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TRANSFORMER AND SUPPORT VECTOR REGRESSION FOR LIPO BATTERY CHARGING TIME PREDICTION

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Abstract. *This study aims to estimate the charging time of Lithium Polymer (LiPo) batteries using a machine learning-based approach. The parameters used in this study include voltage, current, temperature, and State of Charge (SoC), which are obtained through a microcontroller-based monitoring system. Two algorithms, namely Transformer and Support Vector Regression (SVR), are implemented and compared for battery charging time prediction. Data are collected directly during the charging process and processed for model training and testing. The performance of both models is evaluated using regression metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The experimental results show that the SVR model outperforms the Transformer model, achieving an MAE of 14.67 seconds, an RMSE of 20.16 seconds, a MAPE of 11.83%, and an R^2 value of 0.9991. Meanwhile, the Transformer model achieves an MAE of 22.54 seconds, an RMSE of 29.61 seconds, a MAPE of 16.83%, and an R^2 value of 0.9981. These results indicate that both models are capable of accurately predicting battery charging time; however, the SVR model provides better overall prediction performance for the experimental dataset used in this study. This research is expected to contribute to the development of more intelligent and accurate battery management systems.*

Abstrak. Penelitian ini bertujuan untuk mengestimasi waktu pengisian baterai Lithium Polymer (LiPo) menggunakan pendekatan berbasis machine learning. Parameter yang digunakan dalam penelitian ini meliputi tegangan, arus, suhu, dan State of Charge (SoC) yang diperoleh melalui sistem pemantauan berbasis mikrokontroler. Dua algoritma, yaitu Transformer dan Support Vector Regression (SVR), diimplementasikan dan dibandingkan kinerjanya dalam memprediksi waktu pengisian baterai. Data dikumpulkan secara langsung selama proses pengisian baterai dan diproses untuk keperluan pelatihan serta pengujian model. Evaluasi performa dilakukan menggunakan metrik regresi yaitu Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), dan koefisien determinasi (R^2). Hasil penelitian menunjukkan bahwa model SVR memberikan performa yang lebih baik dibandingkan model Transformer dengan nilai MAE sebesar 14,67 detik, RMSE sebesar 20,16 detik, MAPE sebesar 11,83%, dan R^2 sebesar 0,9991. Sementara itu, model Transformer memperoleh nilai MAE sebesar 22,54 detik, RMSE sebesar 29,61 detik, MAPE sebesar 16,83%, dan R^2 sebesar 0,9981. Hasil tersebut menunjukkan bahwa kedua model mampu memprediksi waktu pengisian baterai dengan akurasi yang sangat baik, namun model SVR memberikan performa prediksi yang lebih unggul pada dataset yang digunakan dalam penelitian ini. Penelitian ini diharapkan dapat berkontribusi dalam pengembangan sistem manajemen baterai yang lebih cerdas dan akurat.

1. INTRODUCTION

The need for effective battery charging systems is rising due to the expanding usage of rechargeable batteries in energy storage systems, portable electronics, and electric cars [1]. Among various battery types, Lithium Polymer (LiPo) batteries are widely used because of their high discharge capacity, lightweight design, and high energy density [2]. To improve system efficiency and user convenience, proper charging management is an important aspect in battery-powered applications [3].

However, the charging process of LiPo batteries is influenced by several variables, such as temperature, voltage, current, and State of Charge (SoC). These parameters vary dynamically during operation, making charging time estimation a complex problem [4]. In practical use, users often rely on simple indicators to estimate the remaining charging duration, which may not accurately reflect the actual condition. Therefore, a predictive approach is required to provide better estimation of charging behavior.

Recent developments in machine learning have enabled the use of data-driven models for complex system prediction. The Transformer model has gained attention due to its ability to capture long-range dependencies in sequential data using the self-attention mechanism [5]. In addition, Support Vector Regression (SVR) is widely used for nonlinear regression problems because of its strong generalization ability and robustness in handling limited datasets [6].

