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Elektrikli Araçlarda Veriye Dayalı Doğru SoC Tahmini: Musoshi Pop-Up Mini EV Uygulaması

Data-Driven Accurate SoC Estimation in Electric Vehicles: Musoshi Pop-Up Mini EV Application

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Özetçe

Elektrikli araçların kullanımının yaygınlaşmasıyla birlikte, sürücülerin araçlarının şarjı bitmeden ne kadar yol gidebileceğini bilme isteği, sürücüler üzerinde önemli bir psikolojik bariyer oluşturmaktadır. Menzil kaygısı olarak bilinen bu durumu azaltmak için, araçların kalan menzilini gösteren State of Charge (SoC) doğru bir şekilde tahmini oldukça önemlidir. Bu çalışmada, Musoshi Pop-Up Mini elektrikli aracı kullanılarak SoC tahmini gerçekleştirilmiştir. Çalışma kapsamında, aracın CAN BUS hattı üzerinden toplanan veriler çeşitli ön işlemlerden geçirilmiş, bu veriler modellemeye uygun hale getirilmiş ve ham verideki özniteliklerin önem dereceleri hesaplanarak model performansını etkileyen önemli öznitelikler seçilmiştir. Modelleme sürecinde Random Forest, Gradient Boosting ve Feed-forward Neural Network modelleri MSE, MAE ve R2 metrikleri ile karşılaştırılmış ve FNN modelinin SoC tahmininde daha başarılı olduğu tespit edilmiştir. Elde edilen sonuçlar yöntemin araç üzerinde uygulanabilirliğini ve doğru SoC tahmininin sürücüler üzerindeki menzil kaygısını önemli ölçüde azaltabileceğini ortaya koymaktadır.

Abstract

With the widespread use of electric vehicles, the desire of drivers to know how far their vehicles can travel before running out of charge creates an important psychological barrier on drivers. In order to reduce this condition, known as range anxiety, accurate estimation of the State of Charge (SoC) of the vehicles which indicates the remaining battery, is crucial. In this study, SoC prediction was carried out using the Musoshi Pop-Up Mini electric vehicle. Within the scope of the study, the data collected via the CAN BUS line was applied to various pre-processes, these data were made suitable for modeling, and the important features affecting the model performance were selected by calculating the importance scores of the features in the raw data. During the modeling process, Random Forest, Gradient Boosting and Feed-forward Neural Network models were compared with MSE, MAE and R2 metrics and it was determined that the FNN model was more successful in SoC prediction. The results obtained demonstrate the applicability of the method on the vehicle and that accurate SoC estimation can significantly reduce range anxiety on drivers.

1. Introduction

Nowadays, with increasing environmental concerns and the desire to get rid of fossil fuels, there is a clear trend towards electric vehicles (EVs) in the automotive industry. While 9.5 million EVs were sold worldwide in 2023 [1]. According to the report published by Markets and Markets, the global EV market is expected to grow significantly, reaching 951.9 billion USD by 2030 [2]. Although the proliferation rate of EVs is rapid, inadequate charging infrastructure is still one of the most important obstacles to growth. Although there is 1.4 million fast and 2.5 million normal public charging points worldwide by 2023, these numbers are insufficient to meet the increase in the number of EVs [1]. Inadequate charging infrastructure increases concern about how far vehicles can travel before running out of charge, giving rise to a phenomenon known as *range anxiety*. In addition, the limited number of charging facilities and long charging times create a psychological barrier on drivers [3]. To overcome this situation, many studies have been carried out on SoC estimation in recent years.

The battery SoC is similar to the fuel in gasoline vehicles, showing how much energy is left in the battery to start a vehicle. Accurate estimation of battery status ensures reliable and safe operation of EVs and provides information about the current and remaining charge of the battery [4]. Additionally, an accurate SoC prediction allows drivers to clearly see the remaining range of their vehicle, minimizing range anxiety. By comparing various machine learning and data-driven methods, some studies have shown that reasons such as the need for large data sets, operational requirements, and thermal behavior have an impact on the variability of the results [5-7]. The research conducted by Hannan et al. shown that SoC calculations can be made with various machine learning techniques without having information about the chemical reactions of batteries in EVs, information about filtering systems, battery models and vehicle interior feature information [8]. Vidal et al. conducted in addition to machine learning methods, the suitability of neural network-based methods such as Feedforward Neural Network (FNN), Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN) was indicated by various comparisons [9]. In the study conducted by Shah et al., shown that battery charge states can be predicted with a method based on heuristic algorithms, apart from machine learning and deep learning methods [10]. According to some studies in the literature on SoC estimation, it has been stated that battery charge and discharge characteristics depend on some values (signal energy, average temperature of the cells, slope of the charge and discharge voltage curves, distance traveled by the vehicle, etc.) [11-14].

In this study, SoC prediction in EVs was carried out with models trained on the data collected by using the Musoshi Pop-Up Mini vehicle [15] to help EV users alleviate their range anxiety. The obtained prediction results show that the applied method successfully predicts the SoC.

