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Estimating the battery life of an electric train using the ANFIS model

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Batteries as a power source for electric trains have been considered due to a number of advantages, including flexibility, reduced air and noise pollution, and lower operating costs . Estimating the lifespan of batteries is one of the most basic challenges to evaluating their economic efficiency. This article presents a helpful life forecast of lithium-ion batteries in electric trains, utilizing the Adaptive Neuro-Fuzzy Inference System (ANFIS) to determine replacement time and economic efficiency. To assess battery performance in electric trains, the train dynamic model is simulated for one motion cycle. In this simulation, the speed profile of the train is considered to be constant and repeated, and then, by applying the current consumption of the train to the battery, the battery's life is predicted for a limited length of time using machine learning (ML) models. In the test stage, comparing the ANFIS model to other ML methods indicates that it outperforms all error indicators and has a higher accuracy for estimating battery life.

1. Introduction

In recent years, sustainable development in transportation has been considered as a solution to reduce air pollution and improve energy consumption performance. Electric vehicles (EVs) provide several advantages over typical gasoline vehicles, including less pollution in the air, increased energy efficiency, and a chance to apply a green energy economy strategy [1]. The predicted decrease in carbon dioxide emissions by electric trains until 2050 in Japan and England shows that electric trains may play a key role in minimizing greenhouse gas emissions in transportation by rail [2]. Electric vehicles (EVs) powered by batteries climbed by 63% in 2018 over the previous year and have been growing rapidly over the last decade [3].

Batteries are one of the most important energy sources supporting transportation innovation. In the railway industry, which is mainly dependent on diesel power, batteries are gaining popularity as a sustainable energy source and an alternative to traditional diesel trains [4]. Battery electric trains are a new generation of rail vehicles that combine the advantages of electric trains with the ability to run on diesel routes. Figure 1 shows a battery-electric multi-unit (BEMU) test train. It is one of the globe's first "new generation" battery trains for passenger transport. A battery-electric train fleet can be 20% less expensive than a diesel fleet, decreasing greenhouse gas emissions by 98% [5]. In addition, electric-battery trains emit the least noise pollution compared to other traditional rail vehicles [6].

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Figure 1. The Alstom BEMU test train [5].

Electric-battery trains make it possible to utilize low-cost renewable energy sources [7]. Electric trains can use Transportable battery-based energy storage (TBES) to store energy along the route and distribute it to the grid as needed. This can help increase energy efficiency and save costs [8]. The use of battery propulsion systems to replace diesel engines in typical electric trains is considered a viable alternative. Recent research showed that these systems can replace diesel engines and increase train performance [9].

Li-ion batteries are fast gaining popularity in EV applications due to a number of advantages, including high specific energy, low self-discharge rate, high energy density, long lifespan, high charge and discharge capacity, and high cell potential [10]. Figure 2 compares the energy density of several types of batteries. This figure shows that lithium-ion batteries have the highest energy density among all types of batteries. This makes them suitable for tensile applications [1].

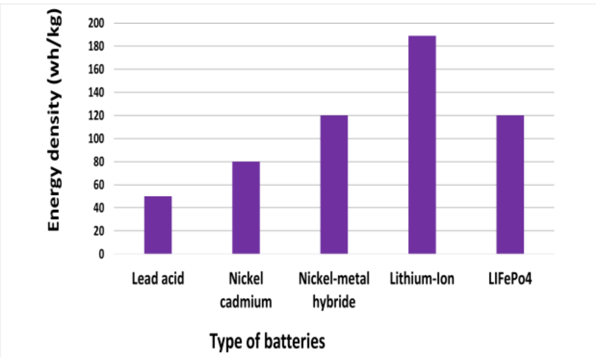

Fig. 2. Comparison of various batteries based on energy density [1].

Traction batteries lose capacity with time, particularly with long-term use. Batteries deteriorate due to chemical and physical reactions that destroy active parts over time [11]. An intelligent battery management system (BMS) is indispensable for improving the performance and efficiency of EVs. Accurate state of health (SOH) estimates by BMS improve battery safety, lifespan, and dependability, resulting in better EV performance and productivity [12].

