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A Kolmogorov-Arnold neural networks approach to state of charge estimation and confidence assessment for Li-ion batteries

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Abstract. This study aims to thoroughly examine the potential of the Kolmogorov-Arnold Network (KAN) and its application to improving energy management efficiency, particularly in lithium-ion batteries. The study employs a novel method that utilizes one-dimensional adaptive activation functions parameterized by splines, in contrast to traditional neural networks, where activation functions are fixed. Traditional methods for activation function selection are based on empirical approaches and do not guarantee accurate approximation, potentially leading to suboptimal results. This approach enables the KAN to flexibly adapt to complex data structures, ensuring precise state-of-charge estimation. To objectively evaluate the algorithm's effectiveness, experiments were conducted on real datasets, focusing on analyzing the accuracy of state-of-charge estimation at confidence intervals of 95%, 90%, and 85%. The test results for various charge-discharge cycles demonstrated that the proposed method achieves high accuracy and maintains stability throughout the operation. The proposed method reduces the maximum error by at least 4.26% and significantly improves key performance metrics such as Mean Absolute Error, Root Mean Square Error. Thus, the obtained results confirm the efficiency and innovative nature of the KAN in energy management. This method holds great potential for energy management and can be effectively implemented in areas requiring precise time-series forecasting, including smart home systems, electric vehicles, and industrial devices. Future research will optimize the network architecture and expand its practical applications. Significantly, this method can be flexibly adapted to different types of batteries and energy systems, broadening its applicability in real-world conditions.

Keywords: state of charge, Kolmogorov-Arnold networks, energy storage, neural network, prediction interval

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ЭНЕРГЕТИКА

Научная статья
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Подход на основе нейронных сетей Колмогорова-Арнольда к оценке состояния заряда и оценке интервала прогнозирования для литий-ионных аккумуляторов

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Резюме. Цель исследования – детальное изучение потенциала сети Колмогорова-Арнольда и его использование для повышения эффективности управления энергией, в частности в литий-ионных батареях.

В работе применяется новый метод, использующий одномерные адаптивные функции активации, параметризованные сплайнами, в отличие от традиционных нейронных сетей, в которых функции активации фиксированы, их выбор эмпирический и не гарантирует точной аппроксимации, что может привести к неоптимальным результатам. Такой подход позволяет сети Колмогорова-Арнольда гибко адаптироваться к сложным структурам данных, обеспечивая точную оценку уровня заряда. Чтобы объективно оценить эффективность алгоритма, были проведены эксперименты на реальных наборах данных, направленные на анализ точности оценки уровня заряда аккумулятора при доверительных интервалах 95%, 90% и 85%. Результаты испытаний при различных циклах заряда-разряда показали, что предложенный метод достигает высокой точности и сохраняет стабильность в процессе работы. Предлагаемый метод снижает максимальную ошибку как минимум на 4,26% и значительно улучшает такие показатели, как средняя абсолютная ошибка и среднеквадратичная ошибка. Таким образом, полученные результаты подтверждают эффективность и инновационность сети Колмогорова-Арнольда в управлении энергией. Данный метод обладает высоким потенциалом в управлении энергетическими системами и может быть эффективно внедрен в области, требующие точного прогнозирования временных рядов, включая системы умного дома, электромобили и промышленные устройства. Дальнейшие исследования будут сосредоточены на оптимизации архитектуры сети и расширении ее практического использования. Примечательно, что этот метод может быть гибко адаптирован к различным типам аккумуляторов и энергетических систем, что значительно расширяет его применение в реальных условиях.

Ключевые слова: степень заряда, сеть Колмогорова-Арнольда, накопитель энергии, нейронная сеть, интервал предсказания

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Для цитирования: Дао Минь Хиен, Во Ван Чыонг, Лю Фанг, Сидоров Д.Н. Подход на основе нейронных сетей Колмогорова-Арнольда к оценке состояния заряда и оценке интервала прогнозирования для литий-ионных аккумуляторов. *iPolytech Journal*. 2025. Т. 29. № 1. С. 66–81. https://doi.org/10.21285/1814-3520-2025-1-66-81. EDN: LFPQGX.

INTRODUCTION

In recent years, the Kolmogorov-Arnold Network (KAN) has become an advanced solution in machine learning, especially for complex nonlinear problems. KAN boosts the accuracy of predictive models and enhances the representation and learning capabilities of neural networks, making them better at handling nonlinear relationships in multidimensional data. This development has broadened the applications of KAN across various fields, particularly in estimating the State of Charge (SoC) of Li-ion batteries.

Accurately estimating the SoC is crucial for effective energy management, optimizing battery performance, and ensuring system reliability [1, 2]. In the context of the rapidly growing electric vehicle and large-scale energy storage systems, accurately determining SoC helps prevent failures, optimize operating costs, and extend the lifespan of equipment. Furthermore, calculating confidence intervals for SoC estimates improves the results' accuracy and reliability and provides a comprehensive assessment tool, aiding in the analysis of KAN's SoC estimation performance in various situations.

Many machine learning methods have been researched and developed to tackle the challenges of estimating the SoC. Traditional methods like Feedforward Neural Networks and Long Short-Term Memory (LSTM) networks are widely used because they can effectively handle nonlinear data and time series [3, 4]. Especially in smart grid applications, these methods have played a significant role in optimizing energy distribution and minimizing waste [5].

Building on our previous work [6], this study further explores the potential of KAN in improving the accuracy of SoC estimation. This study builds on the methods and findings of the previous research to extend the application by focusing on real-time SoC estimation for lithium-ion batteries and integrating the confidence assessment method to significantly enhance the model's accuracy, reliability, and transparency.

This paper is structured as follows: Section 2 presents the research's theoretical foundations. Section 3 describes the architecture and functioning principles of KAN in estimating SoC. Section 4 introduces the dataset and experimental methods. Section 5 presents the results and analyzes the key

findings. Finally, Section 6 summarizes the main contributions and suggests directions for future research.

METHODOLOGY

Kolmogorov - Arnold Networks is a novel neural network architecture that replaces traditional Multi-Layer Perceptrons (MLPs). The concept behind KANs originates from the Kolmogorov-Arnold representation theorem [7, 8], while MLPs are based on the universal approximation theorem [9]. These different theoretical foundations have led to variations in how KANs and MLPs handle and represent complex relationships in data.

The Kolmogorov-Arnold representation theorem suggests that any continuous function of multiple variables f ,which depends on $x=\left[x_1,x_2,...,x_n\right]$, within a bounded domain, can be decomposed into a finite combination of more straightforward, continuous functions that involve only a single variable. Specifically, a smooth, and continuous multivariate function $f:\left[0,1\right]^n\rightarrow\ \mathbb{R}$ can be expressed as a finite superposition of certain univariate functions[10]:

$$f(x)=f(x_1,...,x_n)=\sum_{q=1}^{2n+1}\Phi_q\left(\sum_{p=1}^{n}\phi_{q,p}\left(x_p\right)\right),\quad(1)$$

where $\phi_{q,p}:\left[0,1\right]\rightarrow\ \mathbb{R}$ and $\Phi_q:\mathbb{R}\rightarrow\mathbb{R}$ denote the so-called outer and inner functions, respectively.

In terms of its structure, a KAN layer can be represented as $\Phi=\left\{\phi_{q,p}\right\},\quad p=1,2,\cdots,n_{in},\quad q=1,2,\cdots,n_{out},$ where the functions $\phi_{q,p}$ are parameterized functions with adjustable, learnable parameters. This distinctive structure enables KAN to effectively detect and model complex nonlinear relationships in data, outperforming traditional MLPs.

