

Work-in-Progress: Driving Behavior Modeling and Estimation for Battery Optimization in Electric Vehicles

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ABSTRACT

Battery and energy management methodologies such as automotive climate controls have been proposed to address the design challenges of driving range and battery lifetime in Electric Vehicles (EV). However, driving behavior estimation is a major factor neglected in these methodologies. In this paper, we propose a novel context-aware methodology for estimating the driving behavior in terms of future vehicle speeds that will be integrated into the EV battery optimization. We implement a driving behavior model using a variation of Artificial Neural Networks (ANN) called Nonlinear AutoRegressive model with eXogenous inputs (NARX). We train our novel context-aware NARX model based on historical behavior of real drivers, their recent driving reactions, and the route average speed retrieved from Google Maps in order to enable driver-specific and self-adaptive driving behavior modeling and long-term estimation. Our methodology shows only 12% error for up to 30-second speed prediction which is improved by 27% compared to the state-of-the-art. Hence, it can achieve up to 82% of the maximum energy saving and battery lifetime improvement possible by the ideal methodology where the future vehicle speed is known.

CCS CONCEPTS

• **Computer systems organization** → **Embedded and cyber-physical systems**; • **Computing methodologies** → *Machine learning approaches*; Modeling methodologies; • **Hardware** → *Batteries*; *Power estimation and optimization*;

KEYWORDS

CPS, Electric Vehicle, Battery, HVAC, Statistical Modeling, Neural Network, Model Predictive Control, Power Optimization

1 INTRODUCTION AND RELATED WORK

Electric Vehicles (EV) as a zero-emission method of transportation face challenges that have affected their economy and sustainability [1–3]. Battery as the main energy source in EVs poses stringent design constraints that restrict the stored energy and thereby the driving range. Moreover, the EV utilization and higher discharge rates diminish the battery capacity degrading the battery lifetime. Total power requests of EVs influence the battery operating behavior in terms of EV driving range and battery lifetime.

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Power consumption/generation of electric motors as a major contributor to EV energy depends on the driving behavior on the route and varies for different drivers [4] (see Figure 1). Future reactions of the driver in terms of adjustments to vehicle direction and speed, based on the driver's perception of the route and vehicle condition are described as a driving behavior. Moreover, other accessories in EVs especially Heating, Ventilation, and Air Conditioning (HVAC) system has shown to be another major contributor [2, 3].

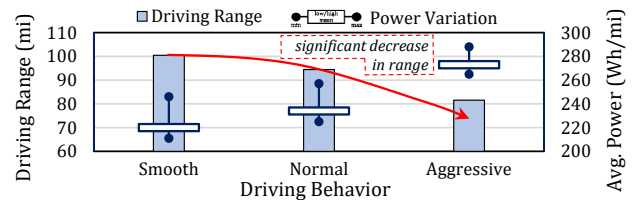


Figure 1: Impact of different driving behavior on EV power consumption variation and driving range [4].

Design challenges of EVs have been addressed by designing more efficient and robust battery cells, device-level Battery Management Systems (BMS), or system-level energy managements [1–3]. As we are focusing on this paper, system-level battery and energy management methodologies have been implemented to optimize the battery utilization by adjusting higher-level power requests in order to improve the battery lifetime and driving range.

Driving route influences the EV energy consumption, thereby the EV driving range and battery lifetime besides the driving time and distance. Hence, automotive navigation system methodologies have been implemented to optimize the route considering these factors. In another work, the prediction of the driving route helps in optimizing the energy split between battery and ultracapacitor in Hybrid Electrical Energy Storage (HEES) system [1]. Furthermore, a battery lifetime-aware automotive climate control has been implemented which considers the near-future driving route to predict the EV power requests and optimize the HVAC operation while maintaining the passenger thermal comfort [2, 3].

Driving behavior modeling has been exploited for driver assistant systems, especially for vehicle safety purposes. These models eliminate the driver's decision-making lag and predict the future reactions up to the next 3 seconds with accuracy of up to 99.5% [5, 6].

However, energy and battery managements in EV do not account driving behavior for optimization, although it affects the operating parameters and accuracy of the power consumption estimation. Moreover, driving behavior modeling methodologies focus only on very recent input information and current state (visible environment around the car). Hence, they fail to provide accurate longer-term speed prediction necessary for battery and energy management resulting in poor control performance.

2 DRIVING BEHAVIOR INTEGRATION WITH BATTERY OPTIMIZATION

EV battery optimization methodologies, as in the battery lifetime-aware automotive climate control, utilize modeling of the EV components for predicting their dynamic behavior and power requests in the near-future. Moreover, the driving behavior estimation is required for accurate estimation of the EV power request. These modeling and estimation are used in optimizing and adjusting the control inputs to improve the EV driving range and battery lifetime.

