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Optimizing Battery Charging Power Cell of Electric Car Battery by Smart Charging Deep Learning Algorithm

Wawan Kurniadi
Department of Computer Science, Universitas Budi Luhur, West Jakarta, Indonesia

Denni Kurniawan
Department of Computer Science, Universitas Budi Luhur, West Jakarta, Indonesia

Abstract: The rapid growth of the automotive industry has accelerated the adoption of electric vehicles (EVs), in which battery systems play a critical role as the primary energy storage component. Efficient battery charging during the production process is therefore essential to ensure product quality, operational efficiency, and long-term battery performance. This study aims to optimize the battery cell charging process in electric vehicle manufacturing by implementing a smart charging strategy based on deep learning techniques, specifically the LSTM model. Historical charging data and relevant operational variables, including voltage, current, and time characteristics, are utilized to train the LSTM model to predict optimal charging parameters. The proposed approach enables adaptive and intelligent control of charging current and voltage profiles during production. The results demonstrate that the LSTM-based smart charging method improves charging efficiency, reduces potential battery degradation, and enhances manufacturing process consistency compared to conventional charging methods. In conclusion, the application of deep learning–based smart charging provides a promising solution for optimizing EV battery production processes. This research contributes to the development of intelligent battery management systems and supports the advancement of sustainable transportation and EV manufacturing technologies.

Keywords: Battery Manufacturing, Charging Optimization, Deep Learning, Electric Vehicle (EV) Batteries, Lithium-Ion Batteries.

Correspondents Author:
Wawan Kurniadi, Department of Computer Science, Universitas Budi Luhur, West Jakarta, Indonesia

Email: 2211601212@student.budiluhur.ac.id

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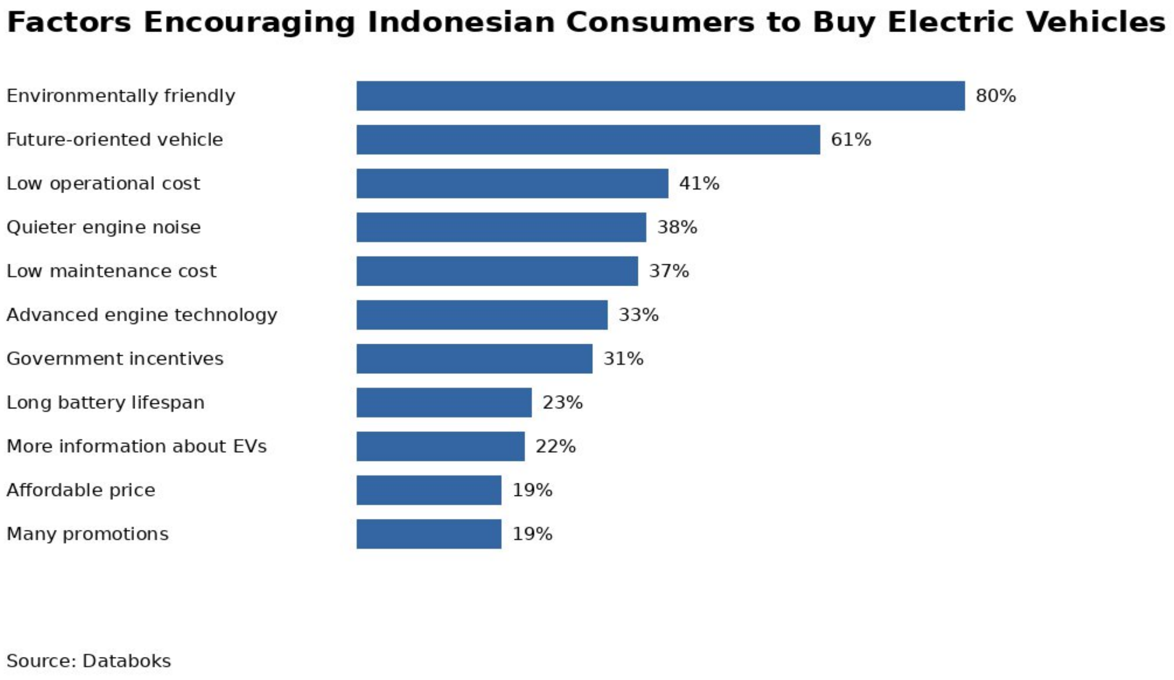
Introduction

The global automotive industry is undergoing a significant transformation driven by the rapid adoption of electric vehicles (EVs). This transition is closely linked to global efforts to reduce greenhouse gas emissions, mitigate climate change, and decrease dependence on fossil fuels. As EV adoption accelerates, battery technology has emerged as a critical determinant of vehicle performance, production efficiency, and overall sustainability. In electric vehicles, batteries function as the sole energy storage system, making their quality, durability, and efficiency central to both consumer acceptance and industrial competitiveness (Lo Franco, Ricco, Mandrioli, & Grandi, 2020). Consequently, the optimization of battery cell charging processes during manufacturing has become an increasingly important research topic, particularly as manufacturers seek to balance energy efficiency, production speed, and battery longevity.

In recent years, Indonesia has shown growing interest in electric vehicles, supported by government policies, public awareness of environmental issues, and the gradual development of EV infrastructure (Shamsuddoha & Nasir, 2025). Consumer perception plays a vital role in shaping the EV market, as purchasing decisions are influenced not only by price and performance but also by environmental considerations and long-term operational benefits.



Source: Databoks

Figure 1 **Factors Encouraging Indonesian Consumers to Purchase Electric Vehicles (June–September 2023)**

Figure 1 illustrates the primary motivations for EV adoption in Indonesia, based on survey data from Databoks. The figure indicates that environmental friendliness is the dominant factor, cited by 80% of respondents, followed by perceptions of EVs as vehicles of the future (61%) and low operational costs (41%). Other contributing factors include quieter engine noise (38%), lower maintenance costs (37%), advanced engine technology (33%), government incentives (31%), long battery lifespan (23%), availability of information about EVs (22%), affordable pricing (19%), and promotional activities (19%).

The interpretation of Figure 1 reveals an important insight for EV-related research and industrial development. While environmental benefits and future-oriented perceptions strongly motivate consumers, battery lifespan and durability are not among the top three factors influencing purchase decisions. This suggests that consumers may implicitly assume battery reliability or lack sufficient awareness of the technical complexities behind battery performance. From an industrial perspective, this gap highlights the importance of upstream processes, particularly battery cell manufacturing and charging optimization, which directly affect battery durability and efficiency. Improving charging strategies during production can enhance battery quality without necessarily increasing production costs, thereby indirectly supporting consumer expectations related to low operational and maintenance costs (Sesotyo, 2025; Windasari, Abdurohman, Ratib, Frihadi, & Montazi, 2025).

