Prediction of State-of-Charge Consumption in electric vehicles- A SURVEY.

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Abstract: **The popularity of electric vehicles (EVs) is growing because they can reduce greenhouse gas emissions and minimize reliance on fossil fuels. However, the limited driving range of EVs is still a significant obstacle. Accurately predicting State-of-Charge (SOC) consumption is crucial for optimizing battery usage, increasing battery life, and enhancing overall EV performance. This survey paper aims to analyze the current state of SOC consumption prediction research for EVs. It investigates several factors affecting SOC consumption, including driving behavior, environmental conditions, battery characteristics, and vehicle design. Additionally, the study discusses various approaches for predicting SOC consumption, including empirical, physics-based, machine-learning, and deep-learning models, analyzing their benefits and limitations. Furthermore, the paper summarizes various techniques for estimating SOC consumption in electric vehicles.**

Index Terms— **Electric vehicles, SOC, deep learning, machine learning**

I. INTRODUCTION:

Electric cars (EVs) are becoming more and more well-liked as a greener substitute for conventional fossil fuel-based vehicles as the globe moves towards cleaner and more sustainable energy sources. Yet, due to the restricted energy storage capacity of their batteries, EVs' short driving range poses one of the biggest obstacles to their general acceptance. The State of Charge (SOC) is a crucial factor in determining the battery's energy level and the driving range of an EV. Accurately predicting the SOC consumption of EVs is crucial for optimizing their energy management and ensuring efficient use of the battery. With the advent of machine learning algorithms and advancements in data analytics, machine learning techniques have emerged as a powerful tool for developing accurate prediction models for SOC consumption in EVs. Machine learning techniques can play a major role in developing such prediction models.

In recent years, several studies have been conducted to develop prediction models for SOC consumption using machine learning algorithms. In this survey paper, various machine-learning techniques used for predicting SOC consumption in EVs are reviewed and provide a comprehensive understanding of the state-of-the-art in this field.

II. LITERATURE SURVEY

J.P. Ortiz et al. (2022) proposed a machine learning model for predicting State of Charge (SOC) consumption in electric vehicles (EVs) using real-world data. To predict SOC consumption accurately, the proposed model combines continual reinforcement learning, meta-experience replay techniques, and an artificial neural network. The model was trained and tested using data from a real-world EV fleet. Unlike traditional machine learning algorithms that need to be re-trained from scratch, this model has the advantage of continuously learning and adapting to new data. However, one disadvantage of this approach is the potential for overfitting to the particular real-world data used for training, which can result in reduced accuracy when applied to new data. The model's maximum MAE and RMSE values are 0.91% and 0.68%, respectively.

Xiaogang Wu et al. (2022) suggested a data-driven method for robust prediction of battery state of charge (SOC) based on battery packaging and consistency deviation of thermoelectric properties. Long short-term memory (LSTM) algorithm input features were chosen as highly correlated aging and thermoelectric characteristic factors using a random forest technique to reduce dimensionality. Grid search was used to optimize the LSTM structure. The proposed method achieved high accuracy in battery SOC estimation with a maximum absolute error (MaxAE) of only 1.539% under different temperatures, battery aging degrees, and operating conditions. However, the disadvantage is that the study was conducted using data from electric vehicles in Beijing, which may not be generalizable to other regions with different driving patterns or operating conditions.

Niri et al. (2021) proposed a state of power (SoP) prediction method for lithium-ion batteries in electric vehicles using wavelet-Markov load analysis. In order to predict the State of Power (SoP) of a battery, the proposed method employs a combination of wavelet decomposition and Markov chain modeling. The battery current signal is decomposed into different frequency bands using the wavelet decomposition technique, and the Markov chain model is then applied to the wavelet coefficients to predict the battery's future current and voltage. This approach proves to be advantageous as it accurately predicts the SoP even when there are varying load conditions. However, the authors caution that this method may not be applicable to all types of lithium-ion batteries, and further research is necessary to evaluate its effectiveness in different scenarios. Overall, Niri et al.'s proposed method presents a promising strategy for enhancing the efficiency and reliability of lithium-ion batteries in electric vehicles.

Hong et al. (2021) presented a method for reliably calculating the State of Charge (SOC) of an Electric Vehicle (EV) battery utilizing real driving cycle (RDC) data and deep-learning approaches. Using an On-Board Diagnostics (OBD)-II dongle, the RDC data was immediately obtained from the author's vehicle and segregated using the Dynamic Time Warping (DTW) algorithm. The SOC trajectory for the subsequent journey was produced using a Functional Mock-Up Interface (FMI)-based EV simulation environment, and acceleration values were predicted using deep learning algorithms. The temporal Attention Long-Short Term Memory (TA-LSTM) model was found to provide the most accurate SOC predictions.