To maximize the potential of KAN, deeper network architectures have been developed. A KAN with a depth L is formed by stacking multiple KAN layers. The structure of this deeper KAN is represented by an integer array $\left[n_0,n_1,\cdots,n_L\right]$, where n_l indicates the number of neurons in the l^{th} layers. Each l^{th} KAN layer, takes an input with a certain number of dimensions and transforms it into an output with n_{l+1} dimensions, effectively converting the input vector from $x_l\in\mathbb{R}^{n_l}$ to $x_{l+1}\in\mathbb{R}^{n_{l+1}}$ [10].

$$x_{l+1}=\underbrace{\begin{pmatrix}\phi_{l,1,1}(\cdot) & \phi_{l,1,2}(\cdot) & \cdots & \phi_{l,1,n_l}(\cdot)\\ \phi_{l,2,1}(\cdot) & \phi_{l,2,2}(\cdot) & \cdots & \phi_{l,2,n_l}(\cdot)\\ \vdots & \vdots & & \vdots\\ \phi_{l,n_{l+1},1}(\cdot) & \phi_{l,n_{l+1},2}(\cdot) & \cdots & \phi_{l,n_{l+1},n_l}(\cdot)\end{pmatrix}}_{\Phi_l}x_l,\quad(2)$$

where Φ_l is represents the function matrix corresponding to the l^{th} KAN layer in the network.

The Kolmogorov-Arnold Theorem states that the function $f(x)$ can be represented as a composition of inner and outer function matrices applied directly to the input vector x [11, 12]:

$$f(x)=\Phi_{out}\cdot\Phi_{in}\cdot x,\quad(3)$$

where Φ_{in} is a matrix consisting of univariate functions:

$$\Phi_{in}=\begin{pmatrix}\phi_{1,1}(\cdot) & \phi_{1,2}(\cdot) & \cdots & \phi_{1,n}(\cdot)\\ \phi_{2,1}(\cdot) & \phi_{2,2}(\cdot) & \cdots & \phi_{2,n}(\cdot)\\ \vdots & \vdots & & \vdots\\ \phi_{2n+1,1}(\cdot) & \phi_{2n+1,2}(\cdot) & \cdots & \phi_{2n+1,n}(\cdot)\end{pmatrix},\quad(4)$$

Φ_{out} is a row vector containing univariate functions:

$$\Phi_{out}=\begin{pmatrix}\Phi_1(\cdot) & \cdots & \Phi_{2n+1}(\cdot)\end{pmatrix}.\quad(5)$$

These matrices represent a Kolmogorov-Arnold layer, which is the KAN's fundamental component by stacking such layers. Thus, a KAN is constructed by layering multiple Kolmogorov-Arnold layers [10]:

$$KAN(x)=\left(\Phi_{L-1}\circ\Phi_{L-2}\circ\cdots\circ\Phi_0\right)x.\quad(6)$$

The depth of the KAN, defined by the number of layers, enables the network to identify and capture more intricate patterns and relationships within the data. Each KAN layer processes the input x through a series of learnable functions, making the network highly flexible and capable of adapting to various scenarios.

The Kolmogorov-Arnold representation theorem enables the development of new neural network architectures by replacing conventional linear weights with univariate B-spline-based functions, which serve as learnable activation functions. These B-splines are expressed through the basis functions $N_{i,j}(t)$. The 0th-order basis function $N_{i,0}(t)$ is defined as follows [13, 14]:

$$N_{i,0}(t) = \begin{cases} 1 & \text{if} \quad t_i \le t \le t_{i+1} \quad \text{and} \quad t_i < t_{i+1} \\ 0 & \text{otherwise} \end{cases}. \quad (7)$$

Higher-order basis functions $N_{i,j}(t)$ are calculated using the recursive formula:

$$N_{i,j}(t) = \frac{t - t_i}{t_{i+j} - t_i} N_{i,j-1}(t) + \frac{t_{i+j+1} - t}{t_{i+j+1} - t_{i+1}} N_{i+1,j-1}(t), \quad (8)$$

where j = 1, 2, ..., p. The B-spline curve is defined by the following equation:

$$C(t) = \sum_{i=0}^{n} \mathrm{P}_i N_{i,p}(t), \quad (9)$$

is called B-spline.

This approach provides flexibility in the design of neural network architecture while also enhancing the KAN model's learning and representational capabilities. It enables the model to handle nonlinear relationships within complex data better.

DATASET DESCRIPTION

This paper explores a Li-ion battery type, using data from Mendeley, specifically the LiPo 5450 mAh battery dataset [15]. This battery is famous for applications requiring high energy and portability while supporting multiple recharges.

The study aims to use this battery to train and test the KAN predictive models and evaluate how well these methods can estimate the battery's SoC and other performance-related parameters. The dataset includes 48 charge-discharge cycles, collected in real-time at 1-second intervals and thoughtfully divided for different purposes within the study.

Additionally, Fig. 1. illustrates the correlation matrix of six indicators, including voltage,

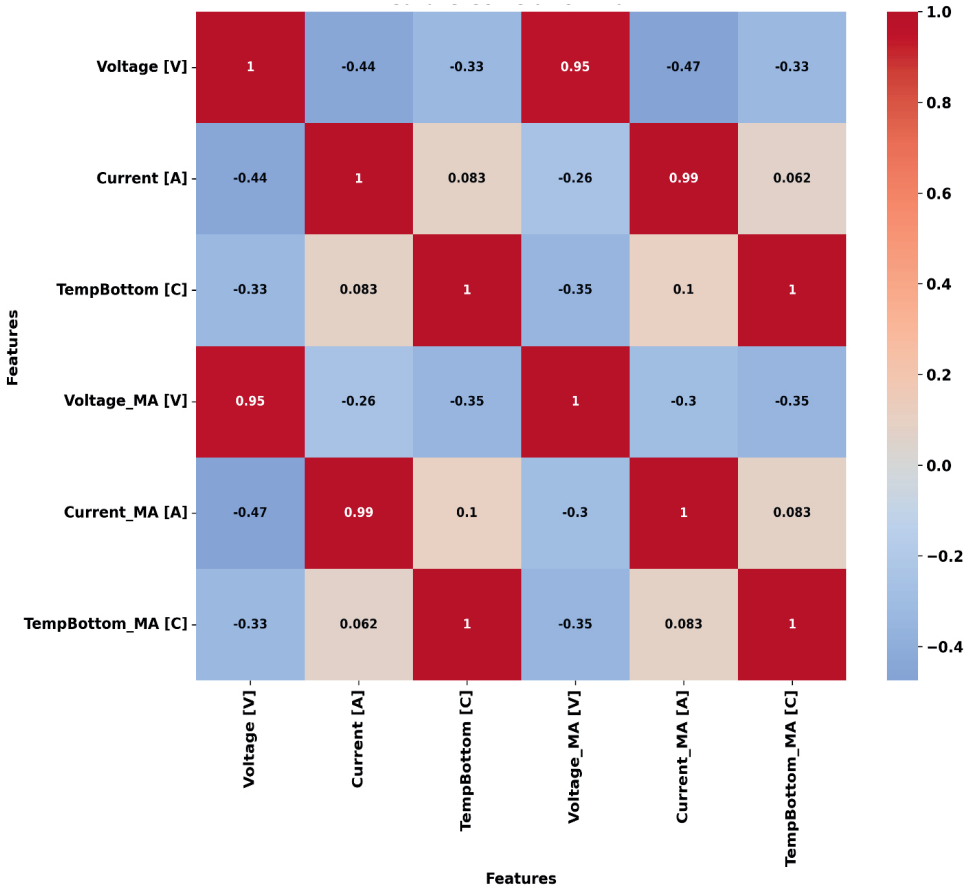


Fig. 1. *Correlation matrix chart of the data*
Рис. 1. *Диаграмма корреляционной матрицы данных*

current, temperature, and their corresponding moving average (MA) values. It shows a robust correlation (>0.95) between the original features and their MA values, meaning the MA values accurately reflect the raw data trend. Notably, a moderate negative correlation exists between voltage and current (around -0.44 to -0.47). At the same time, temperature has a weak correlation with both voltage and current (with correlation coefficients ranging from -0.35 to 0.1). The MA filter in this study plays a crucial role in eliminating noise and short-term signal fluctuations, especially when data is collected at a high frequency (once per second). MA helps smooth out sudden variations in voltage, current, and temperature, thereby providing more apparent trends for KAN predictive models while enhancing the reliability of battery SoC estimation.