2. Methodology

Within the scope of the study, SoC estimation was carried out using the L5 type electric vehicle of Musoshi company. The block diagram explaining the methodology of the study is given in Figure 1, and the details are explained in the following sub-sections.

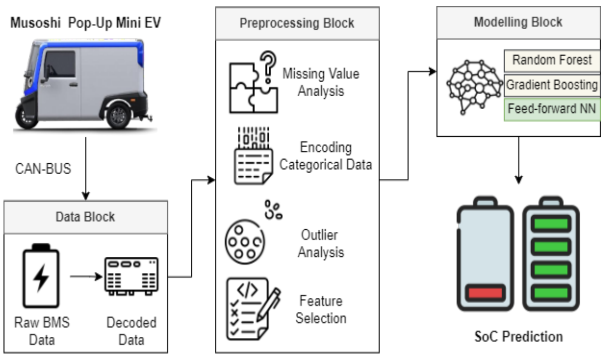

Figure 1: Block diagram of the system

2.1. Data Understanding

Data was collected via the CAN BUS of the EV. This data is stored in csv file containing "*Time_Stamp*" and "*Decoded_Data*" columns. The data in the "*Time_Stamp*" column is organized in date format, and the data in the "*Decoded_Data*" column is organized in key-value pairs. Since any data is read from the vehicle recorded in the csv file, this causes data traffic to occur at a high frequency, the number of data read in one second to vary and to contain different information about the vehicle. In order to make the available data set suitable for modeling, the data contained in each second has been grouped. When grouping, if the recurring key values are numerical, they are represented by the average of the values, and if they are categorical, they are represented by the last value line.

2.2. Data Preprocessing

After the data collection, various pre-processes were conducted to make it suitable for the machine learning model. First, errors in the data set that were easily separated were manually corrected. Then, filling in missing values, encoding categorical variables, eliminating outliers, and calculating feature importance were performed.

2.2.1. Filling Missing Values

Since the "*None*" value in many cells in the data set is not applicable to the prediction model, missing values were filled in the columns by using "*backward*" and "*forward*" filling techniques together.

2.2.2. Encoding Categorical Variables

Since some variables in the data set can take binary values and some variables can take multiple values, the "*One Hot Encoding*" technique was used to encode categorical columns.

2.2.3. Outlier Analysis

In order to eliminate some abnormal observations that are difficult to distinguish, the "*Local Outlier Factor (LOF)*" method, which focuses on the application of outlier detection in local areas of data points and is widely preferred for real-time systems, was used.

2.2.4. Feature Importance

It has been observed that features such as "*PACK_Q*" capacity values in the BMS and the calculated potential range have highly correlated with the SoC value. These values, which include the nominal and total capacitance of the battery, are used in the SoC calculation. Considering that the SoC value is a function of open circuit voltage found through terminal voltage, current and inner resistance of the battery, these features are expected to be important in the prediction model. Similarly, considering the temperature-dependent change of battery inner resistance, which is important in open circuit voltage, it can be said that the temperature value also contributes to the SoC calculation.

The importance scores of the features in the data set used in the study were obtained using SHAP and LIME methods. The importance values of the features for which the model achieved the best prediction results are given in Table 1.

Table 1: Some features with importance scores

Feature	LIME	SHAP
Cell Voltage	0.124	0.545
Cell Current	-0.053	0.246
Cell Temperature	0.091	6.361
Power	0.339	0.472
Vehicle Speed	7.069	3.874
Vehicle Mode (Charge / Discharge)	0.852	7.666
Total CMU1	-0.429	2.603
Total CMU2	0.329	2.528

2.3. Models and Metrics

In the study, SoC prediction was performed using "*Random Forest (RF)*", "*Gradient Boosting (GB)*" and "*Feed-forward Neural Network (FNN)*" methods, and the model results were evaluated "*Mean Squared Error (MSE)*", "*Mean Absolute Error (MAE)*" and "*R2*" metrics.

3. Application

The EV used in the study has a range of 125 km, a load capacity of 400 kg and a cargo volume of 1500 liters; it has a battery life of 3000 cycles/5 years, a battery capacity of 15kWh, the ability to reach 90% charging capacity via a standard home socket in 6 hours, climb a 25% slope and reach a maximum speed of 55km/h. While the raw data collected for training contains a total of 11,937,720 rows and 164 columns, after the preprocessing the training data suitable for the model consists of 27,426 rows and 10 columns. 3-different model were compared in the training for charge and discharge states and the prediction performances are given in Table 2.

Table 2: Model performances for discharge state

Feature	MSE	MAE	R2
Random Forest	5.33	1.91	0.85
Gradient Boosting	3.33	1.49	0.90
Feed-forward NN	1.98	1.17	0.94

As can be seen in Table 2, the most successful results were obtained in the FNN model for all metrics. SoC predictions made using the FNN model are shown in Figure 2.