Driving behavior defines the future vehicle speeds and depends on the route and driver reactions to specific route conditions. State-of-the-art methodologies model the driving behavior as follows:

- 1) **Ideal (IDL)**. In this model, we are able to predict the vehicle speed at any given time with perfect accuracy. In other words, any battery optimization would have access not only to the previous and current vehicle speeds, but also to the future vehicle speeds.
- 2) **Motion-Preserving (MP)**. Typically, in optimization-based or rule-based battery optimization methodologies [5], either there is no assumption about the future, or the assumption is that the vehicle is going to preserve its current motion.
- 3) **Statistical Modeling**. In this approach, the future vehicle speed is predicted based on the past speeds, the current speed, and the information of any other factors that can affect the vehicle speed. The correlation is modeled using machine learning techniques.

Since the correlation between the current speed and predicted speed decreases for further future time instances, the estimation error increases. To address this, as part of our novel methodology, statistical information of the average speed for each road segment extracted from Google Maps APIs is also fed to the model providing the future context and condition of the driving route.

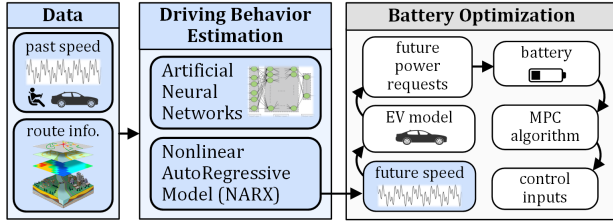


Figure 2: Illustration of our novel driving behavior estimation for battery optimization (contributions highlighted).

To approximate the correlation, we use our novel context-aware Nonlinear AutoRegressive model with eXogenous inputs (NARX) as shown in Figure 2. NARX is a simple architecture of Recurrent Neural Networks (RNN) with feedback edges between two different layers. We focus on NARXs which have inherited the adaptivity properties of their architecture family and have proven to carry out good results for predicting long-term time-series data [6]. Moreover, the pre-trained NARX model has the ability to adopt its behavior to each individual driver's behavior, with very little extra processing power thanks to the feedback from its estimated outputs to its inputs. The model will be trained using real data of the driver's behavior [7]. It will be integrated into the battery optimization. Hence, the control inputs are adjusted according to the future vehicle speeds and EV power requests such that the energy consumption is minimized and battery lifetime is extended.

3 EXPERIMENTAL RESULTS AND ANALYSIS

EV electric motor, HVAC, and battery are modeled for the experiments [2]. Performance is evaluated using the SHRP 2 Naturalistic

Driving Study [7] database. For 30-second future prediction, 8 layers with 76 input features are used before over fitting the data.

Estimation accuracy: the accuracy of the methodologies is compared in terms of Mean Absolute Error (MAE) and Delay (D) for n-second ($n = 1 : 30$) future speed prediction in Figure 3. Longer term estimation increases the error except for the ideal (IDL) methodology. The error and delay of our novel context-aware NARX is less than the others especially for longer estimation ($n > 15$).

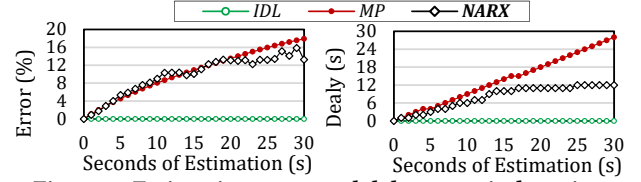


Figure 3: Estimation error and delay v.s. window size.

EV performance: driving range and battery lifetime are the important factors in EVs. The optimization performance in a battery lifetime-aware automotive climate control is analyzed. Figure 4 shows the energy saving, battery lifetime (SoH) improvement, and total optimization cost reduction, compared to the ideal methodology in percentage. Our context-aware NARX methodology can help the controller to improve the driving range and battery lifetime up to 82% of the maximum improvement achievable (by IDL).

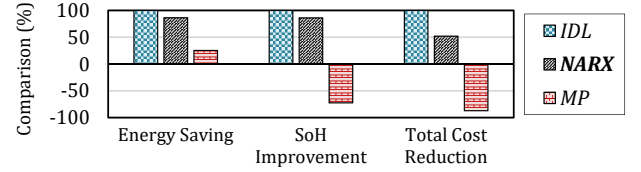


Figure 4: Energy saving, battery lifetime improvement, and total optimization cost reduction compared to ideal case.

4 CONCLUSIONS

We showed that long-term driving behavior modeling and estimation are required for battery optimization in EVs. Our novel context-aware NARX model enabled estimation for up to 30 seconds with <12% error (27% improvement) and improved the control performance up to 82% of the maximum ideal performance.

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