From a manufacturing standpoint, battery cell production involves multiple energy-intensive stages, with charging and discharging cycles playing a crucial role in determining cell consistency, capacity retention, and long-term performance (Arif, Lie, Seet, Ayyadi, & Jensen, 2021). Inefficient charging protocols can lead to increased energy consumption, longer production times, and accelerated battery degradation (Shen, Zhao, Xiang, Lan, & Liu, 2022). As EV production scales up, these inefficiencies can accumulate, leading to higher operational costs and greater strain on the electrical infrastructure. Therefore, optimizing the charging process during battery production is not only a technical necessity but also a strategic requirement for sustainable industrial growth.

The increasing penetration of EVs also raises concerns about electricity demand and load management. Large-scale adoption of EVs, particularly when charging occurs simultaneously, can exacerbate peak load conditions that stress power systems (Lo Franco et al., 2022). This challenge has been widely discussed in the context of public charging infrastructure; however, it is equally relevant in manufacturing environments, where large volumes of battery cells are charged under controlled, yet energy-intensive, conditions (Budiarto, Sumitro, & Taufiq, 2024; Suwoyo et al., 2022). Smart charging strategies that adapt charging parameters such as voltage, current, and time can help mitigate peak demand, improve energy efficiency, and support more stable production operations.

The importance of this research lies in its potential to address multiple challenges simultaneously. By optimizing battery cell charging during production, manufacturers can reduce energy consumption, enhance battery performance, and improve production efficiency. This, in turn, contributes to lower production costs, improved product reliability, and stronger competitiveness in the growing EV market. Moreover, such optimization supports broader sustainability goals by reducing industrial energy waste and promoting efficient use of electrical infrastructure.

Previous studies have demonstrated the effectiveness of data-driven and machine-learning approaches in battery management and prediction tasks. Alanazi stated that the use of electric vehicles (EVs) is currently expanding due to various environmental and economic benefits (Alanazi, 2023). Other studies reported that charging demand can be modeled based on charging start and stop times and the number of charges (Qian, Fachrizal, Munkhammar, Ebel, & Adam, 2023). Sadeghian et al. stated that the role of electric vehicles (EVs) in the energy system will be crucial in the coming years due to their environmentally friendly nature and ability to mitigate/absorb excess electricity from renewable energy sources (Sadeghian, Oshnoei, Mohammadi-Ivatloo, Vahidinasab, & Anvari-Moghaddam, 2022).

Other studies stated that optimizing electric vehicle battery cell charging aims to improve the power-voltage efficiency of the electrical infrastructure during charging, reduce the burden on the electricity grid, and provide users with greater control over the charging process (Aduama, Zhang, & Al-Sumaiti, 2023). The main idea behind the proposed electric vehicle (EV) battery charging strategy is to regulate the charging current to prevent exceeding the contracted power limit (Arafat & Weiwei, 2023). Croziera et al. stated that the implementation of smart charging has the potential to create a more stable and efficient electricity system, resulting in lower costs (Crozier, Morstyn, & McCulloch, 2020). Electric vehicles have the potential to change individual mobility habits and substantially reduce transportation-related emissions (Aghajan-Eshkevari, Azad, Nazari-Heris, Ameli, & Asadi, 2022). Other studies have stated that EV development can offer a safe, comprehensive, and balanced solution for efficient, environmentally friendly energy choices, as well as a wide range of renewable energy sources (Ahmad et al., 2022).

Previous studies proposed an LSTM-based remaining useful life (RUL) prediction model using a many-to-one architecture and multi-channel charging profiles, including voltage, current, and temperature (Shanmuganathan, Victoire, Balraj, & Victoire, 2022). Their results demonstrated significant improvements in MAPE, and more accurate end-of-life (EoL) estimation compared to baseline models. The study highlighted the importance of multidimensional charging data and advanced neural network architectures for improving battery life predictions. Other studies have explored deep learning approaches for battery health monitoring, degradation analysis, and charging optimization, further reinforcing the potential of LSTM-based methods in energy storage research (Rotty, Dewayana, & Habyba, 2022).

Despite these advances, most existing studies focus on batteries already in use or in production, emphasizing post-production performance evaluation, SOC estimation, or lifecycle prediction. Limited attention has been paid to optimizing charging processes during battery cell manufacturing. This represents a critical research gap, as production-stage charging directly influences initial battery quality, consistency, and long-term performance. Furthermore, few studies explicitly address low-voltage charging optimization within controlled production time constraints using deep learning models.

This study introduces a novel approach by applying smart charging optimization based on deep learning, specifically the LSTM algorithm, to the battery cell charging process during production. Unlike prior research that primarily targets operational or post-production scenarios, this work focuses on optimizing voltage usage, charging time parameters, and energy efficiency at the manufacturing stage. Previous research has generally only examined charging optimization during the usage phase or used conventional rule-based and statistical approaches without integrating actual production data. Unlike previous studies, this study's novelty combines real-world production data, low-voltage charging strategies, and predictive deep learning (LSTM) models into a single optimization framework at the manufacturing stage to support intelligent decision-making in the battery manufacturing process.

The objective of this research is to develop an LSTM-based smart charging model capable of optimizing battery cell charging during production under predefined time constraints while maintaining sufficient battery durability and performance. By leveraging historical production data and relevant charging parameters, the proposed model aims to improve charging efficiency, reduce energy consumption, and enhance battery quality consistency. Ultimately, this research seeks to advance intelligent battery manufacturing systems, support sustainable EV production, and strengthen the scientific foundation for applying deep learning techniques to industrial energy optimization.

Research Method

Data Mining

This research uses a data mining approach as the primary foundation for data processing and analysis, given that data mining has been widely applied in business organizations and industrial sectors to support data-driven decision-making. Through data mining, large, complex, and heterogeneous raw data can be processed into meaningful information. Data mining techniques enable the identification of patterns, relationships, and trends that are not readily apparent in conventional analysis. In this research, data mining is used to understand the behavior and characteristics of data related to the smart charging process of electric vehicle batteries. This approach supports achieving efficiency, accuracy, and optimizing the battery production process.

The application of data mining in this research encompasses several key functions: pattern finding, prediction, classification, clustering, anomaly detection, and business process optimization. Pattern finding is used to identify regularities or recurring trends in battery charging and discharging data. Predictions are made to estimate future battery life based on historical data. Classification and clustering processes are used to group data based on specific characteristics, such as battery condition or charging patterns. In addition, anomaly detection is applied to identify data that deviates from common patterns, potentially indicating errors or abnormal conditions in the system, thereby supporting improvements in the efficiency and effectiveness of overall business processes.