Each data sample collected provides three basic input parameters: temperature, voltage, and current, which help define the operating conditions of the energy storage device. However, to improve the quality and accuracy of predictions, the dataset was further expanded with additional parameters like moving average voltage, moving average current, and moving average temperature, as illustrated in Fig. 2. This not only helps reduce noise in the data but also highlights key trends, thereby en-

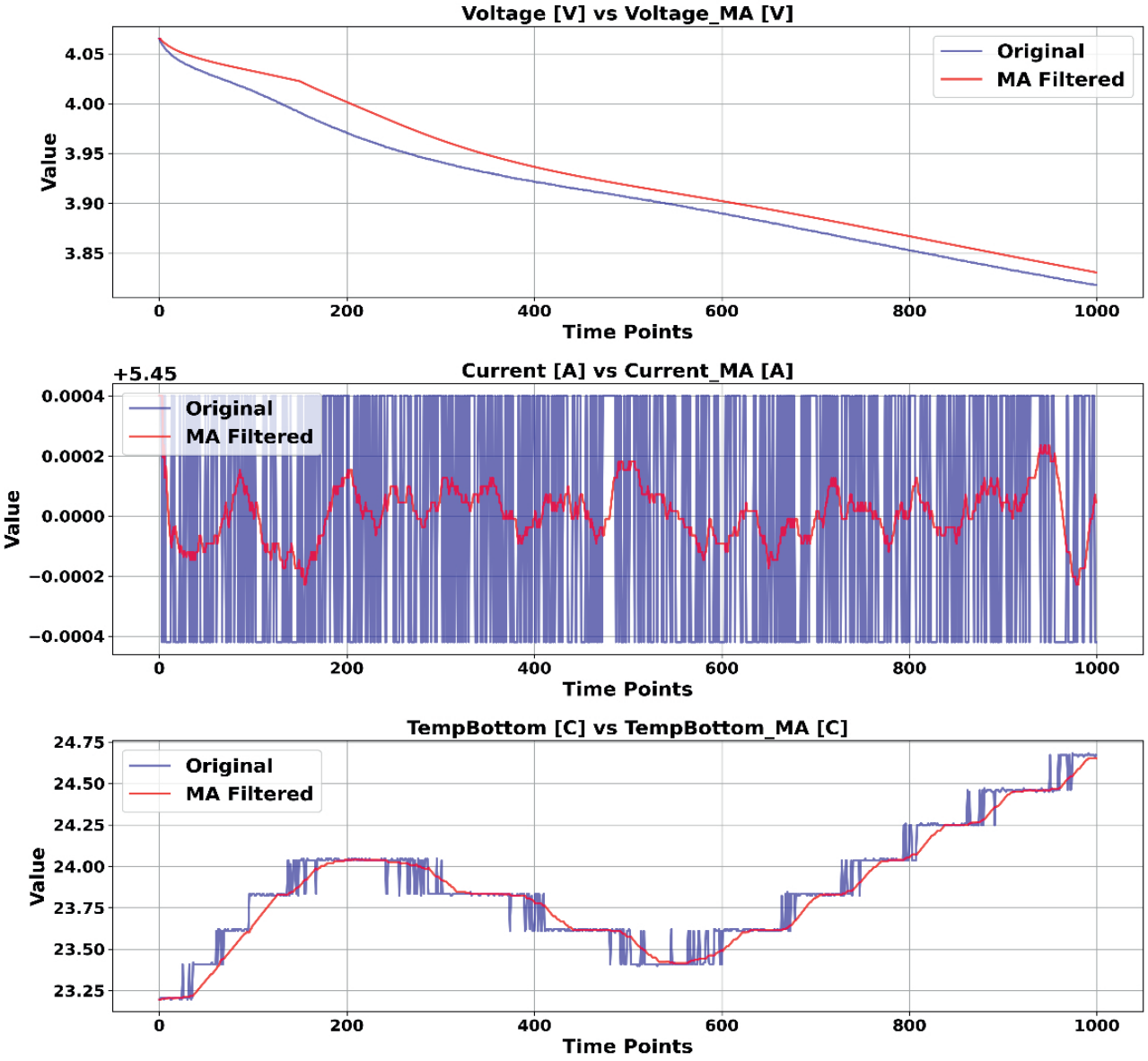


Fig. 2. *Time series analysis chart: voltage, current, and temperature using a moving average filter*
Рис. 2. *График анализа временного ряда: напряжение, ток и температура с использованием фильтра скользящего среднего*

hancing the stability and accuracy of the model when assessing the performance of energy storage devices.

KOLMOGOROV-ARNOLD NETWORKS FOR STATE OF CHARGE ESTIMATION

Let us consider the application of the KANs network to the SoC estimation problem using the LiPo 5450mAh Battery dataset, as illustrated in Fig. 3. The dataset includes six input variables: temperature, voltage, current, moving average voltage, moving average current, and moving average temperature, with the SoC.

The relationship between the inputs and the SoC can be described by a multivariable function as follows [16]:

$$SoC \approx F(T; V; C; T_{MA}; V_{MA}; C_{MA}), \quad (10)$$

where T is temperature , V is voltage, C is current, T_{MA} is moving average temperature, V_{MA} is moving average voltage, C_{MA} is moving average current.

According to the Kolmogorov-Arnold Theorem, this multivariable function can be expressed as a composition of univariate functions that depend independently on individual features:

$$X = f(\phi_T(T) + \phi_V(V) + \phi_C(C) + \phi_{T_{MA}}(T_{MA}) + \\ + \phi_{V_{MA}}(V_{MA}) + \phi_{C_{MA}}(C_{MA})), \quad (11)$$

where X is the representation of univariate functions that reflect the influence of each input variable, ϕ_T is the function representing the influence of T, ϕ_V is the function representing the influence of V, ϕ_C is the function representing the influence of C, $\phi_{T_{MA}}$ is the function representing the influence of T_{MA}, $\phi_{V_{MA}}$ is the function representing the influence of V_{MA}, $\phi_{C_{MA}}$ is the function representing the influence of C_{MA}.

More generally, the relationship can be extended across multiple functions:

$$Y = \sum_{p=1}^{m} f_p(\phi_{T_p}(T) + \phi_{V_p}(V) + \phi_{C_p}(C) + \phi_{T_{p,MA}}(T_{MA}) + \\ + \phi_{V_{p,MA}}(V_{MA}) + \phi_{C_{p,MA}}(C_{MA})), \quad (12)$$

where Y is the sum of multiple nonlinear functions that describe the general relationship between the input variables and the SoC value to be estimated, m is the number of functions f_p that aggregate the input factors, f_p is nonlinear functions. ϕ is the univariate functions depend on each input variable, $T, V, C, T_{MA}, V_{MA}, C_{MA}$ is the input variables.

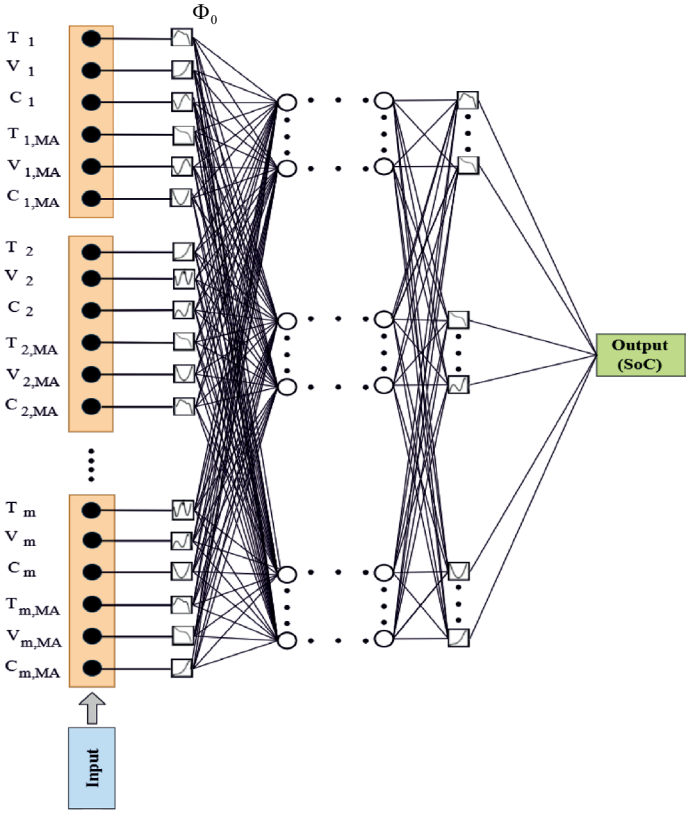


Fig. 3. *Kolmogorov-Arnold network architecture for the State of Charge*
Рис. 3. *Архитектура сети Колмогорова-Арнольда для состояния заряда*

CONFIDENCE INTERVAL

In addition to predicting the SoC as a single value, we also make predictions within a confident interval. We assume that future observed values and prediction errors follow a normal distribution. Below is the formula for calculating the confidence interval [17, 18]:

$$y_{interval} = \hat{y} \pm z_{\frac{\alpha}{2}} \cdot \sigma, \quad (13)$$

where $y_{interval}$ is the confidence interval of the output variable, $\hat{y}$ is the value of the point estimated result, $z_{\frac{\alpha}{2}}$ is normal distribution value, σ is the standard deviation of the estimated distribution.