Although various studies have applied machine learning techniques for battery analysis, most of them focus on State of Charge (SoC) and State of Health (SoH) estimation [7][8][9]. Research related to charging time prediction in LiPo battery systems is still limited. Furthermore, comparative studies between Transformer and SVR models for charging time estimation have not been widely explored.

The purpose of this study is to compare the performance of Transformer and SVR algorithms in estimating LiPo battery charging time based on measured parameters. The system uses data collected from voltage, current, temperature, and SoC sensors integrated with a microcontroller-based monitoring platform. The performance of both models is evaluated using regression metrics to determine the most suitable approach for charging time estimation.

The contribution of this research lies in the development of a data-driven charging time estimation approach using Transformer and SVR models, as well as providing a comparative analysis of both methods in a LiPo battery system. The novelty of this study is the application and evaluation of these two models for charging time prediction based on experimental data, which has not been widely investigated in previous studies. This research is expected to contribute to the development of more intelligent battery management systems.

2. TINJAUAN PUSTAKA

2.1.1. Battery and Charging Process

Electronic systems often use rechargeable batteries because of their ability to effectively store and deliver electrical energy [10]. A battery, also known as a storage battery, is a secondary electrochemical cell that converts chemical energy into electrical energy and can be recharged for repeated use [11].

Among various rechargeable battery technologies, Lithium Polymer (LiPo) batteries are widely used due to their lightweight characteristics, high energy density, and high discharge capability [12]. State of Charge (SoC), current, voltage, and temperature significantly influence battery performance during the charging process. These parameters change dynamically and interact in a nonlinear manner, making the charging process complex. Therefore, modeling the charging process is essential for accurately estimating battery charging time.

2.1.2. Transformer

The Transformer model is a deep learning method designed to process sequential data using a self-attention mechanism [13]. Unlike traditional recurrent models, the Transformer does not rely on sequential processing, allowing parallel computation and improved efficiency.

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (1)$$

The attention mechanism allows the model to concentrate on the most pertinent aspects of the input data by calculating the relationship between queries (Q), keys (K), and values (V).

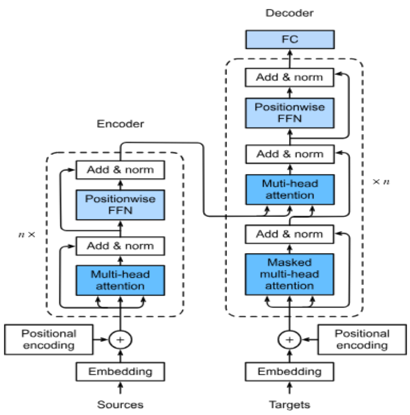

Figure 1. Transformer Architecture

In addition, the Transformer employs multi-head attention, which allows the model to learn multiple data representations simultaneously. The outputs from multiple attention heads are combined and passed through feedforward layers. This structure enables the model to capture complex patterns and long-range dependencies in time-series data, making it suitable for prediction tasks [14].

2.1.3. Support Vector Regression

Support Vector Regression (SVR) is a supervised learning algorithm which utilized the model nonlinear relationships between input and output variables [15]. SVR aims to construct a function capable of estimating target values while keeping prediction errors within a defined acceptable threshold.

$$f(x) = w^T \phi(x) + b \tag{2}$$

The function f(x) serves as the regression model that transforms input data into a higher-dimensional space. When dealing with nonlinear relationships, SVR applies kernel functions to manage complexity. Among the available kernel options, the Radial Basis Function (RBF) is widely preferred:

$$K(x_i, x_j) = \exp(-\gamma \, || \, x_i - x_j \, ||^2) \tag{3}$$

The RBF kernel measures similarity between data points and enables the model to capture complex patterns [16]. SVR model outcomes are largely dependent on key parameters, including the regularization parameter (C) and the kernel parameter (γ).