SOH estimate strategies may be classified into two types: model-based methods and data-driven methods [13]. Model-based techniques describe the degradation of lithium-ion batteries using mathematical models. Methods based on models are divided into three categories: electrochemical model (EM) [14], equivalent circuit model (ECM) [15], and experimental model [16]. These models take into account the internal characteristics and degradation mechanisms of the battery and are partially dependent on the accuracy of the models [17]. Data-driven methods use experimental data to train a machine learning model to estimate SOH without using mathematical models. These models do not require detailed knowledge of the physical and chemical properties of the battery and are less sensitive to disturbances. Recent research results have shown that data-driven methods can reduce many of the disadvantages of model-driven methods [18].

Recently, deep learning networks have been introduced as new methods for forecasting the SOH of lithium-ion batteries. In reference [19], Long Short-Term Memory (LSTM) (LSTMs) are utilized to forecast the SOH of lithium-ion batteries for EVs. These networks estimate SOH

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by extracting battery-related features and modeling the complex relationships between them. In reference [20], features from battery data are extracted using convolutional neural networks (CNN). These measurements include battery terminal voltage, charge/discharge current, battery temperature, and vehicle speed. CNN converts this data into characteristics that may be used to calculate battery SOH in EVs and hybrid vehicles. According to reference [21], the suggested method for estimating the SOH of lithium-ion batteries in EVs uses a support vector machine (SVR) and is more accurate and faster to convergence than the other two methods. The results show that SVR is a suitable choice for this application. The reference [22] uses the radial basis function (RBF) as the basis function in the hidden layer of a radial basis function neural network (RBFNN) to model the nonlinear relationships between battery features and SOH. Because Li-ion batteries show nonlinear behavior, this helps to improve SOH estimate accuracy. In reference [23], ANFIS was utilized to estimate SOH in lithium-ion batteries in rechargeable hybrid and electric vehicles, and the findings show that this technique is highly accurate. Reference [24] presents an ANFIS-based method to predict SOH in an EV. The proposed technique consists of creating a model, training, and SOH estimation.

In this paper, the combination of fuzzy logic and neural networks [25] is studied for the first time in the electric rail system for more exact forecasting of lithium-ion battery life. In electric rail systems, lithium-ion batteries are exposed to hard working conditions such as high charge and discharge currents, high temperatures, and vibration. These factors might cause uncertainty in battery performance. ANFIS is a machine learning method that can take this uncertainty into account and estimate battery life with higher accuracy. Due to advantages such as the ability to model nonlinear relationships, learn from incomplete data, and generalize to new data, this approach is a suitable and innovative alternative for estimating battery life in electric railway systems.

The other parts of this article are organized as follows: Section 2 describes the object and content of this paper with a flowchart of the SOH prediction method based on the ANFIS model.

Section 2.1 examines the basic theoretical knowledge utilized. Section 2.2 presents the dynamic modeling of the train. Section 3 includes the modeling of Li-ion batteries using MATLAB ready-made blocks. Section 4 explains the dataset and data processing for predicting the SOH of lithium-ion batteries in electric trains. Section 5 presents performance evaluation indicators. Finally, Section 6 compares the battery life created by the ANFIS approach to other ML methods based on performance evaluation indicators.

2. Method

Machine learning algorithms for estimating battery life require effective estimation data, such as the train's voltage and current consumption. Dynamic model of an electric train is developed for a designed motion profile. The needed parameters are produced based on the controlled movement of the train; these parameters are applied to the battery, and the life of the battery is obtained for a limited period and finally developed. By simulating an electric train motion cycle, the values of voltage, current, duration, and battery life were obtained in that cycle, and considering the repeatability of the electric train motion cycle, the data has been developed for a limited period. Machine learning models train utilizing 80% of the data (614 hours equivalent to 25 days) and test with 20% of the data (154 hours equivalent to 7 days). Figure 3 presents the ANFIS model, which was created using three input variables: voltage, current, and time, to predict the output variable SOH. Figure 4 shows the flowchart of the ANFIS model-based SOH forecast process.