The value of σ is estimated through the estimation error, called the residual (e_i), with n representing the number of observation, as follows [19]:

$$\sigma = \sqrt{\frac{1}{n-2}\sum_{i=1}^{n} e_i^2}. \quad (14)$$

The process of building a model to estimate SoC using KANs is carried out through several steps, as illustrated in Fig. 4. First, the data is meticulously prepared, including validation, cleaning (removing NAN values), and normalization. Then, the dataset is divided into two parts: 65% for training, 15% for validation, and the remaining 20% for testing. Next, key feature vectors such as voltage, current, and temperature are identified to capture relationships within the data.

In step three, the KAN network architecture is designed with the integration of B-spline activation functions to enhance the accuracy of SoC estimation. Step four focuses on training and validating the model by

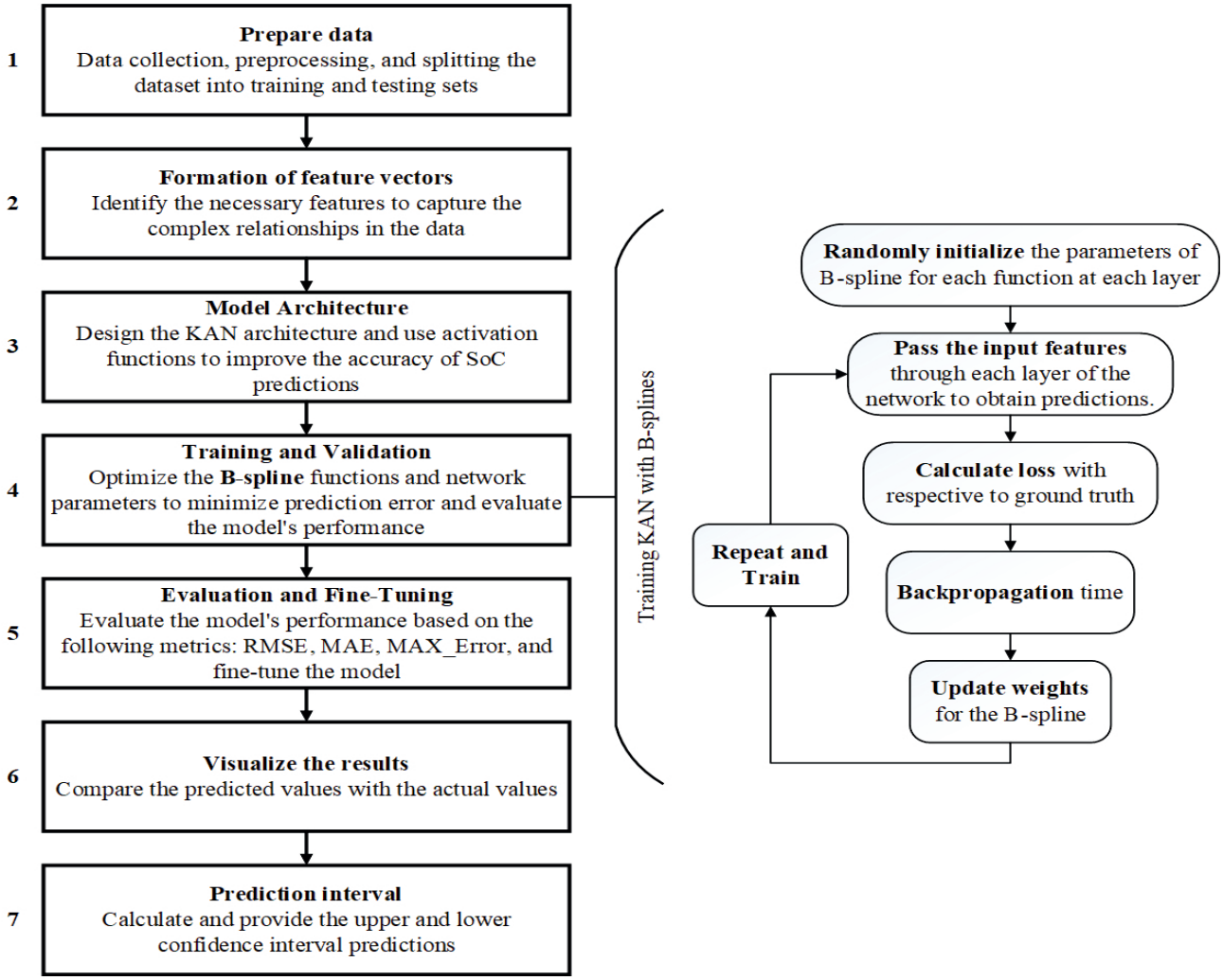


Fig. 4. *Diagram of the training process using Kolmogorov-Arnold networks*
Рис. 4. *Диаграмма процесса обучения с использованием сетей Колмогорова-Арнольда*

optimizing the B-spline functions and network parameters. Subsequently, the model is evaluated and fine-tuned based on performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and MAX_Error. Step six involves visualizing the results by comparing predicted values with actual values.

The final stage involves calculating and providing the upper and lower confidence intervals of the estimated SoC. This helps determine the reliability of the estimates, allowing the prediction of potential fluctuation ranges of the SoC under different operating conditions, thereby assessing the system's performance and stability.

The battery SoC processing and prediction pipeline has five main stages, as illustrated in Fig. 5. First, in Stage 1 (Input Data Sources), the raw battery data is divided into two groups: the feature group (including current, voltage, and temperature) and the SoC label, a key element in data preprocessing and model training. Next, in Stage 2 (Data Preparation Phase), the data undergoes preprocessing steps such as cleaning, removing NaN values, normalization, and applying a moving average filter to improve signal quality. Afterward, the dataset is split into three parts: training (65%), validation (15%), and testing (20%).

Once the data is prepared, Stage 3 (Training) focuses on training the KAN model, the system's core component, using the Backpropagation algorithm to optimize the Loss function. Upon completion of training, Stage 4 (Final Outputs) generates two key outputs: the estimated SoC and its corresponding confidence interval. Finally, in Stage 5 (Testing), the model's performance is evaluated using

