal comfort and component control restrictions. After optimizing the variables of the control window at each time step, the optimal values of the control inputs for the first predicted step will be applied to the system. The controller will continue to the next time step for predicting, optimizing the variables, and applying them to the system again (receding horizon).

### 4.2 Optimization Formulation

The equations modeling the system (e.g. EV power train, HVAC, and battery) are the main equations defining the constraints of the optimization problem in the MPC algorithm for the battery-aware automotive climate control. Since the control has to take place in a discrete-time domain, the continuous-time equations need to be discretized into different discrete-time states. These constraints need to be applied for each time step of the control window in order to model the dynamics of the system. The equations modeling the HVAC system and the battery are discretized and used as the equality constraints in the following.

The thermodynamic behavior of the cabin regarding supply air and environment is described as the following constraint (Equation 20). \(T_z^*\) represents the cabin temperature at the next time step \(t + \Delta T\). Here, \(\Delta T\) is the time step duration of the controller (sample period). The average of the temperature in the current step and the next step has been used as the method of discretization.

\[
C_{EQ1} : \quad M_e \frac{T_z^* - T_z}{\Delta t} = \dot{Q}_{solar} + c_x A_x (T_o - \frac{T_z^* + T_z}{2}) + \dot{m}_e c_p (T_s - \frac{T_z^* + T_z}{2})
\]  

(20)
Other equations describing the behavior of the air temperature and HVAC system power consumption comprise the following equality constraints (Equation 21).

\[ C_{EQ}^2 : \quad T_r = T_z \]
\[ C_{EQ}^3 : \quad T_m = (1 - d_r) \times T_o - d_r \times T_r \]
\[ C_{EQ}^4 : \quad P_h = \frac{c_p \times m_z}{n_h} \times (T_s - T_c) \]
\[ C_{EQ}^5 : \quad P_c = \frac{c_p \times m_z}{n_c} \times (T_m - T_c) \]
\[ C_{EQ}^6 : \quad P_f = k_f \times m_z^2 \] (21)

The battery SoC behavior has been modeled using the Puekert’s Law as a non-linear exponential equation (Section 3.4). However, for implementation of the optimization constraint, the equation can be approximated. Hence, the battery SoC estimation for the next time step \( \text{SoC}^{+} \) has been abstracted into a quadratic equation (Equation 22). \( I = \frac{P_e + P_h + P_f + P_c}{V_{dc}} \) is the current drawn from the battery with the voltage of \( V_{dc} \). Parameters \( \alpha_x \) are evaluated by fitting Equations 15 and 16 into the quadratic form.

\[ C_{EQ}^7 : \quad \text{SoC}^{+} = \text{SoC} - (\alpha_2 I^2 + \alpha_1 I + \alpha_0) \] (22)

The electric motor power consumption is predicted for each time step of the control window and is applied to the \( P_e^{k|t} \) variables by an equality constraint at each time step \( k|t \). The values of the state variables at the beginning of the control window \( (T_z^{0|t}, \text{SoC}^{0|t}) \) should be assigned to the currently measured values of the system using equality constraints. Moreover, the values of the predicted state variables at end of each time step \( (T_z^{+k|t}, \text{SoC}^{+k|t}) \) should be assigned to the current values of the state variables at the next time step of the control window \( (T_z^{(k+1)|t}, \text{SoC}^{(k+1)|t}) \).

The control requirements and restrictions state the following time-varying constraints on control inputs and state variables. They comprise of the limits for heating/cooling coil power consumption and fan speed; tolerance of 10% for cabin temperature\(^3\); and restrictions on the values of the variables for correct operation of the system and right solution of the optimization.