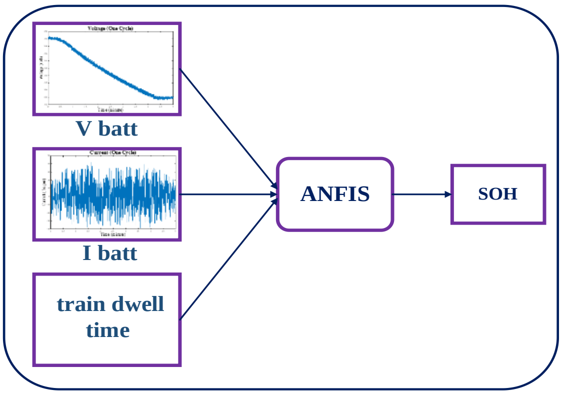

Fig. 3. Structure diagram of ANFIS.

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2.1. Definition of ANFIS

The fuzzy neural network is a hybrid intelligent system that combines the advantages of neural networks and fuzzy systems, outperforming either of them alone. In intelligent

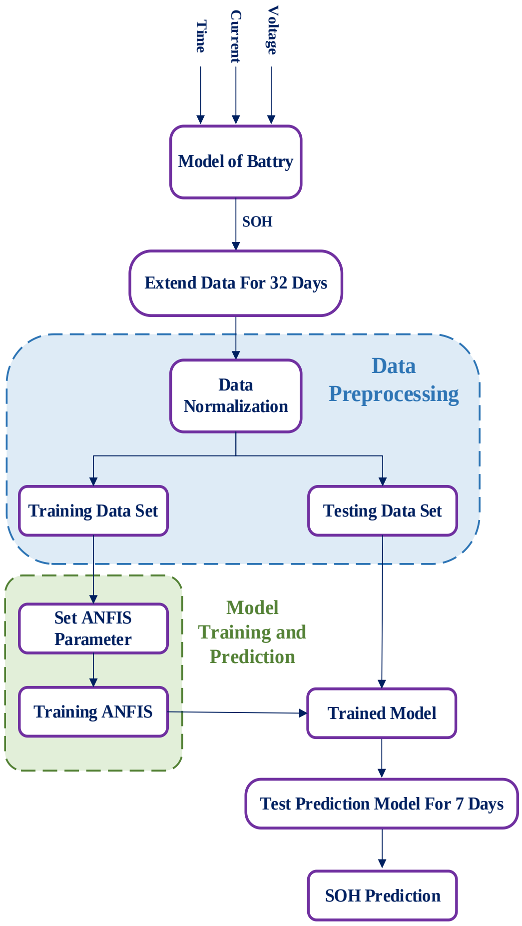

Fig. 4. Flowchart of SOH prediction utilizing an ANFIS model.

systems, fuzzy logic and RNA complement each other for modeling and learning. Neural networks are suited for processing raw data, while fuzzy logic is appropriate for high-level reasoning and decision-making [26]. Fuzzy systems, on the other hand, are unable to learn and adapt to new conditions. However, although neural networks can learn, they are not obvious to the user. Integrated neuro-fuzzy systems combine neural network parallel processing and learning skills with fuzzy systems' data presentation and human-like explanation capabilities to enable complex problems to be solved. In light of Takagi-Sugeno fuzzy systems, ANFIS hybrid neuro-fuzzy systems perform similarly to adaptive neural networks [27]. Neuro-ANFIS fuzzy systems, in contrast to typical fuzzy systems, can adjust during the learning process. In some cases, after the design of fuzzy systems, it is possible to modify the fuzzy membership functions using optimization techniques to improve performance and adapt to new conditions [27]. Several references, such as [28] and [29], present details about the educational process in an ANFIS. ANFIS is utilized in a variety of applications, including control, diagnostics, prediction, and decision-making. Figure 5 displays the ANFIS architecture.

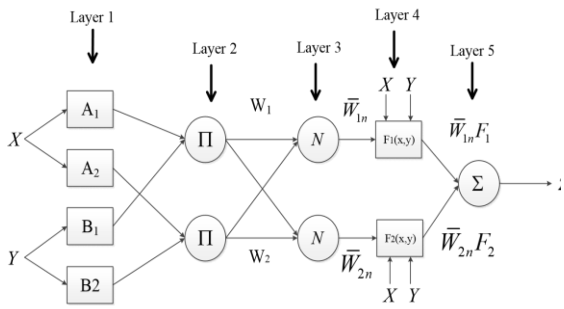

Figure 5. A general adaptive neural-fuzzy inference system [27].

