

An explainable artificial intelligence benchmarking with deep reinforcement learning for telecom battery backup prediction

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ABSTRACT

Accurate prediction of battery backup time is essential for ensuring service reliability and efficient energy management in modern telecommunication networks, particularly during power outages. This study proposes a comprehensive benchmarking framework to evaluate the performance of eleven advanced time-series forecasting models, including deep learning architectures (multi-layer perceptron (MLP), convolutional neural network 1-dimension (CNN1D), long short-term memory (LSTM), bidirectional long short-term memory (BiLSTM), gated recurrent unit (GRU), and temporal convolutional network (TCN)), Transformer-based models (Transformer, Informer-Lite, and patch time-series Transformer-lite (PatchTST-Lite)), and linear baseline approaches (decomposition linear (DLinear) and normalized linear (NLinear)). The models are trained and validated using real-world telecom power system data under varying load and environmental conditions. To improve model transparency and reliability, an explainable artificial intelligence (XAI) framework is incorporated to interpret feature contributions and identify key factors influencing battery performance. Experimental results indicate that Transformer-based models outperform conventional deep learning and linear models in terms of prediction accuracy and robustness across different operating scenarios. Furthermore, XAI analysis highlights that load current, ambient temperature, and battery health indicators are the most influential variables affecting backup time prediction. The proposed framework provides both high accuracy forecasting and interpretability, enabling more effective decision-making and enhancing energy resilience in telecommunication infrastructure.

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1. INTRODUCTION

In recent years, internet communication technologies have become a fundamental backbone for modern businesses and digital services. These technologies enable seamless data exchange across domestic and international networks, resulting in rapid expansion of the telecommunication industry [1]–[3].

Telecommunication systems can be broadly classified into wired, wireless, and satellite-based communication infrastructures [4]–[6], all of which depend on geographically distributed base stations and communication nodes to ensure continuous service coverage and reliability. Ensuring uninterrupted operation of telecommunication infrastructure remains a significant challenge, particularly under power outage conditions or unstable grid environments. Each communication site must maintain continuous operation to preserve network availability and service quality. Consequently, backup power systems are essential components in telecommunication networks. Among these, battery energy storage systems play a critical role in supplying emergency power during grid failures. Despite the development of advanced battery technologies, lead-acid batteries are still widely deployed due to their cost-effectiveness, robustness, and ease of maintenance [7]–[9].

However, accurately predicting battery backup time remains a challenging task in real-world applications. Field investigations conducted in collaboration with a telecommunication service provider indicate that existing estimation methods often rely on periodic testing or simplified assumptions, which fail to capture dynamic operating conditions. In practice, battery performance is influenced by multiple factors, including load demand, ambient temperature, battery aging, and operational patterns, leading to nonlinear, and time-varying behaviors. These complexities often result in discrepancies between estimated and actual backup durations, which negatively impact maintenance planning, fault management, and overall system reliability. Recent advances in artificial intelligence (AI) and time-series forecasting have demonstrated strong potential in addressing complex prediction problems in energy and telecommunication systems [10]–[13]. Deep learning models, including recurrent neural networks (RNNs) and convolutional architectures, have been widely applied to capture nonlinear temporal dependencies. For instance, long short-term memory (LSTM)-based approaches have been used for fault prediction and root cause analysis in communication systems [14], [15], while explainable deep-learning frameworks have shown improved accuracy in battery state prediction [16]. Similarly, convolutional neural network (CNN) and RNN models have been applied to traffic prediction in edge networks, demonstrating improved performance in distributed environments [17]–[19].

More recently, Transformer-based architectures have emerged as powerful tools for time-series forecasting due to their ability to model long-range dependencies. Studies such as [20]–[22] have demonstrated that Transformer models outperform conventional approaches, achieving significant improvements in forecasting accuracy. Advanced variants, including patch time-series transformer (PatchTST) and decomposition linear (DLinear), have further improved performance in both single-step and multi-step prediction tasks [22], [23]. In the context of battery systems, several Transformer-based models have been proposed for state-of-health (SoH) and remaining useful life (RUL) prediction, including nonlinear autoregressive with exogenous inputs-Transformer (NARX-Transformer) [24], growth and seasonal embedding within the Transformer (SGEformer) [25], and hybrid autoencoder-Transformer models [26], [27], which report significant improvements in prediction accuracy and robustness.

In addition to predictive performance, explainability has become an important requirement for practical deployment. Explainable artificial intelligence (XAI) techniques, such as Shapley additive explanation (SHAP), attention analysis, and AIChronoLens, have been applied to interpret model behavior and identify key factors influencing predictions [17], [23], [28]–[31]. These methods provide valuable insights into feature importance and temporal dependencies, supporting engineering decision-making. However, most existing studies focus on individual models and do not provide a comprehensive comparison across multiple architectures. Furthermore, the integration of XAI within a unified benchmarking framework remains limited, particularly in telecommunication energy systems.

To address these gaps, this study proposes a comprehensive and explainable benchmarking framework for battery backup time prediction using real-world telecommunication data. The proposed approach evaluates eleven state-of-the-art models, including deep learning architectures (multi-layer perceptron (MLP), CNN 1-dimension (CNN1D), LSTM, bidirectional long short-term memory (BiLSTM), gated recurrent unit (GRU), and temporal convolutional network (TCN)), Transformer-based models (Transformer, Informer-Lite, and PatchTST-Lite), and linear baseline models (DLinear and normalized linear (NLinear)). The investigated system consists of a 48 V lead-acid battery bank composed of four 12 V batteries connected in series with a nominal capacity of 100 Ah, supplying a typical telecommunication load.

The main contributions of this work are summarized as follows: i) a unified benchmarking framework for evaluating multiple time-series models under consistent conditions; ii) a real-world telecommunication dataset analysis, capturing dynamic battery operating conditions; iii) a comprehensive performance comparison, identifying the most accurate and robust prediction model; and iv) integration of XAI to interpret model predictions and identify key influencing factors. The proposed framework provides both high predictive accuracy and interpretability, offering valuable insights for intelligent energy management and enhancing the reliability and resilience of telecommunication infrastructure.

2. PROPOSED FRAMEWORK

This study proposes a comprehensive and explainable framework for predicting battery backup time in telecommunication energy systems using real-world operational data. The framework is designed to improve prediction accuracy, model robustness, and interpretability for practical engineering applications. The overall system consists of four main stages: data acquisition, data preprocessing, model development, and explainable analysis, as illustrated in Figure 1.