2.1.4. Evaluation Metrics

Model performance is evaluated using several regression metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2).

1. Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \tag{4}$$

MAE measures the average absolute difference between actual values and predicted values [17].

2. Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{5}$$

RMSE emphasizes larger errors by squaring the differences before averaging [17].

3. Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{6}$$

MAPE expresses prediction error in percentage form [18].

4. Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \tag{7}$$

R^2 indicates how well the model explains the variability of the data [17].

3. METHOD

This study is carried out through a sequence of well-defined methodological stages, consisting of system design, system implementation involving both hardware and software components, system testing, and model performance evaluation.

3.1.1. System Design

The system design consists of two main aspects, namely mechanical and electrical design.

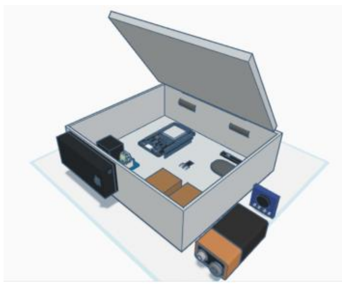

Figure 3. Mechanical Design

The mechanical design focuses on the physical arrangement of system components, including the battery, sensors, and supporting structures. The components are arranged to ensure stable operation, proper spacing, and safe working conditions during system operation.

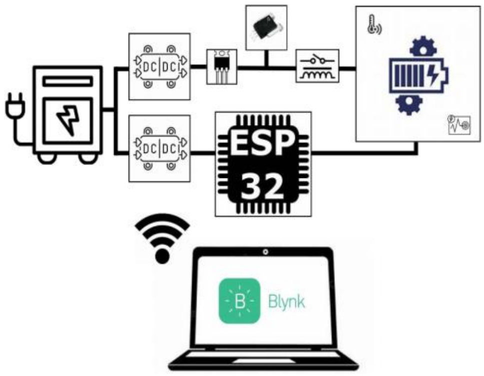

Figure 4. Electrical Design

Meanwhile, the electrical design focuses on the integration of electronic components and signal flow within the system. The system utilizes an ESP32 microcontroller as the main processing unit, connected to a current sensor (ACS758), power monitoring module (PZEM-017), and temperature sensor (GY-906). Each sensor measures specific parameters, which are then transmitted to the microcontroller for data acquisition and processing.

3.1.2. System Implementation

The system implementation integrates both hardware and software components into a single platform. From the hardware perspective, the system consists of an ESP32 microcontroller, current sensor, temperature sensor, and a LiPo battery. These components are used to measure electrical and thermal parameters during the charging process.

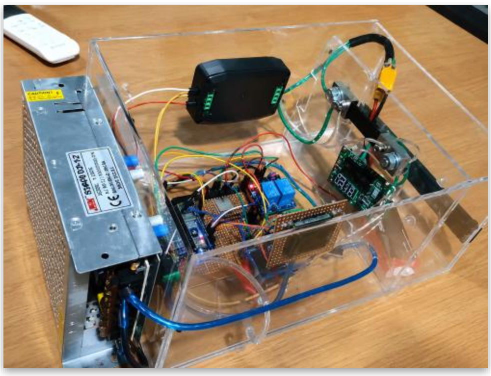

Figure 5. Hardware Implementation

From the software perspective, a data acquisition program is developed to collect and store sensor data, covering key parameters namely current, temperature, and State of Charge (SoC). The resulting dataset is then conditioned for subsequent processing stages.