\[ C_{NEQ}^1 : \quad \underline{m_z} \leq m_z \leq \overline{m_z} \] maximum and minimum air flow to the cabin
\[ C_{NEQ}^2 : \quad T_z \leq T_c \leq T_z \] comfort zone restrictions on cabin temperature
\[ C_{NEQ}^3 : \quad T_c \leq T_s \] heater always increases the temperature
\[ C_{NEQ}^4 : \quad T_c \leq T_m \] cooler always decreases the temperature
\[ C_{NEQ}^5 : \quad T_c \leq T_c \] minimum outlet air temperature by cooler
\[ C_{NEQ}^6 : \quad T_s \leq T_h \] maximum outlet air temperature by heater
\[ C_{NEQ}^7 : \quad 0 \leq d_r \leq \overline{d_r} \] limitation on recirculated air fraction
\[ C_{NEQ}^8 : \quad P_h \leq \overline{P_h} \] heater maximum power output
\[ C_{NEQ}^9 : \quad P_c \leq \overline{P_c} \] cooler maximum power output

\(^3\)The temperature tolerance is the maximum temperature deviation from the target temperature. Although this tolerance has been selected arbitrarily, our methodology is orthogonal to this value or any other value.
The cost function for the optimization problem is defined in the following (Equation 24). \((T^k_{z|t} - T_{\text{target}})^2\) is the thermal comfort cost added for minimizing the deviation of the temperature from the target temperature with weight variable \(w_1\). It ensures that thermal comfort of the passengers is not sacrificed in the optimization. \((\text{SoC}^+_{k|t} - \text{SoC}^k_{z|t})^2\) is the battery SoC cost added for minimizing the SoC deviation with weight variable \(w_2\). Since, the battery lifetime and energy consumption is affected by the battery SoC change, this cost will result in extending the battery lifetime and decreasing the energy consumption for further driving range. The sum of the costs has been normalized by dividing them by \(N\) and \(\Delta t^2\).

\[
C^t = \frac{1}{N} \sum_{k=1}^{N} w_1 (T^k_{z|t} - T_{\text{target}})^2 + w_2 (\text{SoC}^+_{k|t} - \text{SoC}^k_{z|t})^2 / \Delta t^2
\]  

(24)

Although maintaining the cabin temperature is addressed by minimizing the cost function (thermal comfort cost) and defining a constraint on the comfort zone, there might be multiple optimizer solutions with different temperature behavior in the control window which might not be acceptable; since the first step of the control window is applied to the system, the temperature behavior may not be the acceptable optimal solution. Hence, another equality constraint (Equation 25) is added to limit the solution space by enforcing the temperature of the first step and last step of the control window to be equal. It needs to be noted that this equality constraint is just one constraint for the whole control window, unlike the previous constraints which were defined for each time step in the control window.

\[
C_{EQ}^8: T^1_{z|t} = T^{N|t}_{z}
\]  

(25)

The non-linear equations of the system model which define the constraints and the cost function of the optimization problem are convex and quadratic equations. Therefore, the best option might be to apply Sequential Quadratic Programming (SQP) which is an iterative method for non-linear optimization. The optimization problem is solved for the MPC algorithm in each time step. The non-convex non-linear equations have been approximated by adding a convex quadratic term to the cost function using Lagrangian multiplier method [15].

5 EXPERIMENTAL RESULTS

5.1 Experimental Setup

We need to implement the system modeling for our battery-aware automotive climate control. All the equations in Section 3 have been formulated in MATLAB/Simulink [27] for modeling the EV system including the power train, HVAC, and battery as the plant of the controller. The optimization cost function, non-equality constraints, and equality constraints formulated in Section 4.2 are implemented in MATLAB. `fmincon` toolbox has been used with the sequential quadratic programming (sqp) solver. Multiple drive cycles (see Table 1) are modeled as the drive profiles for our experiment benchmarks using AMESim [38].

5.2 Comparison to State-of-the-Art

The performance of our methodology is compared with a baseline in which the power consumption of the HVAC system is adjusted such that the cabin temperature is maintained constant. Fuzzy-based control is implemented which has been the state-of-the-art methodology with the objective of maintaining smooth cabin temperature [14]. In the fuzzy-based control, cooling/heating set points are adjusted based on the cabin temperature which makes the temperature and the HVAC power almost constant. The resulted energy consumption is the lowest compared to the other methodologies such as the on/off methodology [29, 40].
a) **Temporal Analysis:** our battery-aware automotive climate control adjusts the HVAC power consumption regarding the electric motor power requests such that the battery stress is reduced for better driving range and battery lifetime. However, the cabin temperature is also affected due to the change in the HVAC power consumption.