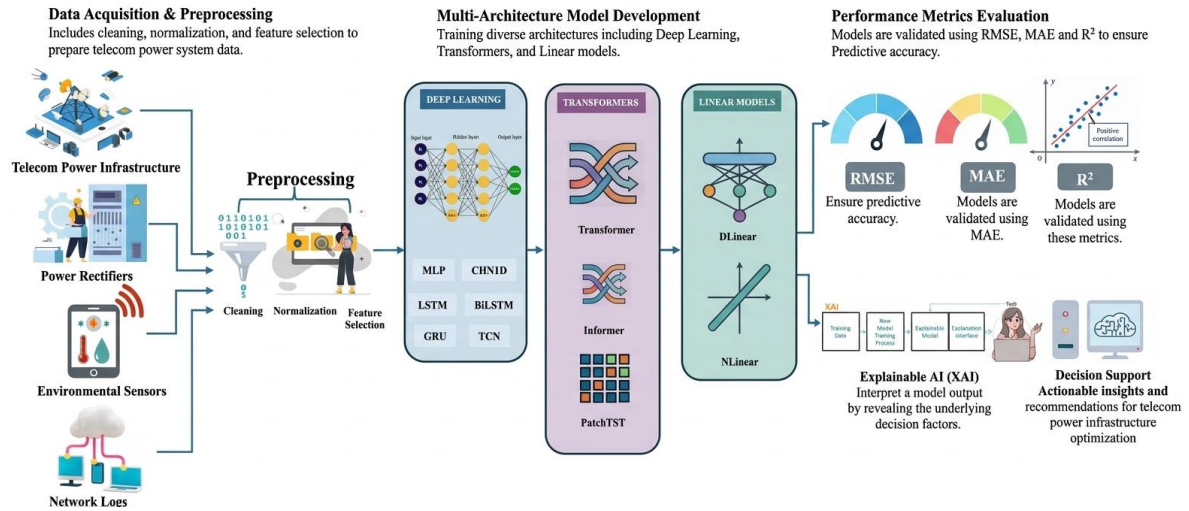


Figure 1. Proposed explainable multi-model framework for battery backup time prediction in telecommunication systems

In the data acquisition stage, operational data are collected from telecommunication sites, including electrical and environmental parameters such as battery voltage, load current, ambient temperature, and internal resistance. These data reflect real-world operating conditions and battery behavior under varying loads and environmental influences. In the data preprocessing stage, the collected data are processed through cleaning, normalization, and feature selection. This step ensures that the input data are consistent, well-structured, and suitable for training machine learning and deep learning models.

In the model development stage, multiple forecasting models are implemented and evaluated. These include deep learning models (MLP, CNN1D, LSTM, BiLSTM, GRU, and TCN), Transformer-based models (Transformer, Informer-Lite, and PatchTST-Lite), and linear baseline models (DLinear and NLinear). Each model is designed to capture temporal dependencies and nonlinear relationships in time-series data from different perspectives. To enhance model transparency and practical applicability, XAI techniques are incorporated in the final stage. These techniques are used to interpret model predictions and identify the contribution of key input variables, enabling better understanding of the factors affecting battery backup duration. The outputs of the framework provide both accurate prediction results and interpretable insights, which can support decision-making in energy management, maintenance planning, and reliability improvement in telecommunication infrastructure.

3. METHOD

3.1. Data collection

The data used in this study are collected from real telecommunication power systems, specifically from battery monitoring units installed at communication sites. The dataset includes both electrical and environmental parameters that reflect the operational behavior of the battery system under real-world conditions. The key variables consist of voltage, load current, temperature, internal resistance, and state-related indicators such as state of charge (SOC) and SoH. To formulate the problem mathematically, the system can be represented as a multivariate time-series model. The state of the battery at time t is defined as in (1) [25].

$$X_t = [X_1, X_2, \dots, X_n]_t \quad (1)$$

Where, X_t represents the state vector at time t , and x_i denotes the i -th feature describing battery characteristics such as voltage, current, temperature, and internal resistance. The target variable in this study is the battery backup time, denoted as y_t in (2) which represents the duration that the battery can supply power under given operating conditions.

$$y_t = BackupTime_t \quad (2)$$

The relationship between input variables and the predicted output is modeled using a nonlinear function as calculated in (3).

$$\hat{y}_{t+1} = f(X_{t-L+1}, \dots, X_t) \quad (3)$$

Where, $\hat{y}_{t+1}$ denotes the forecasted value at time $t + 1$, $f(\cdot)$ represents the nonlinear mapping function of the model, and L indicates the number of past time steps considered.

3.2. Data preprocessing

Since the data used in this study are time-series data with a sequential temporal structure, data preprocessing plays a crucial role in improving model performance. Prior to normalization and feature extraction, the raw operational data were subjected to a data-cleaning process. Missing values caused by communication interruptions or sensor malfunctions were identified and removed when the duration of missing records exceeded a predefined threshold. For isolated missing observations, linear interpolation was applied to preserve temporal continuity. Duplicate records and corrupted measurements were also eliminated from the dataset.

To detect anomalous observations, an interquartile range (IQR)-based outlier detection method was employed. Data points located outside 1.5 times the IQR were flagged for further inspection. However, sudden variations caused by actual telecommunication load fluctuations were retained because they represent realistic operating conditions and provide valuable information for battery behavior modeling. Only observations associated with sensor failures, communication errors, or physically impossible measurements were removed.

Furthermore, consistency checks were performed on voltage, current, temperature, and internal resistance measurements to ensure that all values remained within physically reasonable operating ranges. This procedure improved data quality while preserving the intrinsic temporal characteristics of the battery system. The first step involves scaling the data (normalization) to reduce the differences in value ranges among variables. In this study, min-max normalization is applied [28], as defined in (4).

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (4)$$

Where, x' represents the normalized value of the original data x , obtained using the minimum value x_{min} and the maximum value x_{max} .

After normalization, the data are transformed into a format suitable for model learning using the sliding window technique. This approach groups the previous L time steps as input to predict the value at the next time step [28], as formulated in (5) and (6).

$$X^{(i)} = [X_i, \dots, X_{i+L-1}] \quad (5)$$

$$y^{(i)} = [y_{i+L}] \quad (6)$$

Where, $X^{(i)}$ represents the i -th input sequence and $y^{(i)}$ denotes the corresponding target value to be predicted. This process enables the model to effectively capture temporal dependencies in the data. In addition, feature engineering is performed to better reflect the physical behavior of the battery. For example, the depth of discharge (DoD) is introduced as an additional feature [28], which can be calculated as shown in (7).

$$DoD = \frac{I \times t}{C} \times 100 \quad (7)$$

Where I represents the current, t denotes time, and C is the battery capacity. The SOC can then be calculated as shown in (8).

$$SOC = 100 - DoD \quad (8)$$

Where SOC represents the proportion of remaining energy in the battery, taking into account the energy delivered, as expressed in (9).

$$E = V \times I \times t \quad (9)$$

Where E represents electrical energy, V denotes voltage, and I is the current. Meanwhile, temperature is a critical factor affecting battery lifetime, and its relationship can be described as shown in (10).

$$L_T = L_0 \times 2^{\frac{T-T_{ref}}{8.5}} \quad (10)$$

Where L_T represents the battery lifetime at temperature T , L_0 is the reference lifetime, and T_{ref} denotes the reference temperature. Subsequently, feature correlation analysis is conducted to examine the relationships among variables and to select the most relevant features for model training. This step helps reduce multicollinearity and improves the accuracy of the forecasting results, as illustrated in Figure 2.