Cross Industry Standard Process for Data Mining (CRISP-DM) Method

This research methodology adopts the Cross Industry Standard Process for Data Mining (CRISP-DM) framework as a systematic method for conducting data mining. CRISP-DM was chosen because it is a standard method that is structured, iterative, and flexible, making it suitable for application in industrial data-based research. This framework helps researchers organize each research stage logically, from goal formulation to implementation of results. By using CRISP-DM, research can be conducted consistently and easily replicated. This approach also allows for adjustments to previous stages if obstacles are encountered at any stage.

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The initial stage of CRISP-DM is business understanding, which focuses on understanding the research objectives and the problems encountered in the smart charging process of electric vehicle batteries. The next stage is data understanding, which involves collecting and exploring data to assess the characteristics, quality, and relevance of the data used. The analyzed data comes from predetermined sources and is characterized to obtain initial knowledge. The data preparation stage includes cleaning, transformation, merging, and selecting relevant features to produce a dataset ready for modeling. Next, in the modeling stage, various modeling techniques are selected and calibrated to achieve optimal results. The evaluation stage assesses the model's suitability for the research objectives, while the deployment and monitoring stages ensure the resulting model can be applied and continuously monitored in an operational environment.

Deep Learning Algorithm

This research utilizes a deep learning algorithm as the primary approach to modeling the charging and discharging processes of electric vehicle batteries. The deep learning algorithm was chosen for its ability to learn complex, nonlinear patterns from high-dimensional data. In the context of a battery charging system, the data generated is sequential and dynamic, requiring a model capable of capturing both short-term and long-term relationships. Deep learning is also known to perform highly in terms of prediction accuracy when supported by the right data and parameters. Therefore, this approach is considered suitable for optimizing battery voltage and durability.

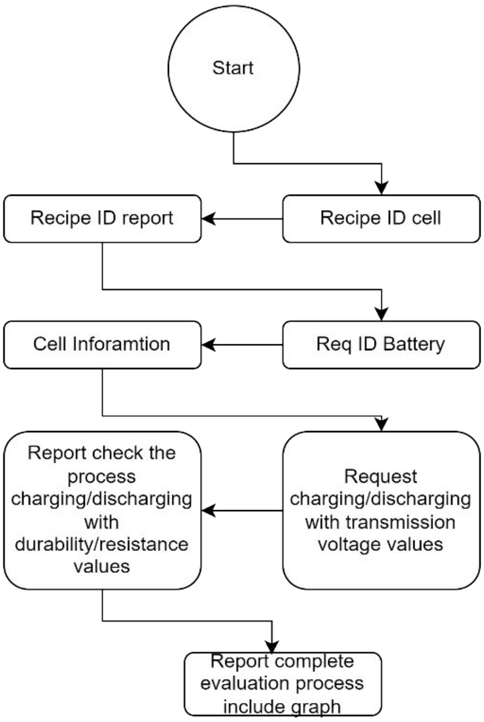


Figure 2 Operation scenario charging/discharging process with Deep Learning Algorithm

Figure 2 depicts an operational scenario of the charging and discharging process using a deep learning algorithm. The interpretation of the figure shows the system flow, starting with battery identification through a unique ID, which is then used to retrieve battery cell information. This information is processed by a deep learning model to determine optimal charging and discharging parameters based on voltage values. The result of this process is an estimate of battery life resulting from charging and discharging optimization. The final stage of this scenario is evaluation of the results and graphical visualization, which facilitates model performance analysis and data-driven decision-making.

LSTM Model

The LSTM model will be the primary architecture in this research due to its ability to handle time series data (Farsi, Amayri, Bouguila, & Eicker, 2021). LSTM is a development of Recurrent Neural Networks (RNN) designed to address the vanishing gradient problem in conventional RNNs. Because of its internal memory structure, LSTM can retain important information over long periods. This is particularly relevant to the battery charging and discharging process, which is heavily influenced by the sequence of events and prior conditions. Therefore, LSTM was chosen to model the temporal relationships in electric vehicle battery data.

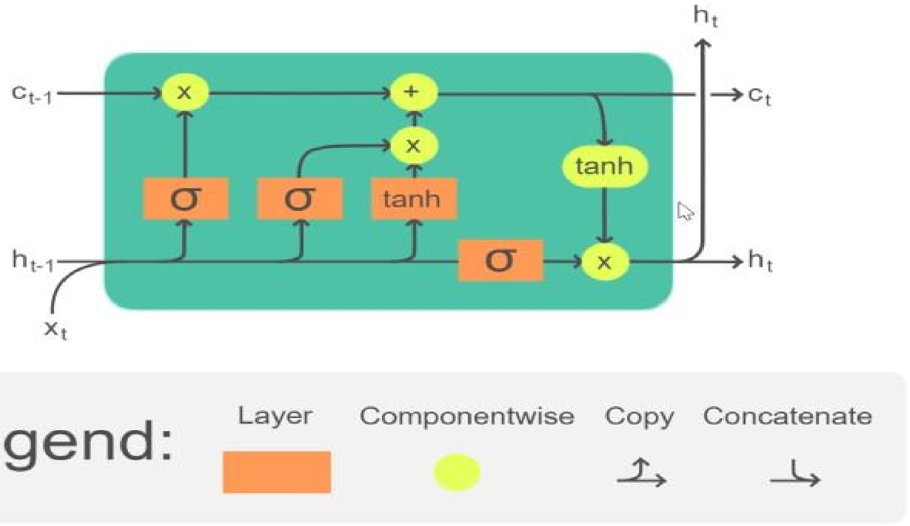


Figure 3 The Long Short-Term Memory (LSTM)

Structurally, LSTM consists of several main components: cell state, input gate, forget gate, output gate, and hidden state. Figure 3 shows the LSTM architecture, illustrating the flow of information through these various gates. The interpretation of this figure demonstrates how the cell state functions as long-term information storage, while the input gate regulates incoming information. The forget gate removes information that is no longer relevant, while the output gate determines which information is output. The hidden state represents the processing results at each time step, which are then used for prediction or further analysis in smart charging systems.

Research Framework and Stages

This research framework is designed to systematically illustrate the problem-solving process based on the problems identified in the research background. The research process begins with identifying smart charging problems, including charging time, power requirements, energy efficiency, and sustainability. Once the problems are identified, supporting data is collected to enrich relevant information, such as historical energy usage data and battery cell characteristics. This data is then analyzed to design a smarter and more efficient charging strategy. This approach ensures that the proposed solution is based on actual data and system requirements.