![Fig. 11. HVAC power adjustment by the battery-aware climate control.](image)

We experimented the battery-aware and fuzzy-based methodologies in the 35°C weather with the target temperature of 25°C while driving the ECE_EUDC drive cycle. In Figure 11, the HVAC power consumption with regards to the electric motor power consumption is shown. When our battery-aware automotive climate control predicts or detects a high electric motor power request in the near-future (control window), it adjusts the HVAC power such that the energy consumption and battery stress reduce.

![Fig. 12. Cabin temperature analysis of resulting from the battery-aware climate control.](image)

In Figure 12, the behavior of the cabin temperature is illustrated while using our battery-aware climate control. Our methodology ensures that the cabin temperature is maintained around the target temperature. Hence, the methodology (pre-)cools the cabin when the electric motor is estimated or detected to be using more power in the control window. In the state-of-the-art fuzzy-based methodology, the HVAC power is adjusted such that the cabin temperature is maintained around the target temperature. However, in our methodology, the cabin temperature fluctuates around the target temperature while adjusting the HVAC power. As a result, the battery stress (battery SoC deviation) reduces for better energy efficiency and battery lifetime. The temperature deviation from the target temperature and increase in the thermal comfort cost are the trade-offs for improving the battery lifetime and driving range.

b) **Scalability and Performance Analysis:** the control window size for the MPC is variable depending on the number of estimated states and time step duration. As the number of states increases, more state variables of the system are being considered for the optimization. Hence, as
shown in Figures 13 and 14, more memory and longer execution time are required by the optimizer to converge and find the solution. The execution time and memory usage will be roughly the constant for the same number of states. However, the slight difference is mainly due to the low accuracy and non-deterministic nature of the memory usage and execution time of the MPC optimization when solving a problem and converging to an optimal solution. Although designing a real-time embedded system controller is out of the scope of this paper, we need to analyze and design control window size such that not to violate the timing and memory constraints. For instance, the maximum execution time of the controller at each time step can be limited to the sampling time or time step duration of the controller. The computing platform used for the experiments is comprised of an Intel Core-i7 3770 CPU with 3.4 GHz clock frequency and an 8 GB of DDR3 RAM.

Fig. 13. Execution time at each time step.  
Fig. 14. Memory usage at each time step.

On the other hand, by increasing the control window size, the optimization gets more flexibility and reaches to a better solution in terms of the cost (smaller cost value). Figures 15(a) and 15(b) show the optimization cost of the final solution for thermal comfort and battery SoC objectives normalized by the maximum value.

The thermal comfort cost is based on the sum of the cabin temperature deviations from the target temperature (see Section 4.2). Therefore, as shown in Figure 15(a), increasing the control window size decreases the thermal comfort cost which results in better maintenance of the cabin.
Battery-Aware Automotive Climate Control for EV

temperature and improving the thermal comfort. It needs to be noted that the thermal comfort cost evaluated for the fuzzy-based methodology is nearly zero which is better than our methodology. This is the trade-off of our methodology for reaching better driving range and battery lifetime. However, the cabin temperature limits specified for the thermal comfort are always met.

The battery SoC cost is based on the sum of the battery SoC differences over time (see Section 4.2). This optimization cost does not have an absolute target like thermal comfort cost. Hence, reducing the battery SoC cost does not necessarily reflect on better battery SoH degradation and energy consumption. As shown in Figures 16(a) and 16(b), the battery lifetime and energy consumption improve compared to the fuzzy-based methodology. However, by increasing the control window size, the battery SoC cost reduction does not reflect in better battery lifetime and energy consumption. The battery SoH degradation reduction reaches up to 13.2% and energy consumption reduction reaches up to 14.4% with 5 states estimated in the control window with time step of 10s. Increasing the number of states, reduces the improvement of the methodology. This is due to the fact that the final battery SoC deviation of the solution is different from the optimization cost. Therefore, increasing the number of states in the control window reduces the MPC algorithm influence on the final battery SoC deviation although the optimization cost function for the battery SoC decreases.

c) Environment Analysis: environment factors such as driving route behavior and ambient temperature influence the performance of our methodology. This is due to the fact that our methodology requires the knowledge of the route behavior for electric motor power estimation and the HVAC system optimization. Moreover, the ambient temperature affects the HVAC system power consumption.