Figure 2 presents the correlation heatmap of all variables used in this study, providing a comprehensive understanding of the behavior and interrelationships among battery parameters. The results indicate that internal resistance variables (cell internal resistance (Cell-IR) and total internal resistance (Total-IR)) exhibit a strong negative correlation with SoH (approximately -0.93), highlighting that an increase in internal resistance is directly associated with battery degradation. At the same time, temperature shows a clear negative correlation with backup time (approximately -0.90), confirming that operation under high-temperature conditions leads to a reduction in battery performance. In contrast, voltage-related variables, particularly voltage-BeforeTest, demonstrate a strong positive correlation with SoH (0.96), suggesting that voltage serves as an effective indicator of battery health.

In addition, some variables, such as Cell-IR and Total-IR, are highly correlated with each other, indicating the presence of multicollinearity. This finding supports the necessity of feature selection to improve both the accuracy and stability of the model. Overall, the analysis highlights those key factors influencing battery performance include internal resistance, voltage, and temperature, which form the foundation for subsequent modeling and analysis.

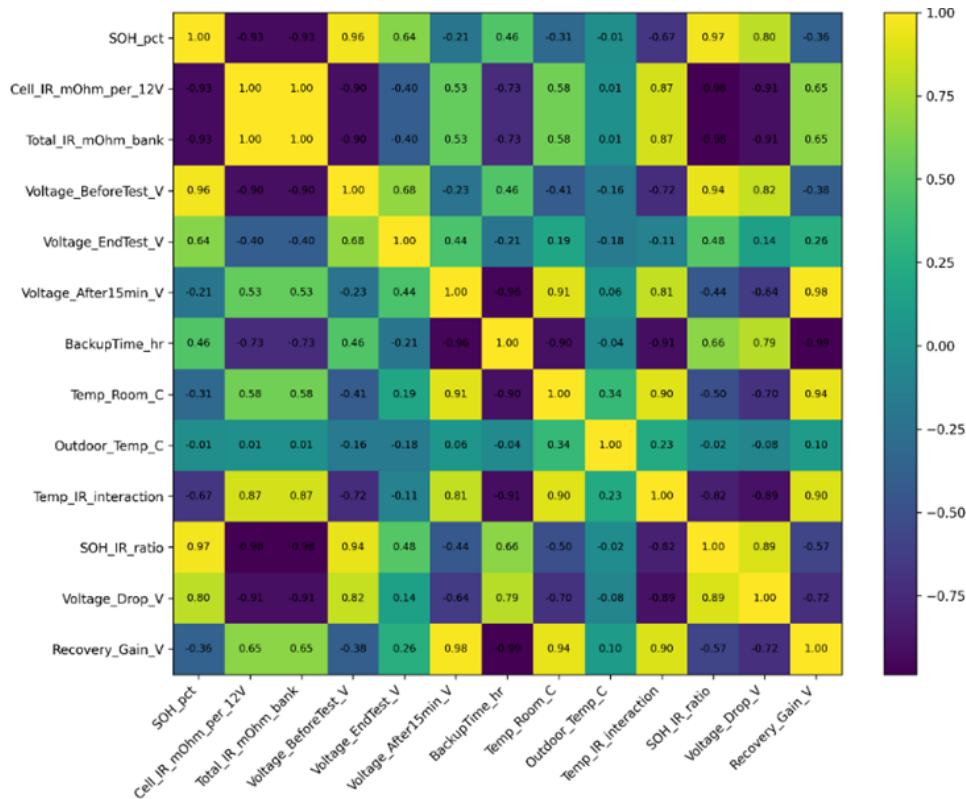


Figure 2. Heatmap illustrating the relationships among variables

3.3. Models' description

This study evaluates and compares the performance of 11 models, encompassing both deep learning and linear approaches, to comprehensively assess their effectiveness in time-series forecasting. Among the RNN architectures, the LSTM model is employed to address the issue of long-term dependency. The LSTM architecture incorporates gating mechanisms that regulate the flow of information within the network, enabling effective learning of temporal patterns [29], as described in (11) to (16).

$$f_t = \sigma(W_f x_t + U_f h_{t-1}) \quad (11)$$

Where f_t denotes the forget gate, which determines the information to be discarded; x_t represents the input at time t ; h_{t-1} is the previous hidden state; and W_f and U_f are the weight matrices of the model.

$$i_t = \sigma(W_i x_t + U_i h_{t-1}) \quad (12)$$

Where i_t denotes the input gate, which controls the new information to be added to the memory cell.

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (13)$$

Where c_t denotes the cell state, c_{t-1} represents the previous cell state, and $\tilde{c}_t$ is the candidate cell state containing newly generated information.

$$h_t = o_t \odot \tanh(c_t) \quad (14)$$

Where h_t denotes the output at time t , and o_t represents the output gate. Meanwhile, the GRU model has a simpler structure while still effectively capturing temporal dependencies.

$$z_t = \sigma(W_z x_t + U_z h_{t-1}) \quad (15)$$

Where z_t denotes the update gate, which determines the proportion of information to be updated.

$$h_t = (1 - z_t)h_{t-1} + z_t \tilde{h}_t \quad (16)$$

Where h_t denotes the current hidden state and $\tilde{h}_t$ represents the newly computed information. For convolution-based models, such as CNN1D and TCN, these are employed to extract temporal features using convolution operations, as described in (17).

$$y = \sigma(W \times x + b) \quad (17)$$

Where W represents the filter, x denotes the input, indicates the convolution operation, and b is the bias. In the case of TCN, dilated convolution is employed to expand the receptive field as in (18).

$$y(t) = \sum_{k=0}^K x(t - d \times k) w_k \quad (18)$$

Where $y(t)$ denotes the output at time t , d is the dilation factor, w_k represents the kernel weights, and K is the kernel size. In addition, models in the Transformer family are employed to capture long-term dependencies through the attention mechanism, as described in (19).

$$\text{Attention}(Q, K, V) = \text{soft max} \left(\frac{QK^T}{\sqrt{d_k}} \right) \times V \quad (19)$$

Where Q , K , and V denote the query, key, and value matrices, respectively, and d_k is the scaling dimension of the vectors. Finally, the DLinear model is employed to decompose the data into trend and seasonal components, as described in (20).

$$x_t = x_t^{\text{trend}} + x_t^{\text{seasonal}} \quad (20)$$

Where x_t^{trend} denotes the trend component and x_t^{seasonal} represents the seasonal component, as defined in (21).

$$y = W_{\text{trend}} x^{\text{trend}} + W_{\text{seasonal}} x^{\text{seasonal}} \quad (21)$$

Where W_{trend} and W_{seasonal} denote the weight parameters of each component, and y represents the predicted value.