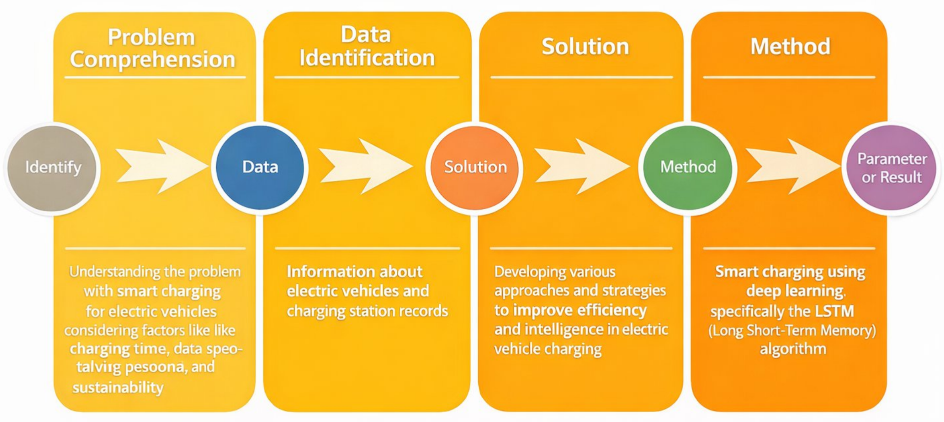


Figure 4 Conceptual Framework of the Research

Figure 4 represents the research conceptual framework, showing the relationship between problem identification, data collection, deep learning implementation, and expected results. Interpretation of this figure confirms that the LSTM-based smart charging solution aims to improve the model's performance in predicting battery life.

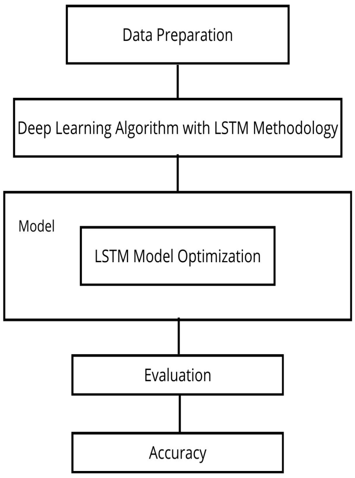


Figure 5 Research methods

Furthermore, Figure 5 illustrates the overall research methodology, from data preparation to model evaluation. Interpretation of this figure demonstrates that each research stage is integrated and supports the development of an optimal model. Evaluation is conducted by comparing the predicted results with actual data using appropriate metrics, allowing the model to be optimized and ready for application in electric vehicle battery production systems.

Result and Discussion

Sample Selection Method and Research Data Characteristics

The sample selection in this study was conducted using purposive sampling, a sampling technique based on specific considerations to ensure the data used is truly relevant to the research objectives. This technique was chosen because not all battery cell production data meets the criteria for smart charging analysis, particularly data containing complete charging and discharging parameters. The purposive sampling approach enabled the researchers to focus the analysis on data that reflect actual operational conditions in the production line. Thus, the data used was of sufficient quality for deep learning-based modeling. This technique aligns with the applied research approach, which emphasizes data accuracy and relevance.

Inclusion criteria included battery cell data with a complete charge cycle (from start to Final Current CHG recorded), fully documented voltage, current, and time parameters, and originating from the same production line to maintain process consistency. Exclusion criteria included data with missing values for key variables, interrupted or incomplete charge cycles, and data with extreme anomalies identified through interquartile limits (IQR) or operational technical thresholds established by the production system. Data were also restricted to specific production date ranges to ensure uniformity of machine configurations and operational procedures.

The sample size was determined based on the availability of production data that met quality and completeness criteria. All data that passed the screening process was used in the analysis to maximize the representativeness of actual operational patterns. A time-based data split strategy was implemented, with the initial period data used as training and the subsequent period data as testing, to reflect real-world prediction scenarios and prevent information leakage. To avoid potential data leakage, unit and production lot identifiers were checked. Data rows from the same production unit or batch were not allowed to be spread between the training and test sets. The split was performed at the unit/lot level to maintain the integrity of the model evaluation and ensure the test results reflect true generalizability.

The study population consisted of 10,000 battery cell data points from the production process, with a set error rate of 5%. Based on these calculations, a sample of 385 battery cell data sets was obtained. This number was deemed adequate to reflect the characteristics of the overall population without introducing significant bias. With this sample size, the analysis results are expected to be highly reliable and valid. This number was deemed adequate to reflect the characteristics of the overall population without introducing significant bias. With this sample size, the analysis results are expected to have a high level of reliability and validity.

The characteristics of the data used in this study reflect the actual conditions of the electric vehicle battery cell charging process in an industrial environment. The data includes technical charging parameters automatically recorded by the production system, ensuring objectivity and consistency. Furthermore, the data is supplemented with production identifiers, allowing individual tracking of each battery cell. This combination of technical and identifier data provides a strong foundation for data-driven analysis and predictive model development. Therefore, the sample selection method used is appropriate for the research needs and the objectives of developing a smart charging model.

Research Variable Description and Dataset Structure

The main variable in this study is the CHG End Current, which is the final electric current measured when the battery cell charging process is complete. This variable is positioned as the dependent variable because it reflects the success and stability of the charging process. A final current value that is too high or too low can indicate potential problems with the battery cell, such as charging inefficiency or the risk of degradation. Therefore, the CHG End Current was chosen as the primary prediction target in the smart charging model. Focusing on this variable enables a more comprehensive evaluation of the charging process's quality.

The independent variables used to predict the CHG End Current include CHG TIME, CHG CAPA, CHG Avg Voltage, and CHG End Voltage. These variables represent the charging duration, charging capacity, and voltage characteristics during the charging process. The combination of these variables provides a comprehensive picture of the battery cell's charging condition. The relationships between these variables are temporal and interdependent, making them highly suitable for modeling using an LSTM architecture. Therefore, the selection of research variables considered both technical aspects and the characteristics of time-series data.

