Path to Eco-Driving: Electric Vehicle HVAC and Route Joint Optimization
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Abstract – Vehicle electrification and Battery Electric Vehicles (BEV) primarily attempt to alleviate the issues of air pollution and fossil fuel consumption. Major challenges of driving range and battery lifetime with BEVs, are addressed by controllers managing propulsion and non-propulsion powers. However, we believe the controllers can benefit from exploiting the relationships between these powers to harvest more energy towards eco-driving path. Hence, we propose a methodology to jointly optimize the Heating, Ventilation, and Air Condition system with driving route while considering electric motor. Our analysis shows that the methodology can increase driving range and battery lifetime up to 13% and 30% based on the driving condition.

Keywords: Electric Vehicle, Model Predictive Control, Energy Management, Battery Optimization

1. Introduction and Background

Vehicle transportation is one of the major contributors to air pollution and energy consumption. Organizations and automotive companies have been improving the performance and quality of vehicles and developing new methodologies in order to address the pollution and energy issues. Recently, electrification of vehicles has been seen as a promising solution towards the eco-driving path; Battery Electric Vehicles (BEV) utilize electric motors powered by batteries to provide the propulsion force required for moving the vehicle. This way of generating power results in zero tailpipe emission and higher tank-to-wheel efficiency compared to the Internal Combustion Engine (ICE) vehicles [1].

Despite the benefits provided by BEVs, customers and daily commuters still have their own concerns; limited driving range and the anxiety associated with it are the main challenges of BEV development which make BEVs harder to penetrate the automotive market. Stringent design constraints such as production cost, vehicle mass, and vehicle size make the development challenging for improving the driving range. Challenges may be mainly associated with the battery design and power management in the BEVs.

Battery design with higher energy or power density provides more available capacity and thereby driving range. However, the design may violate the cost, size, and weight constraints of the BEV. The usable battery capacity depends on the discharge rate and utilization pattern and it degrades over time. The battery lifetime ends when the usable battery capacity reaches around 80% of the rated value. The battery capacity loss results in further driving range degradation and possible expensive battery replacement. Hence, economical materials and architectures are designed for battery and BEV components [2]. Moreover, sophisticated Cyber-Physical System (CPS) controllers are implemented to manage the batteries and the power requests to them.

Power management methodologies are typically implemented in different levels of control - from battery level to system level - throughout the BEVs. These CPS controllers which are the focus of this paper manage the power requests to the battery such that less power is consumed and possibly more energy is harvested. Their correct operation will result in higher BEV driving range and battery lifetime.

There are many contributors to the power requests in the BEV. The main contributor to the battery energy is the electric motor. The propulsion power consumed or generated by the electric motor mainly depends on the vehicle load, driving behavior, and road condition. The electric motor in BEVs can harvest energy in the regenerative braking mode in certain driving condition. Besides electric motor, there are other components such as Heating, Ventilation and Air Conditioning (HVAC) system which also contribute a lot to the battery energy consumption as a non-propulsion power [3]. The amount of this power is variable and depends on the ambient temperature while driving the vehicle which is independent from the propulsion power and vehicle driving. An automotive climate control monitors and controls the HVAC system to maintain the cabin temperature and minimize its power consumption.

Figure 1. BEV and ICE vehicle energy and economy analysis for various conditions [4].
We analyzed the energy consumed by the electric motor and HVAC system in a BEV (Nissan Leaf S). The analysis is done while driving on different routes, speeds, and ambient temperatures. The results show that the driving route and vehicle speed significantly affect the energy consumption and economy; smaller driving load in lower speeds and the regenerative braking are benefiting the BEV to consume less energy by driving on the localway route. This behavior may be different for ICE vehicles since they are more efficient in higher speeds and they lack regenerative braking. However, about 50 minutes of driving is sacrificed compared to the highway route. On the other hand, the HVAC system may contribute up to 40% of the BEV energy consumption. The HVAC energy consumption is not only affected by the ambient temperature, but it is also impacted by the driving route. In other words, the increased driving time on localway route significantly increases HVAC energy consumption. Therefore, these preliminary experiment results and analyses show that the propulsion and non-propulsion powers have implicit relationships with each other since they depend on the driving route. Moreover, they both primarily affect the battery operation in terms of BEV driving range and battery lifetime.