3.4. Hyperparameter settings

To ensure a fair comparison among the 11 models, this study adopts a unified training framework with consistent conditions across all models. The dataset is structured as time-series data on a daily basis and is transformed into sequential input using the sliding window technique prior to the training process. The hyperparameter settings for all models are summarized in Table 1, along with the corresponding training configurations [30]. Table 1 presents the hyperparameter settings of all models in a structured tabular format. The key parameters are organized into major categories, including model dimension, number of layers, and the number of attention heads for Transformer-based models, as well as kernel or patch-related parameters for convolutional and patch-based models. In addition, model-specific parameters are summarized in the final column to ensure a concise and non-redundant presentation. This tabular format facilitates effective comparison across different model groups while preserving the essential structural details of each model.

Table 1. Hyperparameter settings for all models

Model	Main Architecture	Key hyperparameters				
		Hidden/d-model	Layers	Heads	Kernel/Patch	Other
MLP	Fully connected	128	2	-	-	Dropout = 0.1
CNN1D	Conv1D	64 (Channels)	-	-	Kernel = 3	Pool = 2
LSTM	RNN	64	2	-	-	Dropout = 0.1
BiLSTM	Bidirectional RNN	64	2	-	-	Dropout = 0.1, Bi = True
GRU	RNN	64	2	-	-	Dropout = 0.1
TCN	Temporal ConvNet	64	-	-	Kernel = 3	Dil = [1, 2, 4]
Transformer	Attention	64	2	4	-	FF = 128, Dropout = 0.1
Informer-Lite	Efficient Transformer	64	2	4	-	Dropout = 0.1
PatchTST-Lite	Patch Transformer	64	2	-	Patch = 4	Stride = 2
DLinear	Linear (decomposition)	-	-	-	Seq = 14	Trend + Seasonal
NLinear	Linear baseline	-	-	-	-	Input = 14 × F

3.5. Evaluation metrics

Model performance evaluation is a crucial step in determining the suitability of each model. In this study, multiple standard evaluation metrics are employed to comprehensively assess both absolute and relative prediction errors. The mean absolute error (MAE) is used to measure the average magnitude of prediction errors [19], [31], [32], as defined in (22).

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (22)$$

The root means square error (RMSE) places greater emphasis on larger prediction errors [19], [31], [32], as defined in (23).

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (23)$$

The coefficient of determination (R^2) is used to measure the ability of the model to explain the variance of the data [19], [31], [32], as defined in (24).

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (24)$$

Where y_i represents the actual value of the i -th observation, $\hat{y}_i$ denotes the predicted value, N is the total number of observations, and $\bar{y}$ is the mean of the actual values.

3.6. Explainable artificial intelligence analysis

To improve the interpretability of the forecasting models, this study employs the SHAP method. SHAP is a model-agnostic XAI technique based on cooperative game theory that quantifies the contribution of each input feature to the model prediction. By assigning an importance value to each feature, SHAP provides both global and local explanations, allowing the identification of the most influential variables affecting battery backup time prediction. The SHAP value for a feature is computed using the Shapley value formulation [33] as shown in (25).

$$f(x) = \phi_0 + \sum_{i=1}^N \phi_i \quad (25)$$

Where $f(x)$ is the model prediction, ϕ_0 is the baseline prediction, and ϕ_i represents the SHAP value of the i -th feature [33]. The SHAP value can be computed as (26).

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \quad (26)$$

Where ϕ_i represents the contribution of feature i , N denotes the set of all input features, S is a subset of features excluding feature i , and $f(\cdot)$ represents the prediction function of the trained model. The term $f(S \cup \{i\}) - f(S)$ measures the marginal contribution of feature i to the prediction. In this study, SHAP analysis is performed on the best-performing forecasting model to identify the variables that most strongly influence battery backup time prediction. The analysis is conducted through the following steps:

- Step 1: train the forecasting model using the prepared dataset.
- Step 2: apply the SHAP algorithm to compute feature contribution scores for each prediction.
- Step 3: aggregate the SHAP values across all samples to obtain global feature importance.
- Step 4: visualize and interpret the contribution of each feature using SHAP summary plots.

The obtained SHAP results provide valuable insights into the relationships between battery characteristics, environmental conditions, and backup duration. Furthermore, the analysis enhances model transparency and supports engineering decision-making by identifying the key factors that influence battery performance in telecommunication infrastructures.

4. RESULTS AND DISCUSSION

4.1. Benchmarking of deep learning and Transformer-based models

This section presents the experimental results of battery backup time forecasting models under different operating conditions, namely indoor and outdoor environments. The primary objective is to compare the performance of 11 models, including both deep learning and baseline approaches. Model performance is evaluated using standard statistical metrics, including MAE, RMSE, and R^2 , which collectively provide a comprehensive assessment of prediction accuracy and the model's ability to explain data variability. To provide an overall comparison, Table 2 summarizes the prediction errors of all models, ranked from best to worst based on their performance.

From Table 2, Informer-Lite achieves the best overall forecasting performance, yielding the lowest MAE (0.0676), the lowest RMSE (0.0862), and the highest R^2 (0.9964). The superior performance of Informer-Lite can be attributed to its efficient attention mechanism, which enables the model to capture long-range temporal dependencies while reducing computational complexity. Such capability is particularly important for battery backup time forecasting, where the current battery state is influenced not only by recent measurements but also by long-term degradation patterns and historical operating conditions.