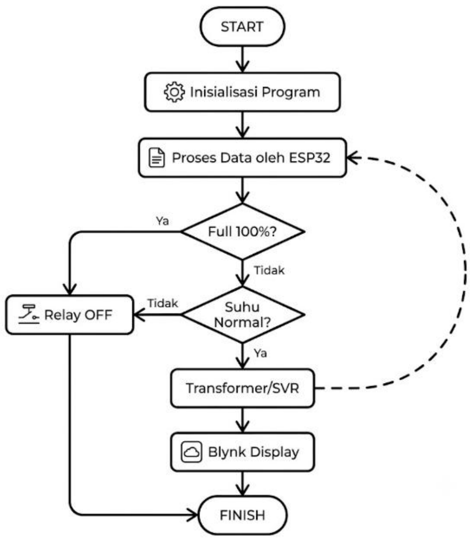

Figure 6. Flowchart of Data Acquisition and Prediction Process

3.1.3. System Testing

Support The system testing stage is conducted to evaluate the functionality of the proposed system and to generate data for model training and validation. Data is collected under various operating conditions to ensure sufficient variability in the dataset. The collected data consists of input parameters, including voltage, current, temperature, and SoC, with charging time as the target output.

Figure 7. Testing / Data Collection

The dataset is subsequently split into two subsets: training and testing. The training portion is utilized to build the machine learning models, whereas the testing portion serves to assess how well the models perform on new, unseen data. This separation ensures that the models are capable of generalizing effectively while preventing overfitting. Both the Transformer and Support Vector Regression (SVR) models undergo training using the training subset and are afterward evaluated against the testing subset.

3.1.4. Evaluation

The evaluation stage is performed to measure the performance of the implemented models in estimating battery charging time. Several regression metrics are used, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). These metrics offer numerical indicators of prediction accuracy and serve as the basis for comparing the performance of both the Transformer and SVR models.

4. RESULT AND DISCUSSION

4.1.1. Data Acquisition

The system successfully collected battery-related data during the charging process. The recorded measurable quantities cover voltage, current, temperature, and State of Charge (SoC). The charging time is defined as the target output. To analyze battery behavior, the relationship between SoC and charging time is presented in Figure 8.

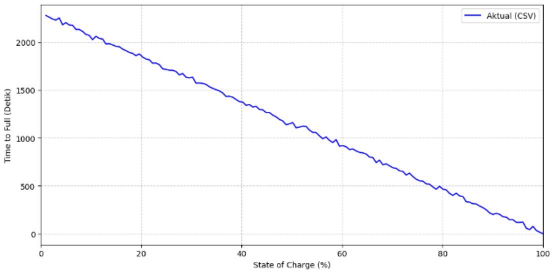

Figure 8. SoC vs Charging Time

The results indicate that charging time decreases as the SoC increases, reflecting the nonlinear behavior of the battery during the charging process.

4.1.2. Transformer Result

The Transformer model is used to estimate the battery charging time based on the processed dataset. The comparison between actual and predicted values is shown in Figure 9.

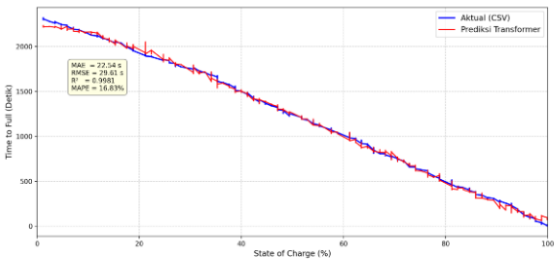

Figure 9. Actual vs Predicted Charging Time (Transformer)

Based on the evaluation results, the Transformer model achieves a Mean Absolute Error (MAE) of 22.54 seconds, a Root Mean Squared Error (RMSE) of 29.61 seconds, a Mean Absolute Percentage Error (MAPE) of 16.83%, and a coefficient of determination (R^2) of 0.9981. The high R^2 value indicates that the model is capable of capturing the data pattern very effectively.

4.1.3. Support Vector Regression Result

The SVR model is used as a comparison to the Transformer model. The comparison between actual and predicted values is shown in Figure 10.