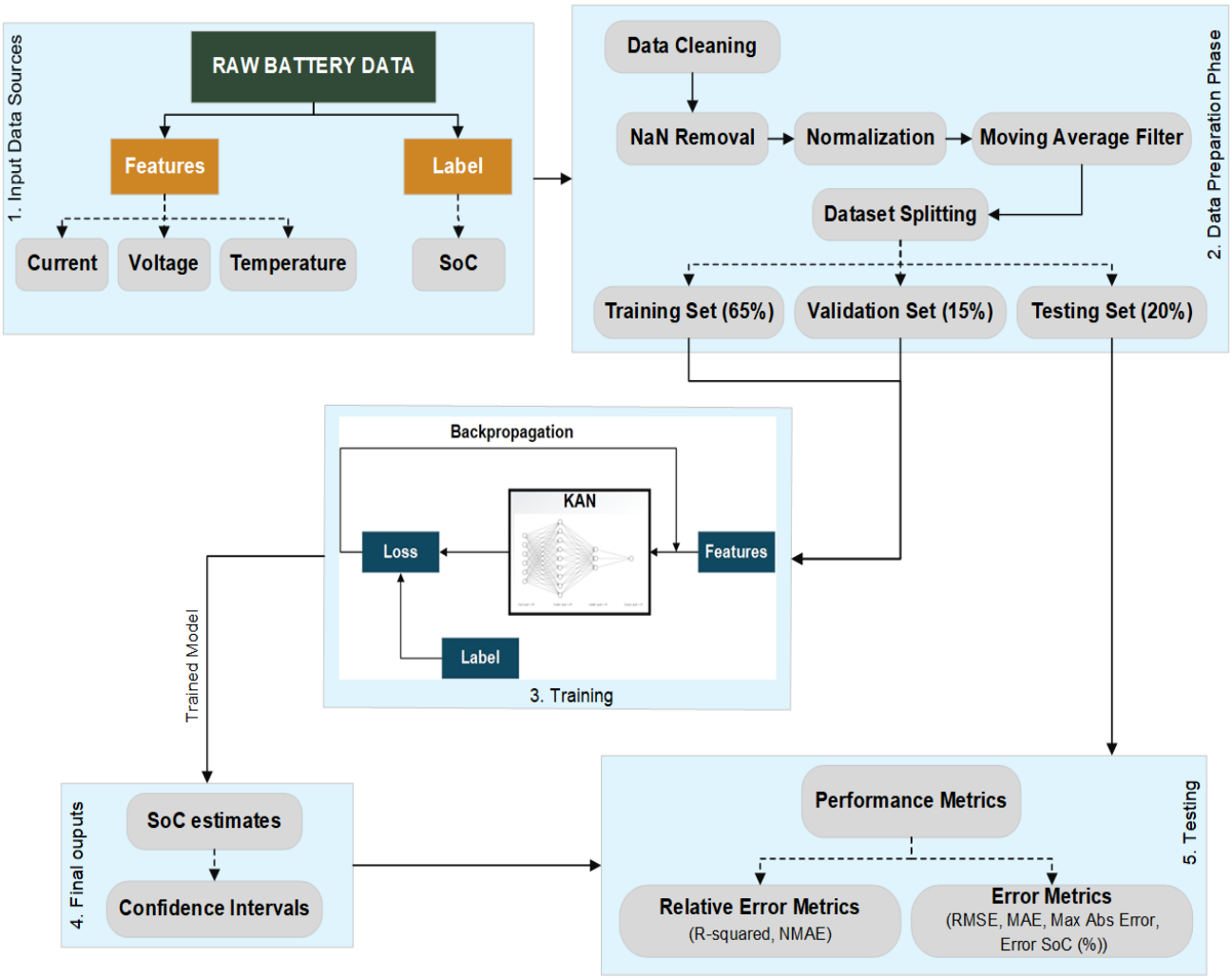


Fig. 5. *State of Charge estimation architecture diagram*
Рис. 5. *Диаграмма архитектуры оценки состояния заряда*

two main groups of metrics: Relative Error Metrics (R-squared, NMAE) and Error Metrics (RMSE, MAE, Max Absolute Error, and Error SoC).

The training process is thorough in the training block, where the KAN network, the core component, takes in the features and labels to calculate the loss. Once training is finished, the model provides two main outputs: an SoC estimate and confidence intervals. In parallel, the testing set is used to assess the model's accuracy through metrics like R-squared, NMAE (Relative error metrics) and RMSE, MAE, and Max Absolute Error (Error metrics).

This structured approach ensures a systematic transition from raw input data to final results, with built-in validation and assessment steps. The clear separation of stages allows for effective tracking, maintenance, and optimization of each system component, ensuring orderly and efficient operation.

RESULTS AND DISCUSSION

This study used the KAN network model [20] to train and estimate the SoC for a 5450 mAh LiPo battery. We use various metrics like RMSE, MAE, NMAE, Max Abs Error, and SoC error rate (%) to assess the model's effectiveness.

The test results presented in Table 1 and Fig. 6 show that the KAN model performed well when predicting point. The model achieved low values in MAE and RMSE, and the high R-squared value reflects its superior accuracy. Additionally, the model demonstrated stability during the prediction process, as the NMAE and MAX Abs Error indicate the reliability of the prediction results.

The error charts in Fig. 7 show that the KAN model maintains high stability throughout the prediction process, with small and consistent error fluctuations, especially within 0 to 100,000 samples. Overall, with superior performance across all evaluation metrics, the KAN model accurately estimates the state of charge of the battery accurately.

An essential part of the study is determining the confidence intervals for the SoC estimates. This enhances the accuracy and reliability of the results and allows for a more detailed assessment of the KAN model's performance. Through this, we can evaluate the reliability of the estimates and identify the expected SoC range under different operating conditions, contributing to a better understanding of the system's stability, as shown through the evaluation metrics in Fig. 14.

The estimation results with 95, 90, and 85% confidence levels, as presented in Tables 2, 3, and 4, indicate that forecast intervals were applied every 1200 steps.

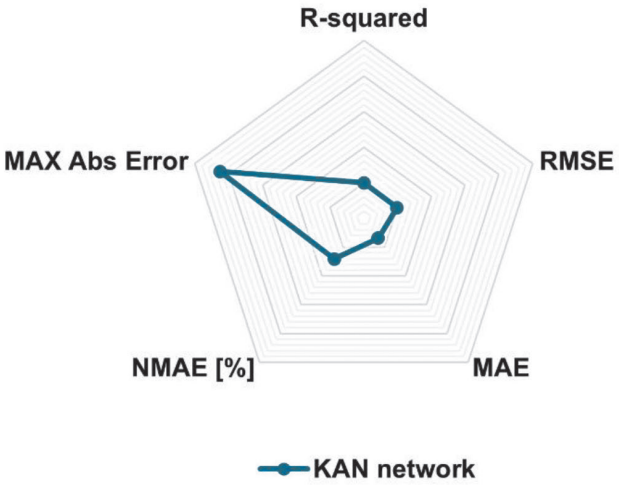


Fig. 6. *Performance metrics of Kolmogorov-Arnold Network models to predict point*
Рис. 6. *Метрики производительности моделей сети Колмогорова-Арнольда для прогнозирования по точкам*

Table 1. Error table of Kolmogorov-Arnold Network models to predict point
Таблица 1. Таблица ошибок моделей сети Колмогорова-Арнольда для прогнозирования по точкам

Index	KAN network
R-squared	0.9987
RMSE	0.98
MAE	0.69
NMAE, %	1.41
MAX Abs Error	4.26

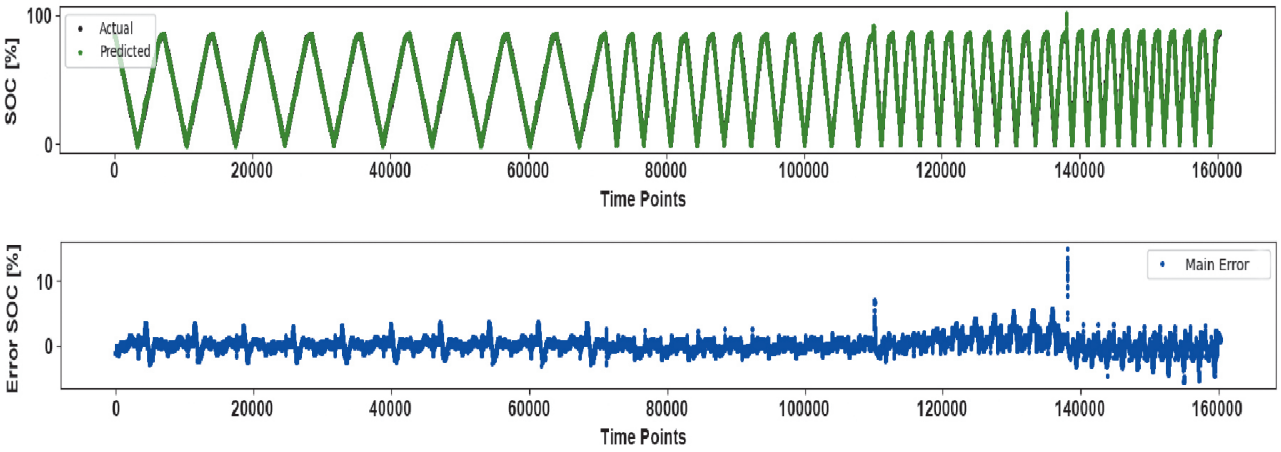


Fig. 7. *Experimental results with Kolmogorov-Arnold Network*
Рис. 7. *Экспериментальные результаты с сетью Колмогорова-Арнольда*

The number of future prediction points was set to 200, with a window size 1200. These parameters help determine the potential fluctuation range of SoC under different operating conditions, enhancing the system's stability assessment. Specifically, in the confidence interval analysis, the model demonstrated high reliability, with 86.41% of actual data falling within the estimated range at a 95% confidence level (Fig. 8 and 9), 81.84% at a 90% confidence level (Fig. 10 and 11) and maintaining 79.16% at an 85% confidence level (Fig. 12 and 13).