Table 2. Comparison of model performance based on evaluation metrics

Model	MAE	RMSE	R^2
MLP	0.1128	0.1357	0.9911
CNN1D	0.0800	0.1001	0.9951
LSTM	0.0985	0.1260	0.9923
BiLSTM	0.0876	0.1118	0.9939
GRU	0.0766	0.0992	0.9952
TCN	0.1272	0.1566	0.9881
Transformer	0.0835	0.1096	0.9942
Informer-Lite	0.0676	0.0862	0.9964
PatchTST-Lite	0.0788	0.1019	0.9950
DLinear	0.1046	0.1298	0.9918
NLinear	0.0745	0.0946	0.9957

Among the deep learning models, GRU, CNN1D, Transformer, and PatchTST-Lite also demonstrate strong forecasting performance, all achieving R^2 values greater than 0.994. These results indicate that advanced neural network architectures are effective in learning the nonlinear relationships among battery condition indicators, environmental factors, and backup duration. Interestingly, the linear model achieves competitive performance, with an RMSE of 0.0946 and an R^2 of 0.9957, outperforming several more complex architectures. This finding suggests that the underlying battery backup time series contains relatively strong trend components that can be effectively captured by simple linear mappings. However, Informer-Lite still provides the highest prediction accuracy, indicating that attention-based architectures offer additional benefits in modeling complex temporal dependencies and nonlinear operating behaviors.

In contrast, MLP and TCN exhibit higher prediction errors, with RMSE values of 0.1357 and 0.1566, respectively. The inferior performance of these models suggests that they are less capable of

accurately representing the long-term temporal dynamics associated with battery degradation and operational variations. Overall, the results demonstrate that attention-based architectures, particularly Informer-Lite, provide the most reliable solution for battery backup time forecasting in real-world telecommunication systems. To gain deeper insights into model performance beyond the statistical evaluation presented in Table 2, the forecasting results are further analyzed in a time-series format. The predicted values are compared with the actual observations at each time step, allowing a detailed assessment of the models' ability to capture temporal trends and fluctuations. The forecasting results under indoor conditions are illustrated in Figure 3.

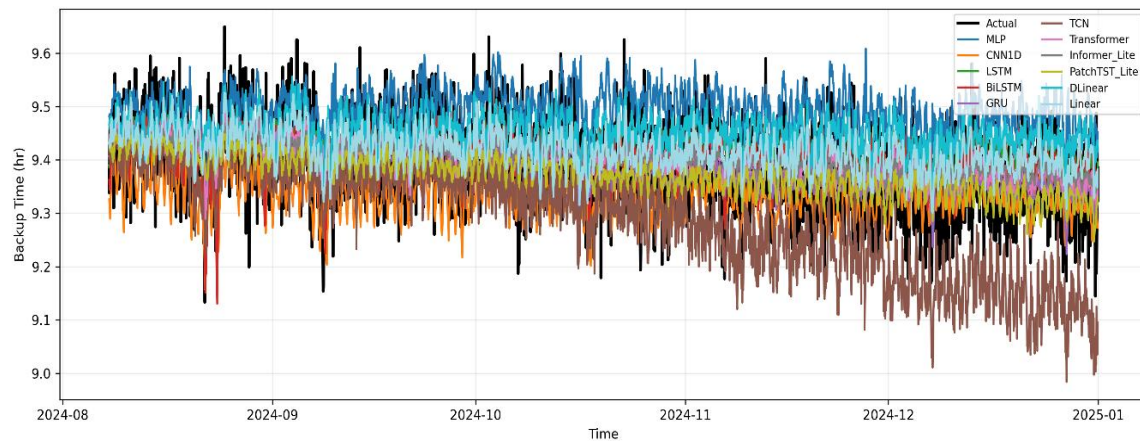


Figure 3. Forecasting results compared with actual values under indoor conditions

From Figure 3, it can be observed that models in the Transformer family, particularly Informer-Lite and Transformer, closely follow the actual values throughout the entire time horizon. The predicted curves largely overlap with the ground truth during both stable periods and fluctuating intervals, demonstrating their strong capability in capturing temporal dependencies effectively. In contrast, RNN models such as GRU and LSTM are able to capture the overall trend of the data; however, noticeable deviations are observed in certain periods, especially during rapid changes. This limitation may be attributed to their relatively weaker ability to model long-term dependencies compared to attention-based architectures. For linear models such as NLinear and DLinear, the predictions appear smooth and stable, but they fail to adequately capture data fluctuations, leading to higher errors during nonlinear variations. Additionally, the TCN model exhibits a consistent underestimation behavior across several time periods, indicating its limitation in accurately learning the true magnitude of the backup time. The results under indoor conditions suggest that models capable of capturing long-term dependencies and complex data structures tend to achieve superior forecasting performance compared to baseline approaches.

From Figure 4, it is evident that the data under outdoor conditions exhibit significantly higher variability compared to the indoor case. This behavior reflects the influence of external factors, such as temperature and dynamically changing environmental conditions, making the forecasting task more challenging. Nevertheless, models in the Transformer family maintain the highest level of accuracy, effectively tracking the underlying trends of the data even during highly fluctuating periods. This demonstrates their strong capability in handling nonlinear patterns and noisy data. In contrast, convolution-based models such as CNN1D and TCN show noticeably increased prediction errors, particularly during periods of high variability. This suggests limitations in their ability to capture complex patterns under unstable environmental conditions.

Figure 5 presents the comparison of training and validation loss across all forecasting models. Figure 5(a) presents the training loss curves of all forecasting models. The loss decreases rapidly during the initial epochs, indicating effective learning and parameter optimization. Figure 5(b) presents the validation loss curves. The relatively small gap between training and validation losses suggests good generalization capability and limited overfitting across all models. It can be observed that the loss values decrease rapidly during the initial epochs, indicating effective learning in the early stage. After approximately a few epochs, both training and validation losses gradually stabilize, demonstrating convergence of the models. Furthermore, the gap between training and validation loss remains relatively small across all models, suggesting that overfitting is minimal and the models are able to generalize well to unseen data. Among the models, most curves exhibit similar convergence behavior, while some models show slightly higher fluctuations in validation loss, reflecting differences in learning stability.