II. Related Work

There exists various work of control design and implementation in BEVs to address the challenges mentioned above. These controllers attempt to manage the power requests to the battery cells in different levels as shown in the following. The objective is to reduce the energy consumption and extend the battery lifetime.

Battery-level monitoring and control tasks are the responsibilities of a Battery Management System (BMS). The BMS monitors the current, voltage, and temperature of the battery cells to prevent and avoid unsafe battery operation such as overcharging, over-discharging, overloading, and overheating. Moreover, the BMS balances the requested power among different battery cells such that they bear an equivalent load on average [5], [6]. This will result in higher energy efficiency and lower battery aging rate. Moreover, the BMS may integrate a Hybrid Electrical Energy Storage (HEES) [7] to improve the energy efficiency and decrease the battery capacity loss further. This is achieved by adjusting the utilization among the ultracapacitors and battery cells. However, in these methodologies, the source and type of the BEV power requests (e.g., electric motor or HVAC) are ignored in the management. This may limit the performance of the controller in terms of flexibility and predictability of the control for reaching higher driving range and battery lifetime.

Propulsion power consumed or generated by the electric motor in BEVs mainly depends on the vehicle load, driving behavior, and road conditions. Hence, routing algorithms and driving management controls are designed and implemented to optimize the driving route and behavior in order to improve driving range and battery lifetime. These methodologies consider future road conditions and BEV dynamics model in order to estimate the power consumption or generation by the electric motor while driving on a certain route. Therefore, they minimize the propulsion energy consumption by selecting the optimal driving route and behavior [8]. However, the optimal solution by these driving management methodologies may influence other components and systems in the BEV which consume non-propulsion power. For instance, a driving route influences not only the propulsion energy consumed by the electric motor, but also the non-propulsion energy consumed by the HVAC. Hence, these methodologies lack the knowledge of the common factors influencing both propulsion and non-propulsion powers.

Non-propulsion power consumed by the components in the BEV is primarily independent of the driving. For instance, the HVAC system as a major contributor to the non-propulsion power is controlled by the automotive climate control which is responsible for maintaining the cabin temperature. The power consumption of the HVAC system mainly depends on the ambient temperature and the cabin target temperature. Hence, further difference between the cabin and ambient temperature puts more load on the HVAC system resulting in higher non-propulsion power consumption. Various climate control methodologies are implemented to reduce the HVAC energy consumption while ensuring the required passenger thermal comfort [9], [10]. They leverage the information of the cabin thermal condition and available power in order to decide on the HVAC temperature set points. Furthermore, in more advanced automotive climate controls [1], future information of the propulsion power requests is also fed to the controller. Hence, the HVAC system will be optimized in order to reduce battery load while ensuring the same thermal comfort. However, these methodologies do not account the factors influencing the non-propulsion power such as driving route and its corresponding propulsion power.

<table>
<thead>
<tr>
<th>Optimizing Factors</th>
<th>Propulsion (Electric Motor)</th>
<th>Non-Propulsion (HVAC)</th>
<th>Battery (Capacity Loss)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Route Optimize</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fastest</td>
<td>✗</td>
<td>✗</td>
<td>✗</td>
</tr>
<tr>
<td>Energy-Aware</td>
<td>✗</td>
<td>✗</td>
<td>✗</td>
</tr>
<tr>
<td>Battery-Aware</td>
<td>✔</td>
<td>✗</td>
<td>✗</td>
</tr>
<tr>
<td>Climate Control</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PID</td>
<td>✗</td>
<td>✗</td>
<td>✗</td>
</tr>
<tr>
<td>Fuzzy-based</td>
<td>✗</td>
<td>✔</td>
<td>✗</td>
</tr>
<tr>
<td>Lifetime-Aware</td>
<td>✗</td>
<td>✔</td>
<td>✔</td>
</tr>
<tr>
<td>Joint Optimize</td>
<td>Eco-Driving</td>
<td></td>
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<td></td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
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</tbody>
</table>