Figure 17 illustrates the average HVAC power consumption for the fuzzy-based methodology and our battery-aware climate control. As you can see the HVAC average power consumption increases as the ambient temperature deviates further from the target temperature (25°C). The reduction of the average HVAC power consumption while using our battery-aware methodology is shown on the right axis of the figure in percentage. When the ambient temperature deviates from the target temperature, the optimizer has less flexibility of adjusting the HVAC variables for maintaining the cabin temperature in these harsh weathers which results in smaller power reduction.
Figure 18(a) shows that the maintenance of the cabin temperature is harder as the ambient temperature deviates from the target temperature, which will result in higher thermal comfort cost. The total energy consumption of the EV has been evaluated for different ambient temperatures and has been compared with the fuzzy-based methodology. As Figure 18(b) shows, the reduction in the total energy consumption is more noticeable in higher temperatures as the HVAC energy consumption is higher. It needs to be noted that heating the cabin in cold weather is easier than cooling the cabin in hot weather, since the solar radiation heats the cabin as well. Moreover, the SoH degradation has been compared for both methodologies and its reduction has been illustrated in Figure 18(c). The SoH degradation reduction is due to the fact that the SoC deviation has been reduced using the battery-aware climate control.

Automotive manufacturers utilize standard driving cycles and drive profiles to test their vehicles for performance and energy consumption. Table 1 lists these drive profiles with the metric showing the variance in the profile. The route coefficient variance is the normalized standard variance (standard variance over average) of the route behavior for the drive profile. The route coefficient variance affects the variation of the electric motor power requests along the route. The performance of the battery-aware methodology has been evaluated for the selected drive profiles. The table also illustrates the energy consumption and SoH degradation reduction achieved by the battery-aware methodology compared to the fuzzy-based methodology with the corresponding thermal comfort cost.

The route coefficient variance influences the electric motor power requests and thereby the control performance. Hence, we have analyzed the performance of the battery-aware control with respect to the variance (see Figure 19). It is shown that our battery-aware methodology reduces the
Table 1. Performance of the battery-aware climate control for different drive profiles [9].

<table>
<thead>
<tr>
<th>Drive Profile</th>
<th>Route Coefficient Variance (-)</th>
<th>Energy Consumption Reduction (%)</th>
<th>SoH Degradation Reduction (%)</th>
<th>Thermal Comfort (-)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CI015</td>
<td>2.43</td>
<td>16.02</td>
<td>14.68</td>
<td>1.94</td>
</tr>
<tr>
<td>ECE_EUDC</td>
<td>1.98</td>
<td>11.68</td>
<td>11.59</td>
<td>3.38</td>
</tr>
<tr>
<td>ECE_EUDC_AT</td>
<td>2.02</td>
<td>11.60</td>
<td>11.53</td>
<td>3.28</td>
</tr>
<tr>
<td>ECE_EUDC_MT</td>
<td>1.98</td>
<td>11.68</td>
<td>11.59</td>
<td>3.38</td>
</tr>
<tr>
<td>FTP</td>
<td>1.90</td>
<td>12.98</td>
<td>13.85</td>
<td>5.27</td>
</tr>
<tr>
<td>HWFET</td>
<td>0.67</td>
<td>8.15</td>
<td>7.56</td>
<td>5.76</td>
</tr>
<tr>
<td>JC08_cold</td>
<td>2.07</td>
<td>14.56</td>
<td>14.40</td>
<td>2.57</td>
</tr>
<tr>
<td>JC08_hot</td>
<td>2.07</td>
<td>14.31</td>
<td>14.72</td>
<td>3.09</td>
</tr>
<tr>
<td>NEDC</td>
<td>1.95</td>
<td>11.58</td>
<td>11.48</td>
<td>3.40</td>
</tr>
<tr>
<td>NEDC_AT</td>
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<td>11.50</td>
<td>11.41</td>
<td>3.32</td>
</tr>
<tr>
<td>NEDC_MT</td>
<td>1.95</td>
<td>11.58</td>
<td>11.48</td>
<td>3.40</td>
</tr>
<tr>
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<td>12.07</td>
<td>11.94</td>
<td>3.12</td>
</tr>
<tr>
<td>SC03</td>
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<td>11.65</td>
<td>9.93</td>
<td>2.86</td>
</tr>
<tr>
<td>UDDS</td>
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<td>13.17</td>
<td>12.47</td>
<td>4.06</td>
</tr>
<tr>
<td>US06</td>
<td>1.14</td>
<td>6.34</td>
<td>5.59</td>
<td>5.78</td>
</tr>
</tbody>
</table>