2.2. Dynamic train modeling

The dynamic equations of a train are a collection of mathematical equations used to model train movements and analyze their dynamic behavior [30]. Position, velocity, and acceleration are the three main variables affecting train movement [31]. As illustrated in Figure 6, Newton's second law of motion [32] relates these variables to the forces affecting the train. The train's motion can be described using Equations (1) to (6) [33].

$$F_{Trac} - \sum F_R = M\frac{dv}{dt} \tag{1}$$

$$F_R = F_{rr} + F_{ar} + F_{gr} \tag{2}$$

$$F_{rr} = f_r M g \cos\alpha \tag{3}$$

$$F_{ar} = \frac{1}{2} C_w A \rho v^2 \tag{4}$$

$$F_{gr} = f_r M g \sin\alpha \tag{5}$$

$$F_{Trac} = f_r M g \cos\alpha + \frac{1}{2} C_w A \rho v^2 + f_r M g \sin\alpha + M\frac{dv}{dt} \tag{6}$$

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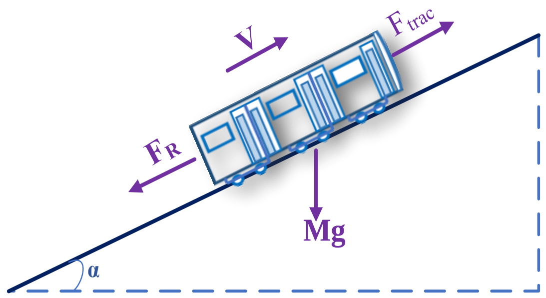

Fig. 6. Forces affecting train motion [32].

A train's dynamic equations calculate the load applied to the shaft of its electric motor based on the track's speed and gradient. Equations (7) and (8) can be used to determine torque and angular velocity given four axles per train. The inputs in these equations are the track's speed and slope, while the outputs are torque and angular velocity. The inclination angle of the track is considered zero here.

$$T = \frac{F_{Trac} r}{4 n_c} \tag{7}$$

$$\omega_w = \frac{v}{r} \tag{8}$$

To describe a train's dynamic behavior, the equations were implemented in MATLAB. This model regarded train motion as a cyclic movement with three stages: acceleration, constant speed, and braking. Figure 7 depicts the speed profile of a train throughout a single operational cycle. The speed controller must match the train's speed to the profile as closely as possible. Figure 8 shows that the speed controller performed well, and the train's speed closely matched the intended profile.

3. Battery modeling

The motion cycle of the train speed is controlled using the modeling described in Section 2.2. The electric train's speed profile is a repeating cycle, as are the train's voltage and current consumption. The repetitive cycle can be continuously replicated. The timeframe of this cycle corresponds to the time the train accelerates, maintains constant speed, decelerates, and comes to a halt at the station.

Battery voltage and current usage are two main factors that dictate the battery life span. The

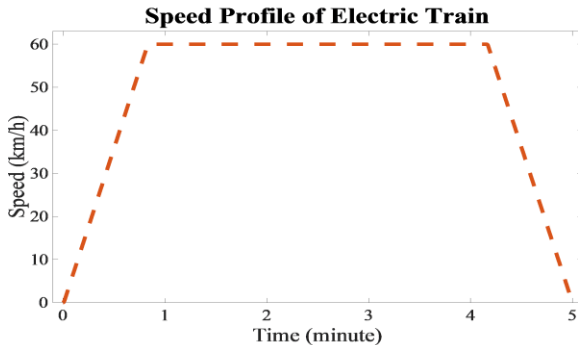

Fig. 7. Speed profile of an electric train.

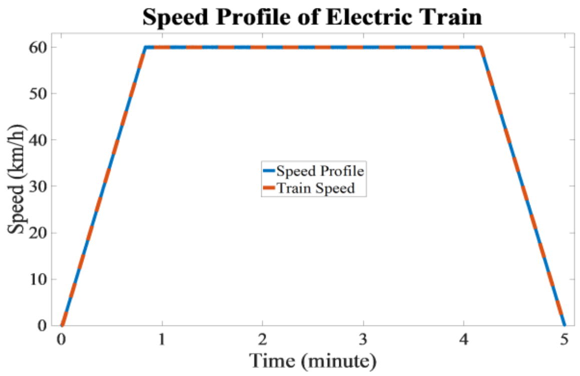

Fig. 8. The speed of the train matches the speed profile.

battery life decreases with increasing voltage and current usage. The current, voltage, and battery life of an electric train during a single stage of the repeated cycle are calculated using the train's features and the repetitive cycle depicted in Figure 9. An electric train's current and voltage are determined and replicated for each cycle until the battery's life is over. This is accomplished with the MATLAB Simulink ready-made lithium-ion battery block. Table 1 shows battery parameter information. The battery's lifespan is computed based on the input data, and the SOH curve is presented in Figure 10.