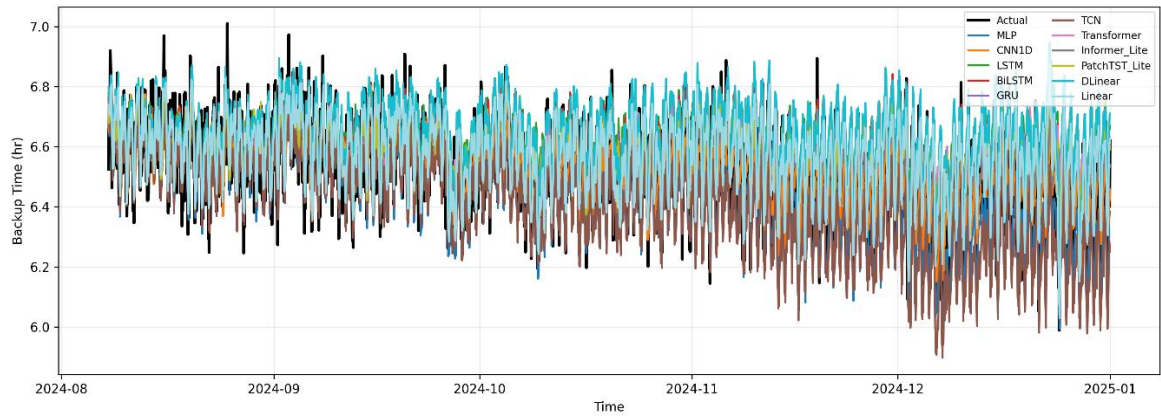
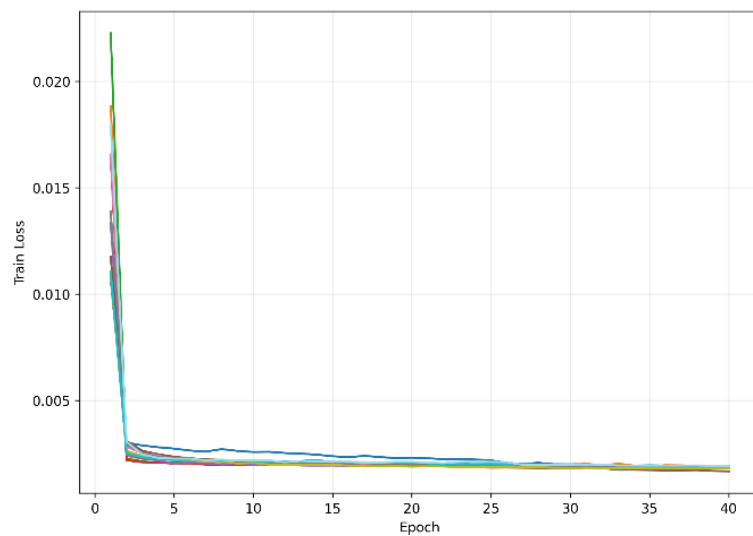
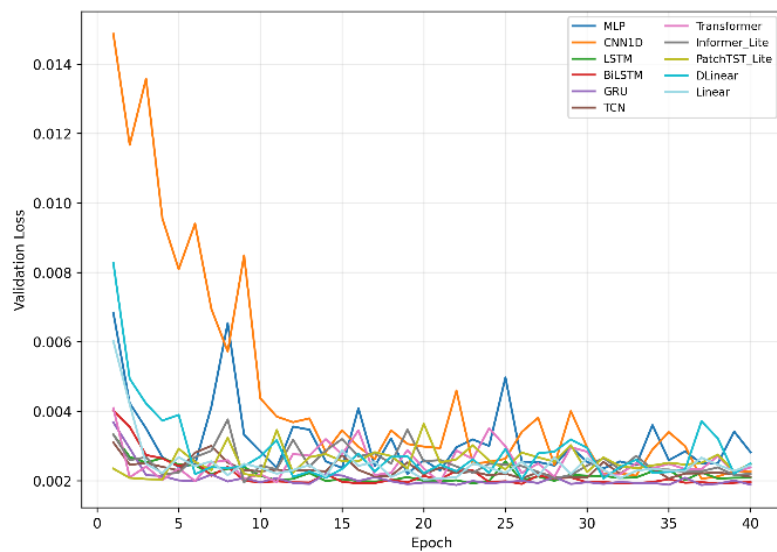


Figure 4. Comparison between predicted and actual values under outdoor conditions



(a)



(b)

Figure 5. The comparison of training and validation loss across all forecasting models (a) training loss curves and (b) validation loss curves over the training epochs

To further evaluate the effectiveness of the proposed forecasting framework, the performance of the best-performing model in this study was compared with related studies reported in the literature. Table 3 summarizes representative studies that applied deep learning and Transformer-based approaches for battery and energy-related time-series forecasting tasks. Table 3 compares the proposed framework with representative battery forecasting studies reported in the literature. Ardakani *et al.* [24] proposed a NARX-Transformer architecture for long-term battery SoH estimation and achieved a mean absolute percentage error (MAPE) of only 1.4%. Fauzi *et al.* [25] developed SGEformer, an enhanced Transformer model incorporating seasonal and growth embeddings, and reported a mean squared error (MSE) of 0.000117 for lithium-ion battery SoH prediction.

More recently, Zhu *et al.* [27] introduced a hybrid variational modal decomposition (VMD)-BiLSTM-Transformer model for simultaneous SoH estimation and RUL prediction, achieving an RMSE of 0.23% on the Oxford battery dataset. These studies consistently demonstrate the effectiveness of Transformer-based architectures in battery-related prediction tasks. Although direct numerical comparison is challenging due to differences in datasets, battery chemistries, operating conditions, and prediction objectives, the overall trend indicates that Transformer-based models provide superior performance compared with conventional deep learning approaches. In this study, Informer-Lite achieved the lowest RMSE (0.0862) and highest R^2 (0.9964) among all evaluated models for battery backup time forecasting in telecommunication systems. The results further confirm the capability of attention-based architectures to model nonlinear battery behavior and long-term temporal dependencies under real-world operating conditions.

Table 3. Comparison with previous studies

Study	Application	Model	Metric	Result
Wang <i>et al.</i> [9]	Telecom backup battery management	Deep learning	Service interruption	Reduced interruption time from 4.7 h to nearly zero
Ardakani <i>et al.</i> [24]	Battery SoH prediction	NARX-Transformer	MAPE	1.4%
Fauzi <i>et al.</i> [25]	Battery SoH prediction	SGEformer	MSE	0.000117
Zhu <i>et al.</i> [27]	Battery SoH/RUL prediction	VMD-BiLSTM-Transformer	RMSE	0.23% (Oxford)
Proposed study	Telecom battery backup time forecasting	Informer-Lite	RMSE and R^2	0.0862 and 0.9964

4.2. Explainable analysis and model interpretation

Following the performance comparison of the forecasting models, this study further conducts an explainability analysis using XAI techniques. The objective is to identify which input variables have the most significant influence on the forecasting results under different environmental conditions, as well as to verify that the learned patterns are consistent with the actual physical behavior of the battery. In this study, feature importance is analyzed using a heatmap representation, which illustrates the average magnitude of influence of each variable across different time steps within the input window. Variables with higher influence are indicated by warmer color tones, while lower influence is represented by cooler tones. This approach enables simultaneous interpretation of both which variables are important and which historical time steps contribute most significantly to the prediction, as shown in Figures 6 and 7.