Lyu et al. (2021) introduced a model-data-fusion method for predicting the remaining usable life (RUL) and measuring the state of health (SOH) of lithium-ion batteries. The paper employs a dynamic and data-driven battery degradation model that simulates the complex degradation behaviors of the batteries by combining the metabolic grey model and multiple-output Gaussian process regression. The internal resistance and polarisation resistance from the battery Thevenin model is used as input variables in the degradation model, which employs capacity deterioration as the state variable. The benefit of this paper is that it can forecast RUL and SOH with high accuracy and reliability at various temperatures. However, the strategy may not be appropriate for batteries with atypical degradation patterns or for batteries operating in harsh environments.

Dao et al. (2021) proposed an effective State of Charge (SOC) estimation method for a Lithium-ion battery pack using an Extended Kalman Filter (EKF) and Artificial Neural Network (ANN).The method suggested for estimating SOC involves the use of EKF during regular battery operation and ANN during periods of battery inactivity. The SOC estimation method based on EKF incorporates a battery's voltage, current, and temperature into an equivalent circuit model. The SOC estimation method based on ANN relies on the battery's OCV and forecasts the SOC value during rest periods.

B. Gou et al. (2020) suggested a new hybrid ensemble data-driven method for predicting the state-of-health (SOH) and remaining usable life (RUL) of lithium-ion batteries. In order to anticipate the trend of the battery's deterioration, they chose a health indicator utilising Pearson correlation analysis as feature inputs. To uncover the underlying connection between the extracted health indicator and real SOH, two random learning algorithms were combined. The abstract made no mention of the specific algorithms. Based on the calculated SOH, a nonlinear autoregressive (NAR) structure was created to effectively employ historical and present data to lower the RUL prediction error of each learning model. Also, they created a Bootstrap-based uncertainty management technique to evaluate the RUL's prediction interval statistically. The proposed method demonstrated accurate predictions of SOH and RUL of batteries, making it suitable for online practical applications such as energy storage systems and electric vehicles.

R. Xiong et al. (2019) created a lithium-ion battery health prognosis algorithm based on a real battery management system used in electric vehicles. The algorithm predicts the battery's remaining useful life using a moving-window-based technique. The partial charge voltage curve of cells serves as the foundation for the algorithm's health indicator. On the basis of experimental information gathered from cells tested at various current rates and temperatures, the capacity estimation and remaining useful life prediction methodologies were put into practice. The root mean square errors of the forecasts of the remaining useful life during the last 20% of battery life were within 20 cycles, while the capacity estimation errors were within 1.5%.

Y. Zhang et al. (2018) developed a method for predicting the remaining usable life (RUL) of lithium-ion batteries using deep learning. To learn the long-term dependencies among the degraded capacities of lithium-ion batteries, the long short-term memory (LSTM) recurrent neural network (RNN) is used. The overfitting issue is addressed by the adaptive optimization of the LSTM RNN utilizing the robust mean square back-propagation approach and the application of the dropout technique. The created LSTM RNN may build an explicitly capacity-oriented RUL predictor whose long-term learning performance is compared to that of other models, as well as capture the underlying long-term dependencies among the deteriorated capacities. The advantage is that the accurate prediction of RUL is independent of offline training data, and when some offline data is available, the RUL can be predicted earlier than traditional methods. The disadvantage is that the method requires significant computational power and time to train and execute, making it less suitable for real-time RUL prediction applications.

Y. Zhang et al. (2017) suggested an adaptive H infinite filter technique for estimating the state of charge (SOC) and state of energy (SOE) of a lithium-ion battery pack. The recursive least square method is utilized by the method to determine the battery model parameters in real-time, while the covariance matching technique is used to adaptively update the covariance of system and observation noises. A hardware-in-the-loop (HIL) platform is established to evaluate the accuracy and reliability of the SOC and SOE estimation. The suggested method is compared with multi-state estimators using an extended Kalman filter and a H infinity filter. However, a drawback of this approach is that HIL platform validation may be costly and time-consuming to set up.

III. CONCLUSION

The survey on the prediction of SOC consumption in electric vehicles reveals a range of approaches and methods used by researchers. The application of machine learning algorithms, specifically deep learning methods, has demonstrated positive outcomes in the precise estimation of SOC consumption. The incorporation of driving data obtained from real-life scenarios like road gradient and vehicle velocity can also enhance the precision of the predictive models. Nonetheless, the predictive models' pace and efficiency can still be enhanced further. The research in this field should focus on designing more effective and precise prediction models to help with managing and utilizing battery systems in electric vehicles optimally.

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