- With 95% confidence interval:

Table 2. Kolmogorov-Arnold Network State of Charge results with 95% confidence interval
Таблица 2. Результаты состояния заряда сети Колмогорова-Арнольда с доверительным интервалом 95%

Index	Evaluate the lower bound estimates	Evaluate upper bound estimates
R-squared	0.9947	0.9952
RMSE	2.15	1.87
MAE	1.84	1.40
NMAE [%]	3.77	2.87
MAX Abs Error	6.66	7.24
Percentage of actual data within the estimation interval: 86.41%		

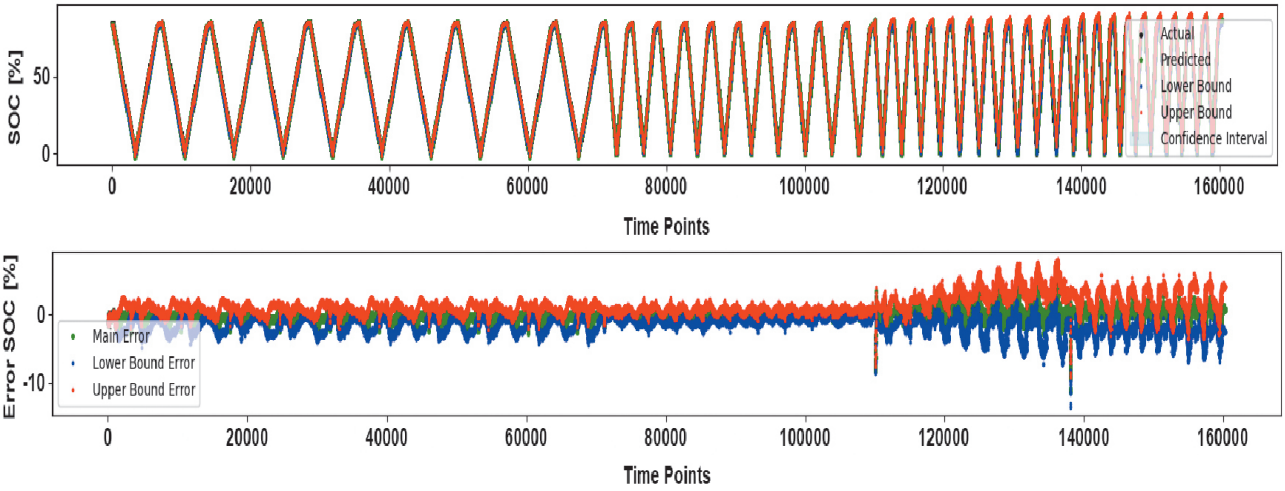


Fig. 8. *Model performance metrics chart with 95% confidence Interval*
Рис. 8. *График метрик производительности модели с доверительным интервалом 95%*

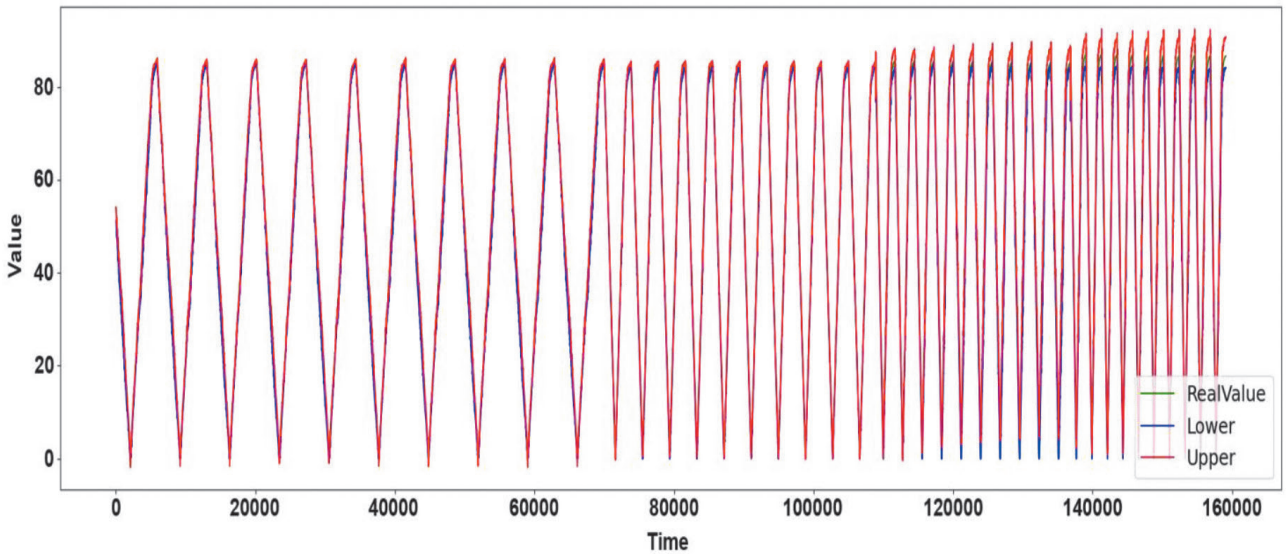


Fig. 9. *Battery State of Charge Estimation with 95% Confidence Interval*
Рис. 9. *Оценка состояния заряда аккумулятора с доверительным интервалом 95%*

- With 90% confidence interval:

Table 3. Kolmogorov-Arnold Network State of Charge results with 90% confidence Interval
Таблица 3. Результаты состояния заряда сети Колмогорова-Арнольда с доверительным интервалом 90%

Index	Evaluate the lower bound estimates	Evaluate upper bound estimates
R-squared	0.9951	0.9968
RMSE	1.97	1.66
MAE	1.59	1.31
NMAE [%]	3.26	2.68
MAX Abs Error	6.39	6.20
Percentage of actual data within the estimation interval: 81.84%		

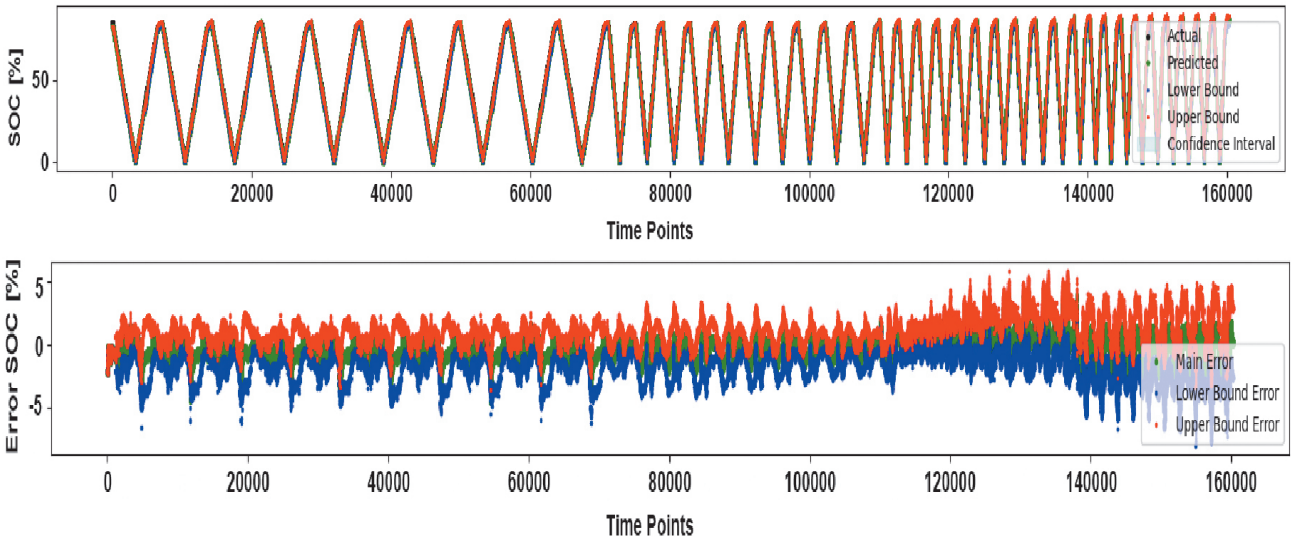


Fig. 10. *Model performance metrics chart with 90% confidence interval*
Рис. 10. *График метрик производительности модели с доверительным интервалом 90%*