Table 1. Lithium-ion battery parameters.

Type	Lithium-ion
Nominal voltage	200 v
Rated capacity	1000 Ah
Initial state of charge	100 %
Battery response time	90 s

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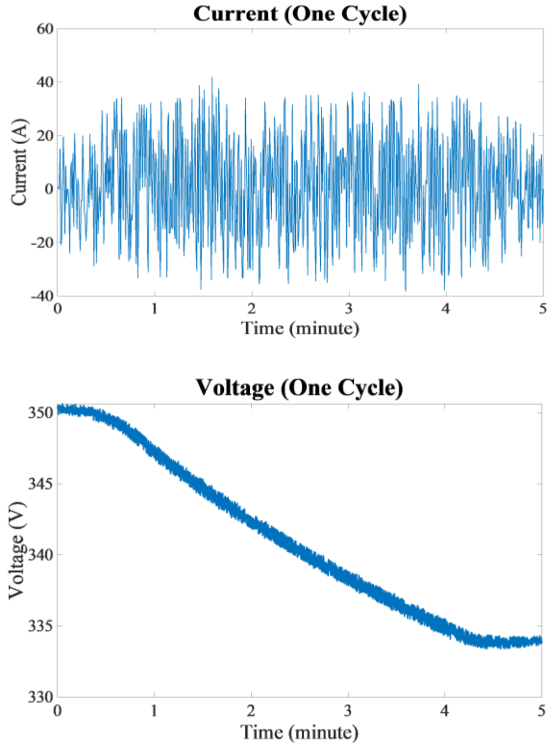

Fig. 9. The Current and voltage used by the electric train from the battery for one cycle.

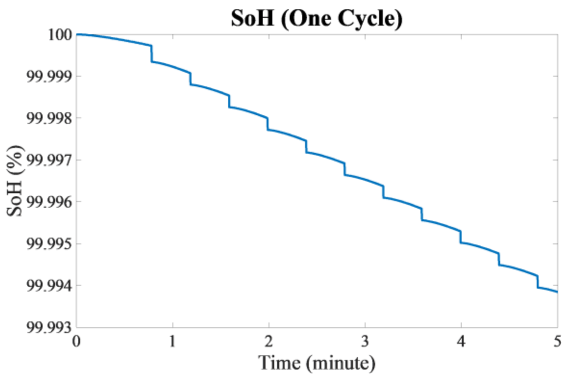

Fig. 10. Battery life for one motion cycle.

4. Data preprocessing

Data preprocessing guarantees that the model isn't distorted by mistaken amounts, and it is also averaged on a regular basis to prevent short-term oscillations. Normalization is one of the important steps in data preprocessing. Data normalization is frequently utilized in deep modeling techniques, where it can improve model convergence and forecasting precision [34]. Data normalization, by scaling the units of data, can improve the performance of ML models.

In this article, the Min-Max method is utilized to normalize the data. This method converts the data into the interval [0, 1]. This is shown in Equation (9).

$$X = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (9)$$

where x represents the sample data, X_{max} represents the maximum value of the sample data, and X_{min} represents the minimum value of the sample data.

5. Performance evaluation indicators

Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2 are used as indicators to evaluate the results of the proposed model. RMSE and MAE assess the error between the predicted and real SOH curves. The model's accuracy will improve when these two error indications decrease. The R^2 criterion evaluates the fit between. The closer the R2 number is to one, the greater the correlation between the predicted and actual values [35]. The three evaluation indicators are specified as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_i - \hat{Q}_i)^2} \quad (10)$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|(Q_i - \hat{Q}_i)\right| \quad (11)$$

$$R^2 = 1 - \frac{\sum_i(\hat{Q}_i - Q_i)^2}{\sum_i(\bar{Q}_i - Q_i)^2} \quad (12)$$

Q_i is the real SOH value, $\hat{Q}_i$ is the model's predicted SOH value, $\bar{Q}_i$ is the average SOH value of the lithium-ion battery, and n is the number of samples.