Table 1 Summary of Power Charging Cell Dataset

Cell ID	Prod Line	Product ID	Charge CHG TIME	Charge Start Time	#1 CHG CAPA (mAh)	Avg Volt #1 (mV)	End Volt #1 (mV)	End Curr #1 (mA)	Temp #1 (C)	#2 CHG CAPA	Avg Volt #2 (mV)	End Volt #2 (mV)	End Curr #2 (mA)	Temp #2 (C)	DCHG CAPA (mAh)
BA03	ADJ01	A1-301	2024-07-08 12:38:47	2024-07-08 11:38:43	29768	3938	4100	16199	30,7	38914	3614	3735	6075	32,8	86715
BA04	ADJ01	A1-302	2024-07-08 12:38:47	2024-07-08 11:38:43	29865	3938	4100	16200	30,7	38695	3616	3735	6075	32,8	86703
BA05	ADJ01	A1-303	2024-07-08 12:38:47	2024-07-08 11:38:43	29772	3938	4100	16200	30,7	38552	3618	3735	6075	32,8	86814
BA06	ADJ01	A1-304	2024-07-08 12:38:47	2024-07-08 11:38:43	29840	3939	4100	16200	30,7	39192	3611	3735	6074	32,8	86884
BA07	ADJ01	A1-305	2024-07-08 12:38:47	2024-07-08 11:38:43	29816	3938	4100	16200	30,7	38905	3615	3735	6075	32,8	86739
BA08	ADJ01	A1-306	2024-07-08 12:38:47	2024-07-08 11:38:43	30002	3937	4100	16200	30,7	38917	3615	3735	6075	32,8	86799
BA09	ADJ01	A1-307	2024-07-08 12:38:47	2024-07-08 11:38:43	29839	3938	4100	16199	30,7	38917	3613	3735	6074	32,8	86799
BA10	ADJ01	A1-308	2024-07-08 12:38:47	2024-07-08 11:38:43	29790	3938	4100	16199	30,7	39039	3613	3735	6075	32,8	86799
BA11	ADJ01	A1-309	2024-07-08 12:38:47	2024-07-08 11:38:43	29886	3938	4100	16199	30,7	38720	3615	3735	6075	32,8	86751
BA12	ADJ01	A1-310	2024-07-08 12:38:47	2024-07-08 11:38:43	29870	3938	4100	16199	30,7	39261	3610	3735	6075	32,8	86718
BA13	ADJ01	A1-311	2024-07-08 12:38:	2024-07-08 11:38:	30008	3937	4100	16199	30,7	38955	3615	3735	6074	32,8	86751

Cell ID	**Prod Line**	**Product ID**	**Charge CHG TIME**	**Charge Start Time**	**#1 CHG CAPA (mAh)**	**Avg Volt #1 (mV)**	**End Volt #1 (mV)**	**End Curr #1 (mA)**	**Temp #1 (C)**	**#2 CHG CAPA**	**Avg Volt #2 (mV)**	**End Volt #2 (mV)**	**End Curr #2 (mA)**	**Temp #2 (C)**	**DCHG CAPA (mAh)**
			47	43											
BA14	ADJ01	A1-312	2024-07-08 12:38:47	2024-07-08 11:38:43	29798	3938	4100	16199	30,7	38732	3616	3735	6074	32,8	86718
BA15	ADJ01	A1-313	2024-07-08 12:38:47	2024-07-08 11:38:43	29751	3938	4100	16200	30,7	38855	3615	3735	6075	32,8	86687

The structure of the research dataset is summarized in Table 1. Summary of Power Charging Cell Dataset. This table displays sample battery cell charging and discharging data for two charging stages, including capacity, voltage, current, and final temperature. Each row of data corresponds to a single battery cell produced during a specific production cycle. Each row of data represents a single battery cell produced in a specific production cycle. The purpose of this table is to provide a concrete overview of the form and complexity of the analyzed data. With a systematic dataset structure, pre-processing and modeling can be carried out more effectively.

Dataset Classification and Data Attribute Determination

The research dataset was obtained from monitoring the charging system during the electric vehicle battery cell production process. This data is internal company data generated automatically by the production system, ensuring a high level of accuracy and consistency. The collected data includes complementary numeric and character data. Numeric data is used for technical analysis and modeling, while character data serves as an identifier and marker for the production process. The combination of these two data types allows for a more comprehensive analysis (Nti, Adekoya, & Weyori, 2020).

The character data in this study includes Cell ID, Prod Line, and Product ID. The Cell ID serves as a unique identifier for each battery cell, allowing for individual data tracking. The Prod Line indicates the sequence of machines or production lines used, which is essential for analyzing production performance. The Product ID represents the type of product produced and relates to the technical specifications of the battery cell. This identity data is crucial in the context of production management and quality control.

Table 2 Research Data Attributes

Attribute	Data Type	Description
Cell ID	Character (Char)	Identifies each battery cell in the production process.
Prod Line	Character (Char)	Represents the production line or sequence of manufacturing machines.
Product ID	Character (Char)	Identifies the product associated with the battery cell.
CHG TIME	Numeric	Indicates the time or duration required to charge the battery cell.
CAPA (mAh)	Numeric	Refers to the charging capacity, representing the amount of electrical energy stored in milliampere-hours (mAh).
CHG Avg Voltage (mV)	Numeric	Represents the average charging voltage measured in millivolts (mV), where 1 mV equals 0.01 volts.
CHG End Voltage (mV)	Numeric	Indicates the final charging voltage at the end of the charging process, measured in millivolts (mV).
CHG End Current (mA)	Numeric	Represents the charging current at the end of the charging process, measured in milliamperes (mA), where 1 mA equals 0.01 amperes.

The overall research data attributes are summarized in Table 2 of Research Data Attributes, which explains the attribute name, data type, and description of each variable. This table serves as the primary reference in the modeling process, ensuring that each variable is treated according to its data characteristics. A clear attribute structure also simplifies the data validation and transformation process. Thus, the determination of research datasets and attributes has been carried out systematically and supports deep learning-based analysis.

Data Preprocessing and Splitting

The data preprocessing stage is a crucial step to ensure that the data used is ready for analysis using machine learning methods (Tiu et al., 2022). At this stage, the data is cleaned of missing or invalid values and formatted for consistency. Furthermore, the numerical data is normalized using the MinMaxScaler method to equalize the range of values between variables. This normalization aims to improve the stability and convergence speed of the LSTM model. With proper preprocessing, data quality can be significantly improved.

After pre-processing, the dataset is split into training and test sets using the train_test_split function. This split is performed at an 80:20 ratio, with 80% for training data and 20% for testing data. The training data is used to train the LSTM model to learn patterns, while the test data is used to evaluate the model's performance on previously unseen data. This approach aims to avoid overfitting and ensure the model's generalizability. This allows for more objective and realistic model evaluation.