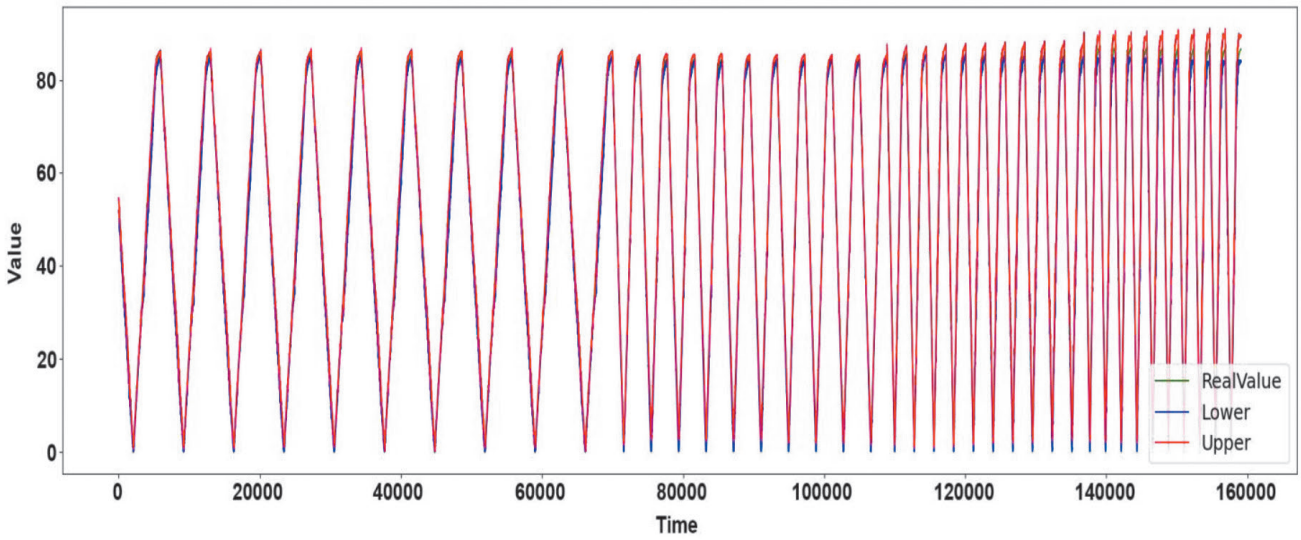


Fig. 11. *Battery State of Charge estimation with 90% confidence interval*
Рис. 11. *Оценка состояния заряда аккумулятора с доверительным интервалом 90%*

- With 85% confidence interval:

Table 4. Kolmogorov-Arnold Network State of Charge results with 85% confidence interval
Таблица 4. Результаты состояния заряда сети Колмогорова-Арнольда с доверительным интервалом 85%

Index	Evaluate the lower bound estimates	Evaluate upper bound estimates
R-squared	0.9937	0.9962
RMSE	1.89	1.52
MAE	1.54	1.22
NMAE [%]	3.16	2.50
MAX Abs Error	6.20	6.20
Percentage of actual data within the estimation interval: 79.16%		

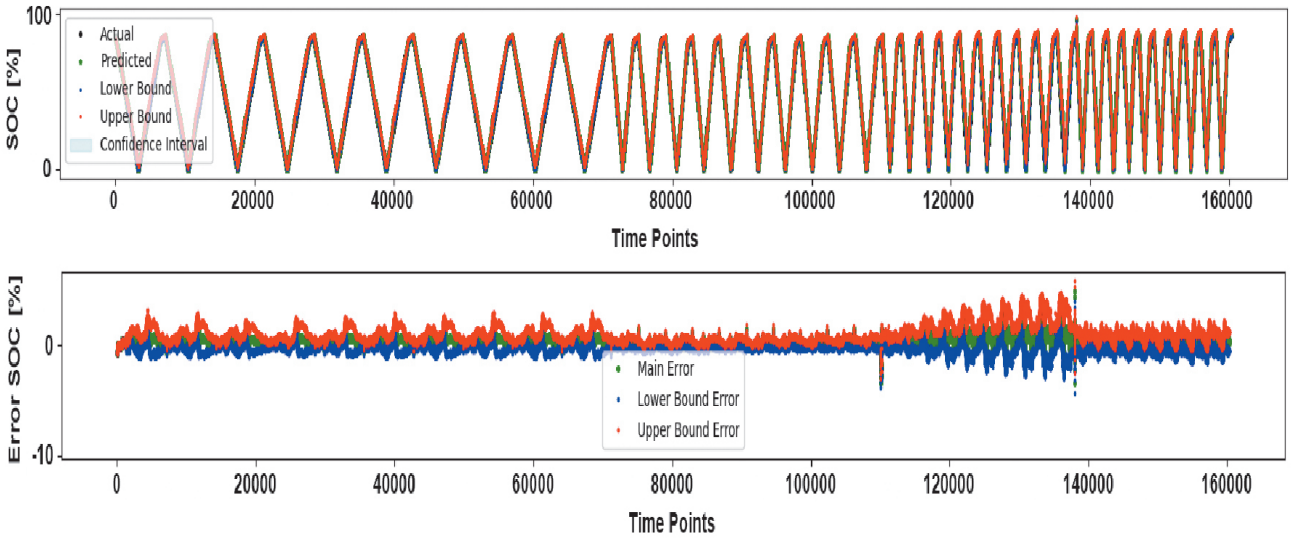


Fig. 12. *Model performance metrics chart with 85% confidence interval*
Рис. 12. *График метрик производительности модели с доверительным интервалом 85%*