6. Results

A comparison of the ANFIS model with three other ML methods (SVR, LSTM, and RBF) is done in this section to show its advantages in battery life estimation. In the battery life evaluation process, the model outputs are evaluated to forecast the battery life. In this example, the training and test data are input into the training models to compare the results to the

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ANFIS model. This comparison is also depicted in Figures 11 and 12.

The RBF model performed well through the training stage, even estimating the stairs at multiple points. This model performed less accurately in the test stage, but it estimated the slope. During the training stage, the SVR model can predict a descent slope with large-amplitude fluctuations. However, some domains cross the target chart and sit at the top of it. But throughout the testing phase, the model's accuracy was low, and it performed poorly in different situations. However, the slope is estimated with a bias below the target chart. In the training stage, the LSTM model is put below the target model, and after several iterations, it has crossed the target curve but detected the slope. In the test stage, with several repetitions from the chart, it fell below the target chart, and on the 27th day, it moved away from the top of the chart. The ANFIS model performed well in the training stage, forecasting the slope with a limited oscillation range. It is better in the testing phase, and while there are fluctuations, they are very

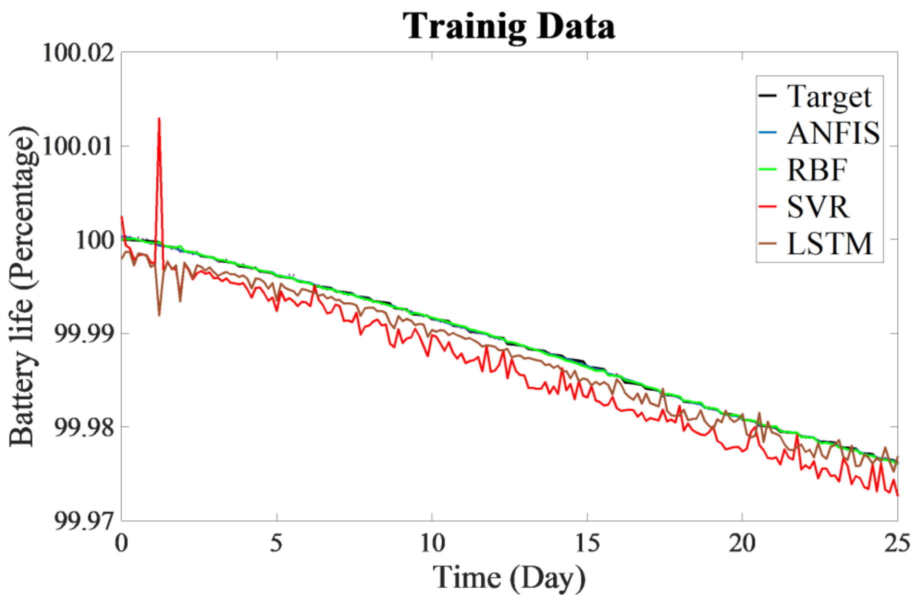

Figure 11. Comparing the output of the trained models with the training data.