[4]:

	CELLID	PRODLINE	PRODID	CHG_TIME	START_TIME	CAPA1	CHG_AVG_VOLTAGE1	CHG_END_VOLTAGE1	CHG_END_CURRENT1	CHG_END_TEMPCHG_CAPA2
0	Cell ID	Prod \nLine	Product \nID	Charge\n CHG TIME	Charge\nStart Time	#1 CHG\nCAPA (mAh)	Charge\n#1 CHG Avg Voltage\n (mV)	Charge\n#1 CHG End Voltage\n (mV)	Charge\n#1 CHG End Current\n(mA)	Charge\n#1 CHG End Temp\n(C)
1	BA03	ADJ01	A1-301	2024-07-08 12:38:47	2024-07-08 11:38:43	29768	3938	4100	16199	30.7
2	BA04	ADJ01	A1-302	2024-07-08 12:38:47	2024-07-08 11:38:43	29865	3938	4100	16200	30.7
3	BA05	ADJ01	A1-303	2024-07-08 12:38:47	2024-07-08 11:38:43	29772	3938	4100	16200	30.7
4	BA06	ADJ01	A1-304	2024-07-08 12:38:47	2024-07-08 11:38:43	29840	3939	4100	16200	30.7
...	...	...	...	...	...	...	...	...	...	...
379	BA381	ADJ01	A1-1079	2024-07-08 12:38:47	2024-07-08 11:38:43	29821	3938	4100	16199	30.7
380	BA382	ADJ01	A1-1080	2024-07-08 12:38:47	2024-07-08 11:38:43	29773	3937	4100	16199	30.7
381	BA383	ADJ01	A1-1081	2024-07-08 12:38:47	2024-07-08 11:38:43	29794	3938	4100	16200	30.7

Figure 6 Open-Source Training Dataset View

The training and test dataset structures are shown in Figure 6. This figure shows that the test data consists of hundreds of rows and several columns representing all the study attributes. This presentation provides a visual illustration of the dataset's complexity and completeness. A well-organized data structure allows for more effective modeling and evaluation. Therefore, preprocessing and data segmentation are crucial foundations for this research.

LSTM Modeling and Training

Modeling was performed using a Long Short-Term Memory architecture designed for time-series data. The LSTM model was built using a sequential architecture with two LSTM layers and a single dense output layer. The first LSTM layer captures the sequential patterns in the data, while the second layer deepens the model's understanding of temporal relationships between variables. The dense layer is used to generate predicted CHG End Current values. This architecture was chosen because it can accommodate the complexity of battery cell charging data.

Model training was performed using the training data with a predetermined number of epochs. During the training process, the loss and validation loss values were monitored to assess model performance. The training results showed a gradual decrease in the loss value until it reached a stable state, indicating that the model successfully learned the data patterns. A summary of the model architecture and the number of parameters indicates that the model has adequate complexity without being excessive. Thus, the developed LSTM model strikes a balance between accuracy and computational efficiency.

Analysis of the training results also shows that the training time per epoch decreases as the training process progresses. This indicates that the model is becoming more stable and efficient in updating weights. The convergence of the loss and validation loss indicates that the model does not overfit. With consistent training results, the LSTM model is deemed suitable for use in the prediction and further evaluation stages. This finding strengthens the effectiveness of the deep learning approach in the context of smart charging.

Prediction, Model Evaluation, and Prototype Implementation

After the training process was completed, the LSTM model was used to generate predictions on the test data, separated by time (time-series split) to prevent data leakage. The data was divided into training and test sets chronologically, with predetermined proportions. To ensure reproducibility, a random seed was set during model initialization and data splitting.

All numerical features were normalized using the Min-Max Scaling method. The scaler fitting process was performed only on the training data, then the obtained scaling parameters were applied to the test data. Missing data were handled using an imputation method appropriate to the data distribution characteristics, while outliers were identified using an interquartile range-based statistical approach and treated as needed for the analysis. Evaluation was conducted using Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2) metrics to describe the model's predictive performance on the test data. The evaluation results present the predictive output of the model and its ability to capture variation in the data based on the applied modeling approach. Thus, the model has proven effective in supporting decision-making.

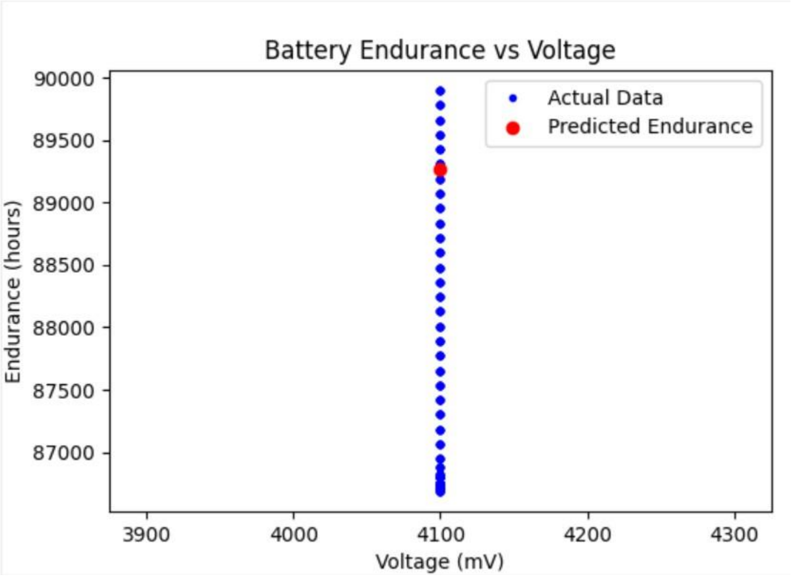
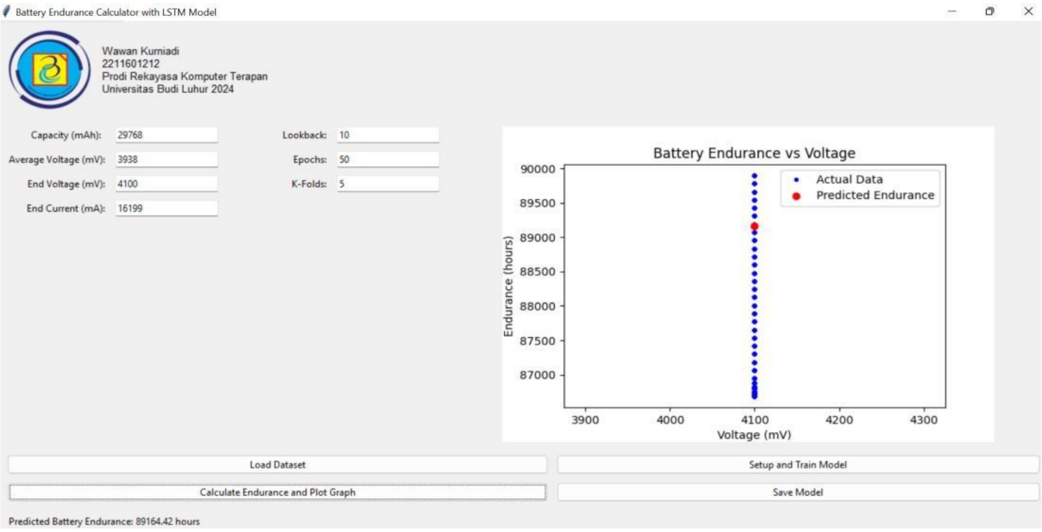