The results of the XAI analysis under indoor conditions are presented in Figure 6. It is observed that the model assigns high importance to battery health-related and voltage-related features, such as SoH-pct, after-15min-Bank-Voltage-V, and Voltage-Recovery-V. In addition, the time-idx variable plays a significant role across multiple historical time steps, indicating that under indoor conditions, the model effectively leverages temporal trends to capture the gradual degradation behavior of the battery. Another noteworthy feature is SoH-IR-ratio, which demonstrates moderate to high importance across several positions. This suggests that the combined feature enables the model to simultaneously capture battery health status and the impact of internal resistance. Overall, the indoor case indicates that the model primarily relies on features that reflect gradual degradation trends and intrinsic battery performance characteristics.

The XAI results under outdoor conditions as shown in Figure 7 reveal a distinct feature importance pattern compared to the indoor case. Internal resistance-related variables, including average-IR-mOhm-per-12 V, Total-IR-mOhm-bank, and SoH-IR-ratio, play a more dominant role, reflecting the stronger impact of environmental stress on battery degradation. While SoH-pct remains a key feature in both cases, the outdoor model relies more on physical battery characteristics, whereas the indoor model emphasizes temporal trends. This observation is consistent with engineering principles, where increased internal resistance leads to faster voltage drop and reduced backup time. The results confirm that the model effectively captures both temporal and physical behaviors of the battery, enhancing its reliability for practical applications.

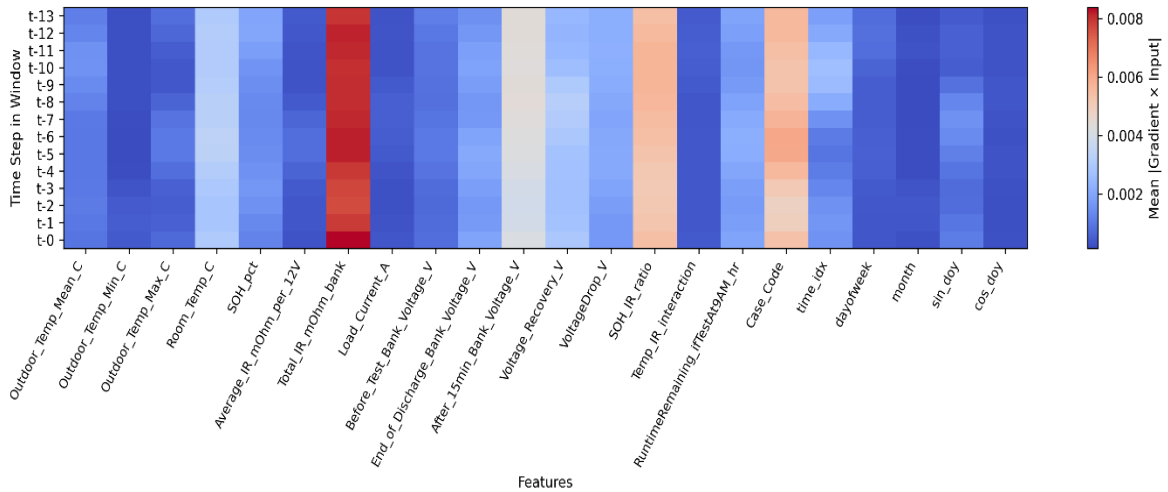


Figure 6. XAI-based feature importance analysis under indoor conditions

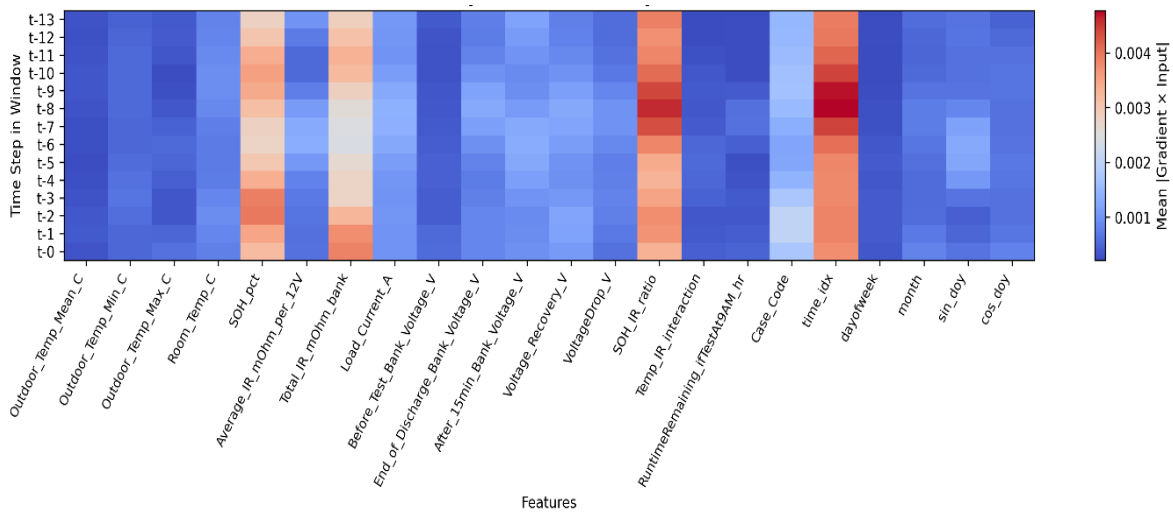


Figure 7. XAI-based feature importance analysis under outdoor conditions

5. CONCLUSION

This study presents a comprehensive benchmarking of deep learning models for battery backup time prediction in telecommunication networks with XAI. The results show that Informer-Lite achieves the best performance, with MAE is 0.0676, RMSE is 0.0862, and R^2 is 0.9964, outperforming all other models. Transformer-based models also demonstrate strong performance ($RMSE < 0.11$, $R^2 > 0.994$), while baseline models such as MLP and TCN show higher errors. Time-series analysis confirms that Transformer-based models can accurately track battery behavior under both indoor and outdoor conditions. XAI results further reveal that SoH-pct is the most important feature, with indoor conditions emphasizing temporal trends and voltage recovery, and outdoor conditions highlighting internal resistance effects. The proposed framework improves both prediction accuracy and interpretability, making it suitable for predictive maintenance in telecommunication systems.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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- C : Conceptualization
- M : Methodology
- So : Software
- Va : Validation
- Fo : Formal analysis
- I : Investigation
- R : Resources
- D : Data Curation
- O : Writing - Original Draft
- E : Writing - Review & Editing
- Vi : Visualization
- Su : Supervision
- P : Project administration
- Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

The author declares that there are no known conflicts of interest associated with this publication. There are no financial or personal relationships that could inappropriately influence or bias the content of this work.

INFORMED CONSENT

Not applicable. This study did not involve human participants, human data, or any personally identifiable information. All data used were either publicly available, fully anonymized, or derived from non-human sources, and therefore no informed consent was required from individuals.