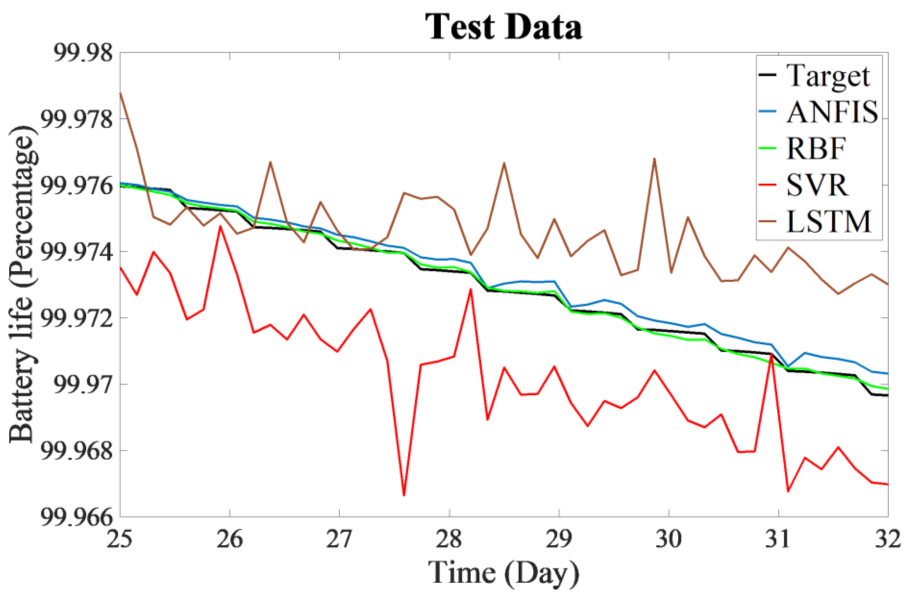

Figure 12. Comparing the output of the trained models with the testing data

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near the target chart. Figures 11 and 12 show graphic comparisons of the models. However, accuracies cannot be discerned by the eye. To correctly compare the outputs of these models, the criteria explained in Section 5 were used. The results of this comparison are presented in Table 2.

Table 2. Comparison of model structure.

	Train			Test		
	R^2	MAE	RMSE	R^2	MAE	RMSE
SVR	0.55852	2.9246e-05	6.0617e-05	0.64903	2.8681e-05	5.2939e-05
RBF	0.99985	8.7012e-07	1.1163e-06	0.77376	3.1531e-06	4.4416e-05
LSTM	0.96162	1.51e-05	1.7983e-05	0.9617	1.45e-05	1.7017e-05
ANFIS	0.99979	8.20e-07	1.0609e-06	0.96267	3.08e-06	3.5217e-06

As shown in Table 2, the ANFIS model's RMSE and MAE evaluation indices throughout the training and testing stages are lower than those of other models. This matches the results presented in Figures 11 and 12. In the testing stage, the ANFIS model has a higher R^2 index compared to other models.

The ANFIS model, which combines neural networks with fuzzy logic capabilities, outperforms the RBF model. The RBF model operates well in the training phase but weakly in the testing phase. In the test phase, the RMSE index of the RBF model is 12 times higher than that of the ANFIS model. During the R^2 index test phase, the RBF model outperforms the ANFIS model by less than 0.001%.

Figures 13 and 14 include bar graphs comparing the performance of machine learning models based on error indicators in the training and testing stages. In the testing stage, the RMSE and MAE values for the ANFIS model are 3.5217×10^{-6} and 3.08×10^{-6}. This is less than other models, making it the most efficient model among them. In the test stage, the value of R^2 is

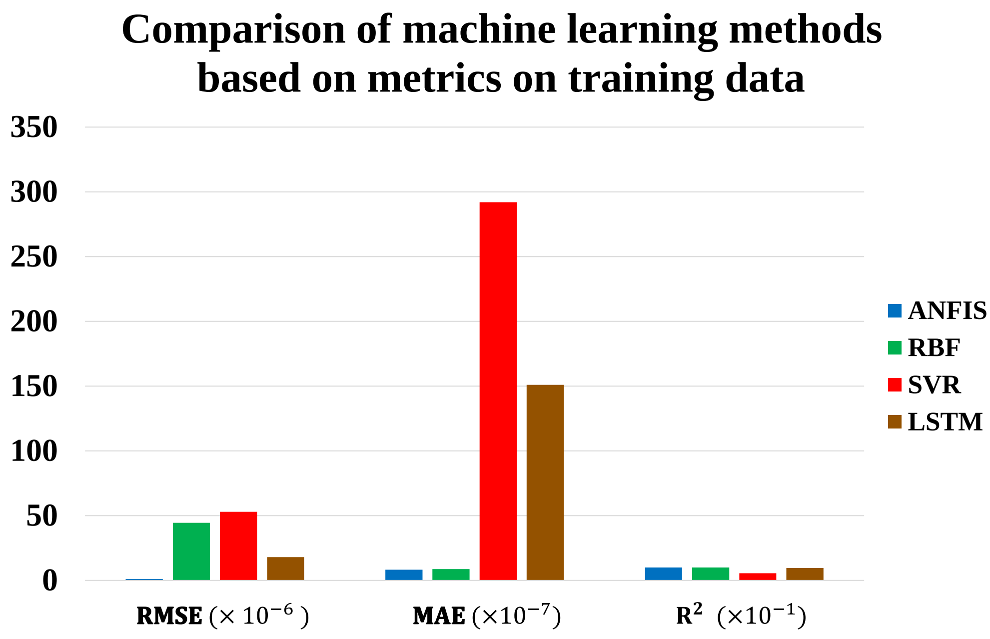

Fig.13 Comparison of Machine Learning models based on error parameters in the training phase.