Different types of controllers and their limitations are listed in Table 1. We need to address the above-mentioned challenges to develop control methodologies towards the path of eco-driving for BEVs. Hence, a joint optimization methodology for the propulsion and non-propulsion powers is proposed which integrate:

- **Automotive Climate Control**: which optimizes the HVAC system control inputs and variables by having the predicted route behavior in the near-future in order to reduce the battery stress for extending the battery lifetime and driving range.
- Driving Route Optimization: which selects the optimal route towards a specific destination for longer battery lifetime and driving range considering the propulsion power (electric motor) and non-propulsion power (HVAC).
- Performance Analysis: will be conducted for this methodology since it will be applicable to any BEV in any weather and route condition.

III. System Modeling and Estimation

System dynamics and behavior are necessary to be known as part of the predictive controller. This information is typically provided as a system model which later is used at runtime for estimation of the system dynamics. The predictive controllers, especially in CPS, utilize multiple sensors and the system model for evaluating the current state of the system as well as predicting the future states in order to make an optimal decision on the control inputs to the system. For instance in BEVs, a model of the electric motor is required to find out how much propulsion power is being consumed or generated as driving a model of the HVAC system is necessary in order to estimate the power consumption of the HVAC (non-propulsion power) while maintaining a certain temperature; and behavioral model of the energy storage (battery) is required to estimate how the power requests influence the status of the battery in terms of energy consumption and battery lifetime.

Electric motor is the main component in a BEV to provide the required force for propelling the vehicle at a desired speed and acceleration. The generated tractive force overcomes the road load forces \( F_{rd} \) on the vehicle. These forces are caused by the rolling resistance \( F_{roll} \), aerodynamic drag \( F_{aero} \), and gravitational \( F_{gr} \) forces. The road and driving conditions such as driving speed, wind speed, and road slope are the major parameters that influence the value of these forces. Typically, the values for these parameters can be extracted from the map databases in order to evaluate the forces. Moreover, the tractive force can be produced by the electric motor either in the motor mode or generator mode depending on the torque direction required. This benefits the BEV in order to harvest energy while braking (i.e. regenerative braking) [4].

HVAC system is controlled by an automotive climate control in order to maintain the cabin temperature. The air supply temperature is controlled by adjusting the temperature set points on heating and cooling coils. Moreover, variable air valves are utilized in more complex HVAC system in order to maintain the required thermal comfort for the passengers even in multi-zone cabin. These systems utilize variable-speed fans and air ducts to provide the supply air to the zone(s) [1].

Typically, the thermodynamics of the cabin (zone) temperature \( T_z \) is modeled by energy balance differential equations. The cabin temperature is influenced by the supply air \( T_s \) to the cabin and other thermal loads including the heat exchange with outside and the solar radiation. The power consumption of the cooling \( P_c \) and heating coils \( P_h \) depends on the energy difference between their inlet and outlet air flows. Moreover, the power consumption of the variable-speed fans \( P_f \) is quadratically related to the air flow rate \( m_z \).

Battery is the main source of powering the BEV components such as electric motor and HVAC system. The battery pack may contain multiple battery cells connected in series or parallel to provide the power and capacity as per the requirements. Here in, lithium-ion battery cells are mainly focused since they are the most used family of battery cells to enable the BEV with adequate energy and power density.

Dynamic behavior of a battery cell can be described using an equivalent electric circuit model; the cell is modeled as a variable-voltage power supply in series with an internal resistance. The ratio of the available charge to the battery capacity is represented by State-of-Charge (SoC) which changes as the battery charges or discharges. Moreover, lithium-ion batteries demonstrate less usable capacity in higher discharge rates (rate-capacity effect). This characteristic is described by the Peukert’s Law [11]. Hence, reducing the instant discharge rate of the battery can extend available capacity and thereby the driving range. Moreover, 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 (VSoH) or capacity loss rate \( (Q_{loss}) \) is mainly influenced by the stress on the battery cell defined by the pattern of utilizing the battery cell [12].

IV. Eco-Driving Joint Optimization

The CPS models explained in the previous section will be integrated into a system-level controller to implement our eco-driving joint optimization methodology. Figure 2 illustrates the methodology modules and steps.