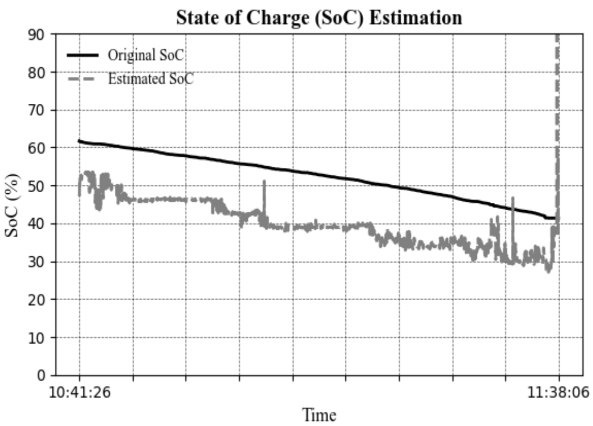

Figure 2: Original SoC prediction

As can be seen in Figure 2, the prediction results are not smooth enough and there are some spikes. To overcome this situation, some post-processing steps were applied to ensure that the model predictions were more accurate. First, the Kalman filter was used, which helps make more accurate predictions by reducing noise and errors. Rounding mean filter and anti-aliasing processes were applied to ensure the understandability of the results, smoothing and eliminating spikes. The post-processed result is given in Figure 3.

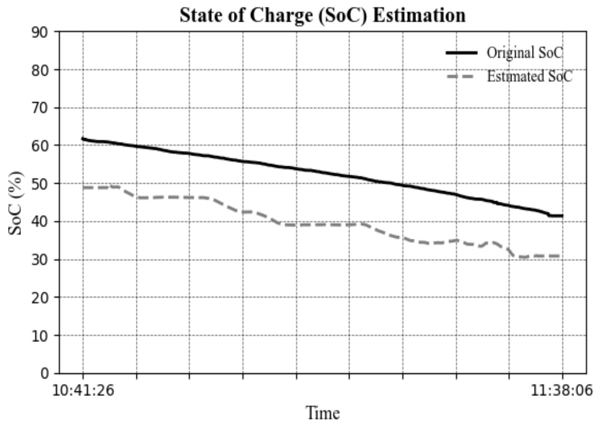

Figure 3: Post-processed SoC prediction

Although the model is capable of SoC prediction, it has problems finding the initial state of the SoC value. Therefore, the initial state of the SoC value was determined by reading the received data, balancing the difference between the prediction and the reality, and offset the prediction results by the difference value. The final prediction is given in Figure 4.

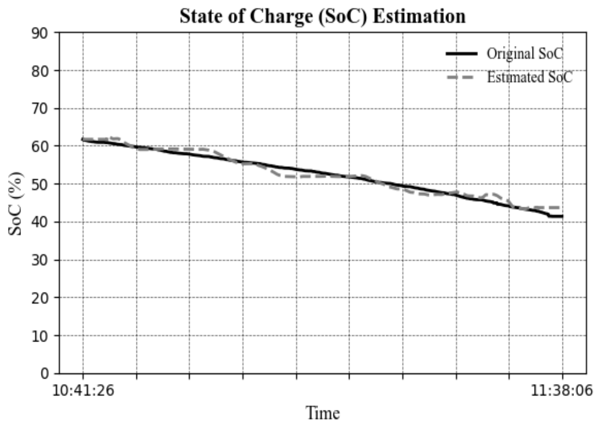

Figure 4: Final SoC prediction

In similar manner, in the tests performed on charging data using the FNN model, the performance was found to be 1.64, 0.99, 0.98, considering the *MSE*, *MAE* and *R2* metrics, respectively. The obtained charging state prediction result is visualized in Figure 5.

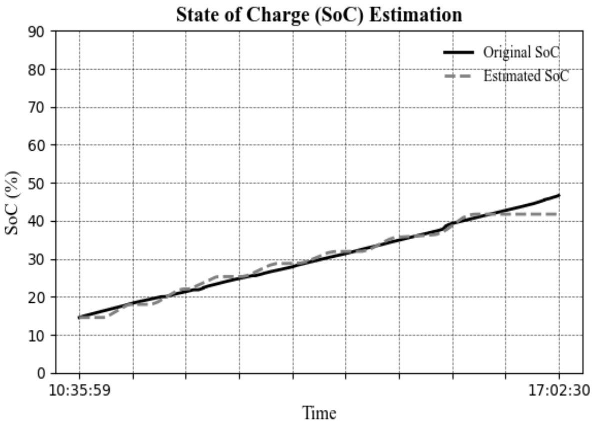

Figure 5: Final SoC prediction for charging state

4. Conclusions

With the increasing use of EVs, range anxiety, which refers to how far the vehicles can travel before their battery runs out, creates a psychological barrier on vehicle drivers. An accurate and successful SoC prediction allows drivers to minimize this concern by providing a clear view of their vehicle's remaining range. In this study, SoC prediction was carried out using the Musoshi Pop-Up Mini EV. In the study, the data collected via the vehicle's CAN BUS line was made suitable for modeling by undergoing some pre-processing, and the important features that were effective in the model performance were selected by calculating the importance scores in the raw data. During the modeling process, the performances of different models were compared with *MSE*, *MAE* and *R2* metrics and it was seen that the FNN model fruited more satisfactory results in SoC prediction. Various post-processing steps have been applied to make the prediction results more apprehensible. The successful application of the methods proposed in this paper highlights the practical applicability of SoC prediction.

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