Figure 7 Graphic Interface Display

The prediction and evaluation results are visualized in a graphical interface, as shown in Figure 7. This graph compares actual and predicted battery life values, facilitating interpretation of the model results. This visualization helps users understand prediction patterns and potential deviations. The graphical presentation also enhances the transparency of the research results. With informative visualizations, model evaluation becomes more intuitive.


Battery Endurance Calculator with LSTM Model

Wawan Kurniadi
2211601212
Prodi Rekayasa Komputer Terapan
Universitas Budi Luhur 2024

Capacity (mAh): 29768
Average Voltage (mV): 3938
End Voltage (mV): 4100
End Current (mA): 16199
Lookback: 10
Epochs: 50
K-Folds: 5

Predicted Battery Endurance: 89164.42 hours

Figure 8 User Interface Prototype

As a practical implementation, this research developed a prototype user interface, shown in Figure 8. This prototype allows users to load the dataset, train the LSTM model, enter charging parameters, and view the prediction results visually. This interface is designed to be easy to use and flexible for analysis needs. The presence of this prototype demonstrates that the developed model is not only theoretical but also applicable in industrial settings. Thus, this research makes a significant contribution to the development of deep learning-based smart charging systems.

The results of this study demonstrate that a deep learning-based smart charging method using a LSTM algorithm can optimize the charging process of electric car battery cells during the production phase. The developed LSTM model demonstrated stable, convergent performance, characterized by low training and validation losses that were consistent across training and testing. Predictions of the CHG End Current variable as the target indicate that charging patterns can be effectively learned from the parameters of charging time, capacity, and average voltage. These findings indicate that charging at relatively low voltages can still produce optimal battery life when intelligently controlled. Thus, this study confirms that charging optimization during the production phase can directly contribute to energy efficiency and battery cell quality.

These findings align with previous research showing that LSTM is effective at modeling the life-cycle behavior of lithium-ion batteries using initial sequential data. However, the key difference lies in the application context: this study focused on post-production cycle life prediction, whereas the other study emphasizes charging optimization during the production phase (Brenna, Foiadelli, Leone, & Longo, 2020). Furthermore, these results also support the findings of Park et al. This study demonstrates that the LSTM architecture can capture the complex dynamics of battery data and improve the accuracy of remaining useful life predictions. However, this study does not explicitly use a multi-channel approach; instead, it focuses on the key charging parameters available in production data. This demonstrates that even with more limited parameters, the LSTM can still provide reliable predictions (Hadian, Akbari, Farzinfar, & Saeed, 2020).

Furthermore, this study is consistent with previous studies that emphasize the importance of intelligent charging management to reduce the burden on the electric power system (Wang et al., 2023). In this context, the results of this study extend previous findings by demonstrating that charging optimization is relevant not only at the user or grid level but also at the battery cell manufacturing level.

The main contribution of this study lies in applying the LSTM algorithm to optimize electric vehicle battery cell charging directly in the production process, a topic that has been relatively rarely discussed in previous research. Furthermore, this study provides empirical evidence that the use of lower charging voltages, when combined with deep learning-based control, does not significantly degrade battery performance. The development of a user interface prototype also provides a practical contribution, enabling the direct implementation of this research in industrial settings. Thus, this research not only contributes theoretically to the development of battery prediction models but also practically to support operational decision-making in the electric vehicle battery manufacturing industry.

However, this study still has several limitations that could provide opportunities for further research. Future research is recommended to integrate more operational parameters, such as ambient temperature and dynamic current variations, to improve model accuracy and generalization. Furthermore, the use of other deep learning architectures, such as Gated Recurrent Units (GRUs) or hybrid models, can be explored to compare with LSTM performance. Further research can also expand the data coverage by involving more production lines or longer time periods. With these developments, it is hoped that deep learning-based smart charging systems will be increasingly optimized and better adapted to the needs of the electric vehicle battery industry in the future.

Conclusions

This study demonstrates the application of a deep learning-based intelligent charging method with a LSTM architecture to adaptively model and analyze the charging process of electric vehicle battery cells during the production stage. This approach is used to process production data and evaluate charging patterns to support the formulation of a more structured charging strategy during the manufacturing stage. Based on historical data on battery charging and voltage, the LSTM model can capture complex temporal patterns, enabling smarter, more stable charging decisions aligned with established operational constraints. The results of this study confirm that sequential modeling of battery cell voltages enables control of the charging process to maintain safe, optimal conditions, while simultaneously supporting efficient energy use and reducing the burden on the electrical infrastructure. The main contribution of this study to science lies in the development of a data-driven approach for battery charging optimization during the production phase, extending the application of LSTM not only to the battery use stage but also to the manufacturing process. Thus, this study provides a scientific basis for integrating deep learning technology into electric vehicle battery production systems to support sustainability and energy efficiency and to improve battery quality.

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References

Aduama, P., Zhang, Z., & Al-Sumaiti, A. S. (2023). Multi-feature data fusion-based load forecasting of electric vehicle charging stations using a deep learning model. *Energies*, *16*(3), 1309. https://doi.org/10.3390/en16031309

Aghajan-Eshkevari, S., Azad, S., Nazari-Heris, M., Ameli, M. T., & Asadi, S. (2022). Charging and discharging of electric vehicles in power systems: An updated and detailed review of methods, control structures, objectives, and optimization methodologies. *Sustainability*, *14*(4), 2137. https://doi.org/10.3390/su14042137

Ahmad, A., Khalid, M., Ullah, Z., Ahmad, N., Aljaidi, M., Malik, F. A., & Manzoor, U. (2022). Electric vehicle charging modes, technologies and applications of smart charging. *Energies*, *15*(24), 9471. https://doi.org/10.3390/en15249471

Alanazi, F. (2023). Electric vehicles: benefits, challenges, and potential solutions for widespread adaptation. *Applied Sciences*, *13*(10), 6016. https://doi.org/10.3390/app13106016

