Predicting Electric Vehicle Energy Consumption from Field Data Using Machine Learning

Qingbo Zhu, Yicun Huang, Chih Feng Lee, Peng Liu, Jin Zhang, Torsten Wik

April 28, 2025

Current road transport, heavily relying on fossil fuels, has caused severe public concerns over the energy crisis, air pollution, and global warming. To achieve a sustainable transport system, the mass deployment of electric vehicles (EVs) is imperative and has become an unstoppable trend. Such electric revolution in the transport sector entails various studies include but are not limited to battery sizing, charging planning, driving range prediction, routing, speed control, energy optimization, and environmental analysis. To tackle these problems, a common and fundamental task is the development of a reliable and accurate model for EV energy consumption. In addition, such an energy consumption model is a basis for making EV regulations and policies, and for analyzing the supply risks of battery resources.

Considerable research efforts have been devoted to the modeling of EV energy consumption. The obtained results can generally be categorized into empirical models, physics-based models, and data-driven models. Empirical models exhibit lower prediction accuracy due to their reliance on assumptions such as a constant energy consumption rate or a simplified function correlating energy consumption with ambient temperature, curb weight, travel distance, and trip duration. Physics-based models rely on fundamental principles but are often insufficient for capturing all the microscopic dynamic behaviors exhibited by EVs during both individual and typical trips. Data-driven modeling approaches using machine learning have gained popularity for addressing energy consumption issues, despite challenges such as data scarcity and inappropriate feature selection. The state-of-the-art machine learning method achieves a Percentage Mean Absolute Error (PMAE) of 7.84% and a Root Mean Squared Error (RMSE) of 0.2193.

To maintain both physical interpretability and predictive power, the proposed method introduces a comprehensive machine learning pipeline aimed at predicting EVs energy consumption by physics-informed features using real-world fleet data. Initially, a robust data processing technique was developed to handle the large volume of raw data, addressing issues and outliers inherent in the dataset. Following data cleansing, a new set of features grounded in physical principles was meticulously constructed through systematic correlation analysis. These features served as inputs for four innovative quantile-based machine learning algorithms designed to predict both the energy consumption and the associated uncertainties. The framework's novelty lies in its dual approach: leveraging global machine learning models for a broad understanding and applying online adaptations for individualized predictions. This combination allows for continuous improvement in accuracy and reliability. Specifically, the best-performing global model, the quantile regression neural network (QRNN), was adapted online to each vehicle, significantly enhancing the precision of energy consumption forecasts.

The accuracy and efficacy of the developed machine learning models were validated through extensive testing on real-world EVs data. This validation focused on comparing different data processing steps, global models, and online adaptive models. The results demonstrated that the online adaptive QRNN model achieved a substantial reduction in the average PMAE in prediction to 5.04%, marking an improvement of over 35% compared to the best state-of-the-art models. Additionally, online adaptation enhanced the coverage probability of the 95% prediction interval to 91.27% and reduced the average width of prediction intervals to 0.51, indicating tighter and more reliable predictions. Moreover, the computation time required by the best model averaged only 15 microseconds for prediction. These findings underscore the advantage of integrating physics-informed features and vehicle-specific online adaptations, representing a significant step forward in accurately predicting EV energy consumption and providing a robust foundation for future developments in this field.