Typically the driving route information such as: average vehicle speed, road slope, and distance in each section of the route is provided by map databases and is known before driving. The electric motor equation-based models will use the driving route information to estimate the electric motor power consumption and generation at each section of the driving route. On the other hand, the HVAC system models are utilized to estimate the thermal dynamic behavior of the HVAC and its power consumption in a certain ambient temperature...
while driving. Therefore, the total power request to the battery pack is known and will be used by the battery model to estimate the energy consumption and battery lifetime. The eco-driving joint optimization methodology will implement a near-future estimation of the BEV dynamic states. The estimation will help in finding the optimal driving route and adjusting the HVAC control inputs while driving to increase the driving range and reduce the battery stress while maintaining the cabin temperature. This integration helps the methodology to consider the trade-off and relationships existing between the propulsion power of the electric motor and the non-propulsion power of the HVAC system regarding their common factor of driving route. Hence, the methodology will integrate two main components of optimal route prediction and HVAC optimization.

Furthermore, the joint (multi-objective) optimization finds the pareto-optimal solutions considering not only the driving time, but also the battery energy and capacity loss. Weights given to these factors may vary based on the user/designer preference in their trade-off.

a. HVAC Optimization

Automotive climate control adjusts the control inputs into the HVAC system to maintain the cabin temperature around a certain target and within a comfort range. The climate control is implemented using a Model Predictive Control (MPC). The MPC leverages the HVAC system dynamic models to estimate the state, auxiliary, and output variables according to specific control inputs for a certain prediction horizon in the future. The controller utilizes an optimizer to adjust the control inputs such as heating and cooling coil temperature set points and the fan speed of the prediction horizon while considering the propulsion power in the horizon. It also minimizes a cost function for the prediction horizon. The cost function of the optimization (Equation 1) may include the 1) cabin temperature variation, 2) HVAC energy consumption, and 3) battery capacity loss. Moreover, there are certain constraints on the control inputs and state variables which should be satisfied during the optimization and control process. This reduces battery stress by adjusting the non-propulsion power such that it compensates for the propulsion power:

\[ \begin{align*}
\min & \quad w_1 \times (T_z - T_{\text{target}})^2 \\
& \quad + w_2 \times (P_f + P_c + P_h) \\
& \quad + w_3 \times (Q_{\text{loss}}) \\
\text{s.t.} & \quad \text{nonlinear HVAC models} \\
& \quad \text{linear control limits}
\end{align*} \]

Equation 1

b. Optimal Route Prediction

A routing algorithm is also implemented in order for the eco-driving methodology to find the optimal driving route in terms of the energy consumption and battery lifetime [4]. Typically, routing algorithms address the shortest path problems. There exist different algorithms and data structures to solve the problem which demonstrate various memory and time complexity. The routing algorithm traverses through a weighted directed graph; the graph is generated in the eco-driving methodology using the real world map database. The weight of each edge in the graph associates with the cost function of our routing algorithm for that route section. The cost function may consist of the weighted values of the driving time, driving distance, energy consumption, and the battery capacity loss. The routing algorithm traverses through the edges to find the route with the minimum total weight. For instance, if the driving time is the main factor in the cost function, the driving route with the minimum total weight would be the fastest route. The routing algorithm should be able to provide the optimal route to the destination from any starting point. There are two reasons for the optimal route prediction: (1) the first main reason is to use the optimal route for navigating the BEV; and (2) the automotive climate control also uses the predicted route to estimate the propulsion power of the electric motor and adjust the HVAC utilization accordingly to reduce battery stress.

V. Performance Analysis

The real-life databases provided by Google Maps and OpenStreetMap are utilized to generate the directed graph and help the methodology estimate the driving route behavior and the geographical details [4]. A real-life BEV – Nissan Leaf – is modeled using equations by knowing its parameters and the models provided by AMESim and ADVISOR, automotive design and simulator tools. In order to analyze the influence of the joint optimization on the performance of the BEV, the experiments have been conducted on various driving conditions in terms of the ambient temperature, for instance, in California regions [10°C - 40°C] and the driving route (Table 2).