Arafat, Y. B., & Weiwei, H. U. (2023). The Development of a Matlab-Based Fuzzy PID Controller and The Simulation. *International Journal of Engineering Continuity*, *2*(1), 14–26. https://doi.org/10.58291/ijec.v2i1.85

Arif, S. M., Lie, T. T., Seet, B. C., Ayyadi, S., & Jensen, K. (2021). Review of electric vehicle technologies, charging methods, standards and optimization techniques. *Electronics*, *10*(16), 1910. https://doi.org/10.3390/electronics10161910

Brenna, M., Foiadelli, F., Leone, C., & Longo, M. (2020). Electric vehicles charging technology review and optimal size estimation. *Journal of Electrical Engineering & Technology*, *15*(6), 2539–2552. Retrieved from https://link.springer.com/article/10.1007/s42835-020-00547-x

Budiarto, S. P., Sumitro, A. H., & Taufiq, M. (2024). Intelligent system design for oyster mushroom cultivation using Mamdani fuzzy inference with Internet of Things (IoT). *International Journal of Engineering Continuity*, *3*(2), 86–106. Retrieved from https://ejournal.sultanpublisher.com/index.php/ijec/article/view/301

Crozier, C., Morstyn, T., & McCulloch, M. (2020). The opportunity for smart charging to mitigate the impact of electric vehicles on transmission and distribution systems. *Applied Energy*, *268*, 114973. https://doi.org/10.1016/j.apenergy.2020.114973

Farsi, B., Amayri, M., Bouguila, N., & Eicker, U. (2021). On short-term load forecasting using machine learning techniques and a novel parallel deep LSTM-CNN approach. *IEEE Access*, *9*, 31191–31212. Retrieved from https://ieeexplore.ieee.org/abstract/document/9356582

Hadian, E., Akbari, H., Farzinfar, M., & Saeed, S. (2020). Optimal allocation of electric vehicle charging stations with adopted smart charging/discharging schedule. *IEEE Access*, *8*, 196908–196919. Retrieved from https://ieeexplore.ieee.org/abstract/document/9239896

Lo Franco, F., Cirimele, V., Ricco, M., Monteiro, V., Afonso, J. L., & Grandi, G. (2022). Smart charging for electric car-sharing fleets based on charging duration forecasting and planning. *Sustainability*, *14*(19), 12077. https://doi.org/10.3390/su141912077

Lo Franco, F., Ricco, M., Mandrioli, R., & Grandi, G. (2020). Electric vehicle aggregate power flow prediction and smart charging system for distributed renewable energy self-consumption optimization. *Energies*, *13*(19), 5003. https://doi.org/10.3390/en13195003

Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2020). A systematic review of fundamental and technical analysis of stock market predictions. *Artificial Intelligence Review*, *53*(4), 3007–3057. Retrieved from https://link.springer.com/article/10.1007/S10462-019-09754-Z

Qian, K., Fachrizal, R., Munkhammar, J., Ebel, T., & Adam, R. C. (2023). The impact of considering state-of-charge-dependent maximum charging powers on the optimal electric vehicle charging scheduling. *IEEE Transactions on Transportation Electrification*, *9*(3), 4517–4530. Retrieved from https://ieeexplore.ieee.org/abstract/document/10044725

Rotty, A. N. H. A. K., Dewayana, T. S., & Habyba, A. N. (2022). Cross-Industry Standard Process for Data Mining (CRISP-DM) Approach in Determining the Most Significant Employee Engagement Drivers to Sales at X Car Dealership. *Proc. 3rd Asia Pacific Int. Conf. Ind. Eng. Oper. Manag. Johor Bahru, Malaysia*, 3368–3379. Retrieved from https://mmsi.binus.ac.id/2020/09/18/cross-industry-standard-process-for-data-mining-crisp-dm/

Sadeghian, O., Oshnoei, A., Mohammadi-Ivatloo, B., Vahidinasab, V., & Anvari-Moghaddam, A. (2022). A comprehensive review on electric vehicles smart charging: Solutions, strategies, technologies, and challenges. *Journal of Energy Storage*, *54*, 105241. https://doi.org/10.1016/j.est.2022.105241

Sesotyo, P. A. (2025). Evaluating the Damage Cost of Vehicle to Grid Integration in Indonesia Power Grid for Sustainable Energy System. *International Journal of Engineering Continuity*, *4*(1), 85–117. https://doi.org/10.58291/ijec.v4i1.368

Shamsuddoha, M., & Nasir, T. (2025). The road ahead for hybrid or electric vehicles in developing countries: market growth, infrastructure, and policy needs. *World Electric Vehicle Journal*, *16*(3), 180. https://doi.org/10.3390/wevj16030180

Shanmuganathan, J., Victoire, A. A., Balraj, G., & Victoire, A. (2022). Deep learning LSTM recurrent neural network model for prediction of electric vehicle charging demand.

Sustainability, *14*(16), 10207. https://doi.org/10.3390/su141610207

Shen, X., Zhao, H., Xiang, Y., Lan, P., & Liu, J. (2022). Short-term electric vehicles charging load forecasting based on deep learning in low-quality data environments. *Electric Power Systems Research*, *212*, 108247. Retrieved from https://www.sciencedirect.com/science/article/pii/S0378779622004503

Suwoyo, H., Abdurohman, A., Li, Y., Adriansyah, A., Tian, Y., & Hajar, M. H. I. (2022). The Role of Block Particles Swarm Optimization to Enhance The PID-WFR Algorithm. *International Journal of Engineering Continuity*, *1*(1), 9–23. https://doi.org/10.58291/ijec.v1i1.37

Tiu, E. S. K., Huang, Y. F., Ng, J. L., AlDahoul, N., Ahmed, A. N., & Elshafie, A. (2022). An evaluation of various data pre-processing techniques with machine learning models for water level prediction. *Natural Hazards*, *110*(1), 121–153. Retrieved from https://link.springer.com/article/10.1007/S11069-021-04939-8

Wang, S., Zhuge, C., Shao, C., Wang, P., Yang, X., & Wang, S. (2023). Short-term electric vehicle charging demand prediction: A deep learning approach. *Applied Energy*, *340*, 121032. Retrieved from https://www.sciencedirect.com/science/article/pii/S0306261923003963

Windasari, S., Abdurohman, A., Ratib, A. A., Frihadi, A., & Montazi, K. (2025). Optimization Model of IoT and Machine Learning for Renewable Energy-Powered Aeroponic Systems. *International Journal of Engineering Continuity*, *4*(2), 40–56. https://doi.org/10.58291/ijec.v4i2.426