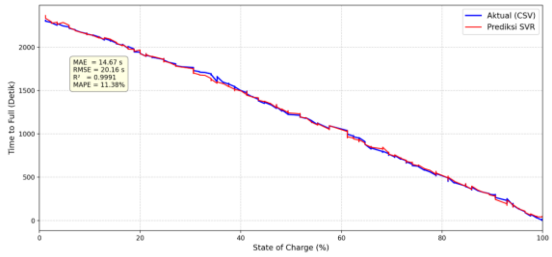

Figure 10. Actual vs Predicted Charging Time (SVR)

Based on the evaluation results, the SVR model achieves a Mean Absolute Error (MAE) of 14.67 seconds, a Root Mean Squared Error (RMSE) of 20.16 seconds, a Mean Absolute Percentage Error (MAPE) of 11.83%, and a coefficient of determination (R^2) of 0.9991.

4.1.4. Model Comparison

The performance comparison between the Transformer and SVR models is presented in Table 3.

Table 3. Model Comparison

Model	Transformer	SVR
MAE (s)	22.54	14.67
RMSE (s)	29.61	20.16
MAPE (%)	16.83	11.83
R^2	0.9981	0.9991

Based on the results, the SVR model consistently outperforms the Transformer model across all evaluation metrics. The SVR model achieves lower MAE, RMSE, and MAPE values, indicating higher prediction accuracy and smaller prediction errors. In addition, the higher R^2 value demonstrates that the SVR model explains the variability of the charging time data more effectively than the Transformer model. Although the Transformer model also provides excellent prediction performance, the SVR model offers better overall accuracy for the battery charging time estimation task.

4.1.5. Discussion

The results demonstrate that both machine learning models are capable of estimating battery charging time with high accuracy. The prediction curves generated by both models closely follow the actual charging profile, indicating that voltage, current, temperature, and State of Charge (SoC) are effective predictors of battery charging time.

Among the evaluated models, Support Vector Regression (SVR) provides the best overall performance. It achieves the lowest prediction errors with an MAE of 14.67 seconds, RMSE of 20.16 seconds, and MAPE of 11.83%, while also obtaining the highest coefficient of determination (R^2 = 0.9991). These results indicate that the SVR model is capable of accurately modeling the nonlinear relationship between the measured battery parameters and charging time.

The Transformer model also demonstrates excellent prediction capability, achieving an R^2 value of 0.9981, which indicates that the model successfully captures the charging characteristics of the LiPo battery. However, compared with the SVR model, the Transformer produces slightly larger prediction errors across all evaluation metrics.

Overall, both models are suitable for battery charging time estimation. However, based on the experimental results obtained in this study, the SVR model is the more effective approach, as it consistently achieves better performance in terms of prediction accuracy and goodness-of-fit.

5. CONCLUSION

This study presents a comparative analysis of Transformer and Support Vector Regression (SVR) models for estimating battery charging time based on current, voltage, temperature, and State of Charge (SoC) data.

The experimental results demonstrate that both models are capable of predicting battery charging time with excellent performance. The Transformer model achieved a Mean Absolute Error (MAE) of 22.54 seconds, Root Mean Squared Error (RMSE) of 29.61 seconds, Mean Absolute Percentage Error (MAPE) of 16.83%, and a coefficient of determination (R^2) of 0.9981. Meanwhile, the SVR model achieved better overall performance with an MAE of 14.67 seconds, RMSE of 20.16 seconds, MAPE of 11.83%, and an R^2 value of 0.9991.

Based on these findings, the SVR model provides more accurate and reliable charging time estimation than the Transformer model for the dataset used in this study. Although the Transformer model also demonstrates excellent predictive capability, the SVR model consistently produces lower prediction errors and a higher coefficient of determination.

Therefore, the SVR model is considered the more suitable approach for LiPo battery charging time estimation under the experimental conditions investigated in this study. This research contributes to the development of intelligent battery management systems by demonstrating the effectiveness of machine learning techniques for charging time prediction and providing a comparative evaluation of Transformer and Support Vector Regression models.

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