<table>
<thead>
<tr>
<th>Route</th>
<th>From:</th>
<th>To:</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>UCL: 33.6439°, -117.8345°</td>
<td>Beach: 33.8439°, -117.8476°</td>
</tr>
<tr>
<td>(2)</td>
<td>UCL: 33.6439°, -117.8345°</td>
<td>Shopping Center: 33.6136°, -117.8685°</td>
</tr>
<tr>
<td>(3)</td>
<td>UCL: 33.6439°, -117.8345°</td>
<td>Airport: 33.6776°, -117.8604°</td>
</tr>
<tr>
<td>(4)</td>
<td>UCL: 33.6439°, -117.8345°</td>
<td>Grocery Store: 33.6657°, -117.8263°</td>
</tr>
</tbody>
</table>

We compare the performance of our joint optimization methodology with the state-of-the-arts as the baseline:

- **Fastest**: the route with the least driving time is selected when optimizing: HVAC is controlled by a fuzzy-based controller to maintain the cabin temperature around a target temperature without considering the driving route [10].
- **Battery-Aware**: the route with the least battery energy and capacity loss is selected when optimizing: HVAC is controlled by the fuzzy-based controller [10]; HVAC energy consumption is also estimated and considered in the route optimization.
- **HVAC-Tuned**: the fastest route is selected and the HVAC system is controlled using the MPC algorithm according to the predicted route to maintain the cabin temperature around a target temperature and minimize the battery energy and capacity loss [10].
a. Weather ( Ambient Temperature )

The HVAC system power consumption is primarily dependent on the ambient temperature and the cabin target temperature (as shown in Figure 3). By keeping the cabin target temperature constant (25°C), the ambient temperature will become the only main factor.

As shown in Figure 3, in severe weather conditions, the faster route is more preferable since more driving time results in more energy consumption by the HVAC. Moreover, the climate control has less flexibility of adjusting the HVAC utilization due to drastic changes in cabin temperature. While, in less severe weather conditions, the joint optimization has more flexibility to choose longer routes and adjust the HVAC utilization. It may even consume extra energy to improve total battery lifetime. This trade-off can be adjusted by the weight parameters. Hence, the eco-driving can increase the driving range and battery lifetime up to 13% and 30%.

b. Route ( Speed Behavior )

The driving routes consist of various up hills and down hills with different driving speeds. Hence, specific route conditions enforce certain power request behavior on the electric motor as driving. Primarily, this affects the electric motor energy consumption. Moreover, since the automotive climate control is adjusting its HVAC utilization according to the propulsion power request, the HVAC energy consumption will be impacted as well.

As shown in Figure 4, various driving routes result in different battery capacity loss and energy consumption. The joint optimization eco-driving methodology is making up for the propulsion power variance by adjusting the HVAC utilization (non-propulsion power). Typically, with higher variance in the driving speed, there is more flexibility for the joint optimization to reduce the battery stress by changing the HVAC power. Hence, the eco-driving can increase the battery lifetime up to 30%. It needs to be noted that, according to the weight parameters set for the optimization, improving the battery lifetime may affect the energy consumption; this trade-off can be avoided by tuning the parameters.

VI. Concluding Remarks

Battery electric vehicles deployment as a main mean of transportation has been hindered by major design challenges. We noticed that the driving route is a primary common factor affecting the electric motor (propulsion) power and the HVAC system (non-propulsion) power. Hence, we exploited this behavior to joint optimize the driving route and the HVAC system together. This joint optimization enables the path towards eco-driving by further improving the driving range and battery lifetime. We analyzed the performance of the methodology for various driving conditions like ambient temperatures and driving routes. The methodology demonstrates different performance in terms of driving range and battery lifetime improvement for each driving condition. For instance, the power requirement by the HVAC system changes for each weather condition and specific driving routes enforce certain power request behavior on the electric motor. Therefore, the maximum improvement achievable by the joint optimization depends on the driving condition. Our analysis shows that the methodology can increase driving range and battery lifetime up to 13% and 30%. Since more systems are being added to the CPS of BEVs, there will be more opportunity to exploit in terms of joint optimization towards the path of eco-driving.

VII. Acknowledgment

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References


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