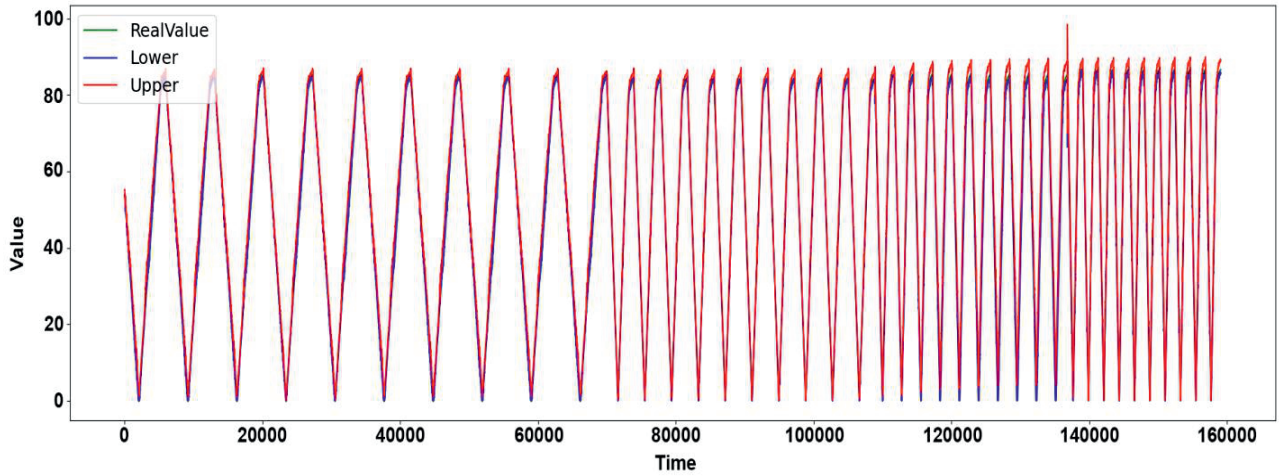
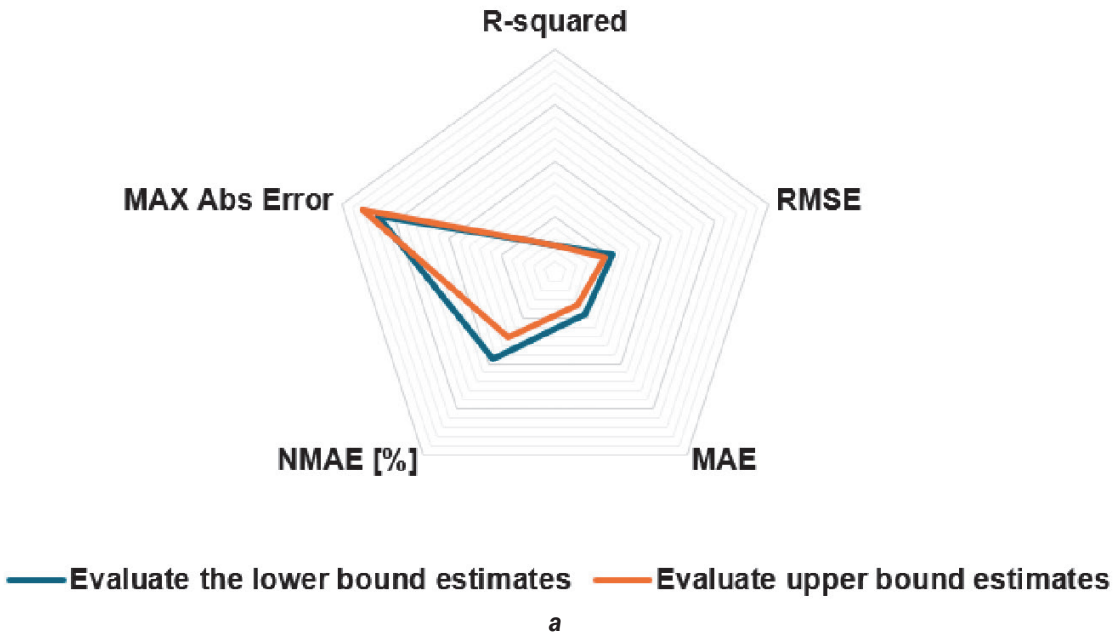
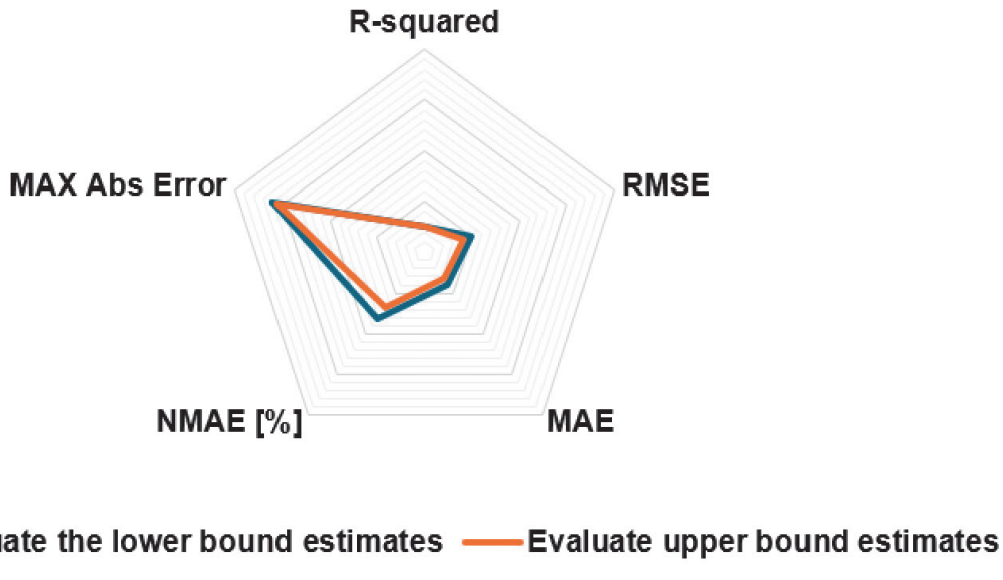


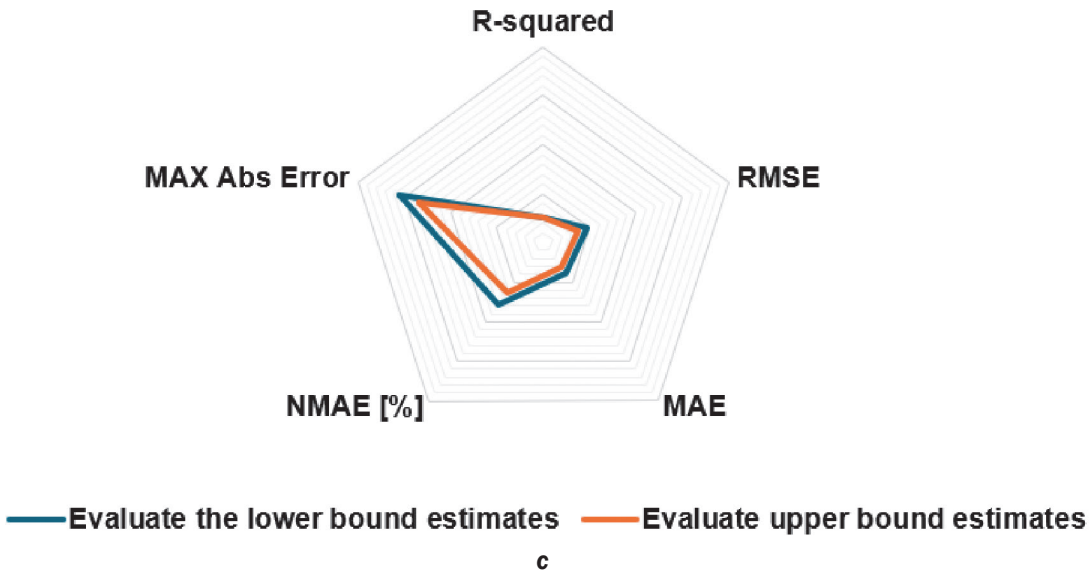
Fig. 13. *Battery State of Charge estimation with 85% confidence interval*
Рис. 13. *Оценка состояния заряда аккумулятора с доверительным интервалом 85%*



a



b



c

Fig. 14. *Performance metrics: bounds estimation with 95% (a), 90% (b) and 85% (c) confidence interval*
Рис. 14. *Метрики производительности: оценка границ с доверительными интервалами 95% (a), 90% (b) и 85% (c)*

Above, we analyzed the results of the KAN neural network method combined with a confidence interval to assess the accuracy and reliability of the state of charge estimates for lithium-ion batteries. At the same time, we highlighted this method's advantages and disadvantages. Next, we will move on to the conclusion.

CONCLUSION

The results from our experiments indicate that the KAN Network can estimate the SoC with greater accuracy. Moreover, KAN has shown remarkable effectiveness in generating prediction intervals, as a significant portion of actual values falls within these estimated ranges. This capability boosts the reliability and stability of SoC predictions, making them more dependable. However, to maximize the potential of KAN and minimize the risk of overfitting, it's crucial to adjust the network's architecture and activation functions carefully. This fine-tuning becomes especially important when dealing with smaller datasets or more complex modeling scenarios. Looking ahead, we aim to broaden our research by integrating KAN with other types of neural networks, such as LSTM and possibly Transformer architecture, along with various traditional neural models. Our objective is to create a hybrid model that delivers the highest level of performance for estimating SoC in energy storage systems.

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Denis N. Sidorov has been a member of the editorial board of the iPolytech Journal since 2021, but he did not take part in making decision about publishing the article under consideration. The article was reviewed following the Journal's review procedure. The authors did not report any other conflicts of interest.

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