energy consumption, the SoH degradation, and thermal comfort cost further when the coefficient variance is higher. This shows that our methodology benefits from the higher variance of the electric motor power requests in order to reduce the battery stress by adjusting the HVAC power.

It needs to be noted that the estimation error of the driving route behavior that depends on its prediction algorithm may influence the performance of the climate control. However, the MPC algorithm implemented in the climate control is very stable with regards to limited outliers in the estimation window. Moreover, the optimization always ensures a safe and comfort range of cabin temperature using the constraints. Therefore, the safe range of HVAC control inputs and passenger comfort will not be violated for any estimation error.

d) Plant Modeling Error Analysis: the EV system, especially the HVAC system and the cabin are modeled and estimated as part of our battery-aware automotive climate control methodology (Section 3). However, the cabin thermodynamic behavior may not be accurate in the model and may change according to the interior, e.g. seat material, passenger body heat, etc. Hence, inaccurate estimation of the system behavior may result in different performance of the climate control.
The performance of the battery-aware climate control methodology has been analyzed in terms of the thermal comfort cost and the battery SoC cost for different modeling error rate of the cabin thermal capacity ($M_C$). As shown in Figures 20(a) and 20(b), the methodology attempts to make up for the cabin temperature estimation error and maintain the thermal comfort and minimize the battery SoH degradation. Therefore, 30% of the modeling error rate only changes the thermal comfort cost and battery SoC cost up to 2% from their nominal value (when there is no error). This shows that our battery-aware automotive climate control is adequately robust and tolerant to the modeling and estimation error of the physical plant.

![Graph of Thermal Comfort Cost](image-a)

![Graph of Battery SoC Cost](image-b)

Fig. 20. Analyses for different plant modeling error rates of cabin thermal capacitance.

It needs to be noted that as the battery cell degrades, their capacity and internal resistance change which will result in lower performance in the charging and discharging cycles. Hence, the implemented model may underestimate the discharge-rate effect of the battery cell. We have analyzed the performance resulted from this modeling and estimation error for HVAC which will behave the same. It shows that the battery-aware automotive climate control is robust and tolerant to the modeling and estimation error. Moreover, this can be compensated by generating a more detailed model which is out of the scope this paper and the methodology of the climate control.

6 CONCLUSIONS

Design of EVs has been challenging due to the battery restrictions and characteristics which hinder the process of its development as a zero-emission mean of transportation. Different battery management systems to manage battery cells and automotive climate controls to maintain the passenger thermal comfort have been developed. However, it has been observed that the HVAC system contributes a lot to the power consumption which significantly influences the EV driving range and battery lifetime. This influence on the battery has not been considered in the state-of-the-art battery management systems and automotive climate control methodologies. In this paper, we proposed a novel methodology of automotive climate control which considers the battery behavior in terms of energy consumption and battery lifetime while monitoring and controlling the HVAC system. Our battery-aware automotive climate control predicts the power requests from the electric motor and adjusts the HVAC power consumption such that the battery stress reduces. The methodology has been implemented and experimented for different control window sizes, ambient temperatures, drive profiles, and modeling error rates. The performance and scalability of the methodology has been analyzed and compared to the state-of-the-art. It has been shown that our methodology diminishes the battery lifetime degradation by up to 13.2% and decreases the total energy consumption by up to 14.4% with prediction of 5 states in the future with time step of 10s.
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