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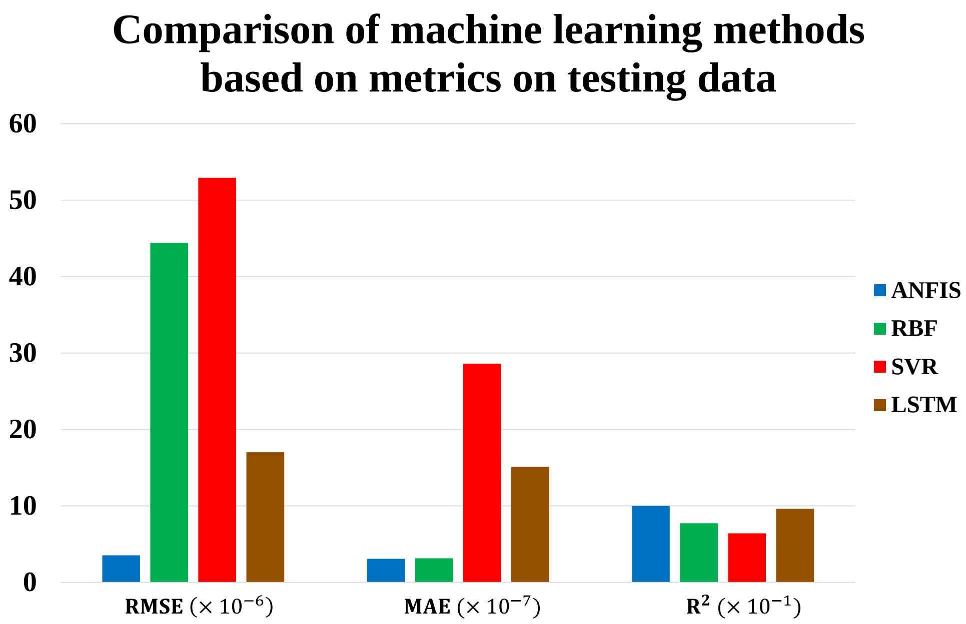

Fig.14 Comparison of Machine Learning models based on error parameters in the testing phase.

equal to 0.96267, showing that the ANFIS model shows a higher correlation between predictions and actual values than other models.

7. Conclusion

Considering the safety and dependability of lithium-ion batteries in electric trains, this paper proposes an ANFIS model for predicting the SOH of lithium-ion batteries. The ANFIS model utilizes fuzzy logic to account for the uncertainty in the performance of lithium-ion batteries, resulting in an accurate estimation of their SOH. The ANFIS model receives three inputs: time, voltage, and current, while the output is an estimate of the battery's remaining life.

The study on lithium-ion battery SOH forecasting shows that the ANFIS model outperforms other ML methods in terms of RMSE and MAE in both training and testing stages. In the training stage, the RMSE of the ANFIS model is 1.0609×10^{-6}, and the MAE is 8.20×10^{-7}. In the testing stage, the RMSE is 3.5217×10^{-6} , and the MAE is 3.08×10^{-6}. This advantage indicates that the ANFIS model predicts the SOH of lithium-ion batteries more accurately than other ML methods.

The proposed method's high accuracy in estimating battery lifespan can help accurately estimate the time of battery replacement, reducing battery replacement costs and improving train useful life.

List of symbols

A	Projected frontal area of the vehicle /train.
C_w	Drag coefficient.
F_{trac}	Tractive force.
F_R	Resistive forces.
F_{rr}	Rolling Resistive force.
F_{ar}	*Aerodynamics drag force.*
F_{gr}	*Gradient force due to slope/inclination of the rail.*
G	*Acceleration due to gravity (9.81 m/s2).*
M	*Effective mass of the train.*
n_c	*Numbers of cars of the train.*
R	*Radius of the train's wheel.*
f_r	*Rolling resistance coefficient.*
v	*Imposed train velocity.*
A	*Inclination angle.*
P	*Air density.*

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