ETHICAL APPROVAL

Not applicable. This research did not involve human subjects, human biological materials, or experimental procedures on animals. The work was conducted solely on computational models, publicly available datasets, or non-sensitive data that did not require intervention with living organisms. Therefore, ethical approval from an institutional review board or animal ethics committee was not necessary for this study.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [TB], upon reasonable request. The data are not publicly available due to confidentiality agreements with the telecommunication service provider.

REFERENCES

[1] M. A. Seibert, D. S. S. Lim, M. J. Miller, D. S.-Materese, and M. T. Downs, “Developing future deep-space telecommunication architectures: a historical look at the benefits of analog research on the development of solar system internetworking for future human spaceflight,” *Astrobiology*, vol. 19, no. 3, pp. 462–477, 2019, doi: 10.1089/ast.2018.1915.

[2] A. Hanlon, “Telecommunications infrastructure | Definition, types and examples,” study.com. Accessed: Aug. 05, 2025. [Online]. Available: <https://study.com/academy/lesson/telecommunications-infrastructure-definition-types-examples.html>.

[3] IEEE Standards Association, “IEEE recommended practice for maintenance, testing, and replacement of valve-regulated lead-acid (VRLA) batteries for stationary applications,” *IEEE Std 1188-2005*, 2006.

- [4] J. Ibrahim, T. Agadi Danladi, and M. Aderinola, "Comparative analysis between wired and wireless technologies in communications: a review," *International Journal of Electrical, Electronics and Data Communication*, vol. 5, no. 5, pp. 20-23, 2017.
- [5] N. U. L. Hassan, C. Huang, C. Yuen, A. Ahmad, and Y. Zhang, "Dense small satellite networks for modern terrestrial communication systems: benefits, infrastructure, and technologies," *IEEE Wireless Communications*, vol. 27, no. 5, pp. 96–103, 2020, doi: 10.1109/MWC.001.1900394.
- [6] Y. Chen, X. Ma, and C. Wu "The concept, technical architecture, applications and impacts of satellite internet: a systematic literature review," *Heliyon*, vol. 10, no. 13, Jul. 2024, doi: 10.1016/j.heliyon.2024.e33793.
- [7] S. S. Misra, "Advances in VRLA battery technology for telecommunications," *Journal of Power Sources*, vol. 168, no. 1, pp. 40–48, May 2007, doi: 10.1016/j.jpowsour.2006.11.005.
- [8] R. Kobus, P. Klis, and P. Godlewski, "Maintenance of lead-acid batteries used in telecommunications systems," *Journal of Telecommunications and Information Technology*, vol. 2015, no. 4, pp. 106–113, 2015, doi: 10.26636/jtit.2015.4.993.
- [9] F. Wang, X. Fan, F. Wang, and J. Liu, "Backup battery analysis and allocation against power outage for cellular base stations," *IEEE Transactions on Mobile Computing*, vol. 18, no. 3, pp. 520–533, Mar. 2019, doi: 10.1109/TMC.2018.2842733.
- [10] X. Song, L. Deng, H. Wang, Y. Zhang, Y. He, and W. Cao, "Deep learning-based time series forecasting," *Artificial Intelligence Review*, vol. 58, no. 1, 2024, doi: 10.1007/s10462-024-10989-8.
- [11] W. Li and K. L. E. Law, "Deep learning models for time series forecasting: a review," *IEEE Access*, vol. 12, pp. 92306–92327, 2024, doi: 10.1109/ACCESS.2024.3422528.
- [12] R. A. Rajagukguk, R. A. A. Ramadhan, and H.-J. Lee, "A review on deep learning models for forecasting time series data of solar irradiance and photovoltaic power," *Energies*, vol. 13, no. 24, Dec. 2020, doi: 10.3390/en13246623.
- [13] N. Maleki, O. Lundström, A. Musaddiq, J. Jeansson, T. Olsson, and F. Ahlgren, "Future energy insights: time-series and deep learning models for city load forecasting," *Applied Energy*, vol. 374, Nov. 2024, doi: 10.1016/j.apenergy.2024.124067.
- [14] Y. Özüpak, E. Aslan, and I. Zaitsev, "Explainable LSTM-AdamW based fault diagnosis of aircraft rotating components using airborne acoustic signals under dynamic operating conditions," *Scientific Reports*, vol. 16, no. 1, Feb. 2026, doi: 10.1038/s41598-026-41889-2.
- [15] A. Alkhalaf, "Optimizing fault prediction and analysis in radio site systems using deep learning: assessing temporal accuracy, root cause identification with LSTM and SHAP models," M.Sc. Thesis, School of Electrical Engineering and Computer Science (EECS), Stockholm, Sweden, 2023.
- [16] J. N. Njoku, C. I. Nwakanma, and D.-S. Kim, "Explainable data-driven digital twins for predicting battery states in electric vehicles," *IEEE Access*, vol. 12, pp. 83480–83501, 2024, doi: 10.1109/ACCESS.2024.3413075.
- [17] A. Petrella, M. Miozzo, and P. Dini, "Mobile traffic prediction at the edge through distributed and deep transfer learning," *IEEE Access*, vol. 12, pp. 191288–191303, 2024, doi: 10.1109/ACCESS.2024.3518483.
- [18] H. Uzel, Y. Özüpak, F. Alpsalaz, E. Aslan, and I. Zaitsev, "Acoustic-based fault diagnosis of electric motors using Mel spectrograms and convolutional neural networks," *Scientific Reports*, vol. 16, no. 1, Dec. 2025, doi: 10.1038/s41598-025-33269-z.
- [19] N. Khortsriwong *et al.*, "Performance of deep learning techniques for forecasting pv power generation: a case study on a 1.5 MWp floating PV power plant," *Energies*, vol. 16, no. 5, Feb. 2023, doi: 10.3390/en16052119.
- [20] S. Joseph, A. A. Jo, and E. D. Raj, "Improving time series forecasting accuracy with transformers: a comprehensive analysis with explainability," in *2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT)*, Jul. 2024, pp. 1–7, doi: 10.1109/ICEEICT61591.2024.10718609.
- [21] M. Hertel, S. Ott, B. Schäfer, R. Mikut, V. Hagenmeyer, and O. Neumann, "Evaluation of transformer architectures for electrical load time-series forecasting," in *Proceedings-32. Workshop Computational Intelligence: Berlin, 1.-2. December 2022*, Nov. 2022, pp. 93–110, doi: 10.5895/ksp/1000151141-6.
- [22] P. F. Pérez, C. Fiandrino, M. Fiore, and J. Widmer, "An in-depth analysis of advanced time series forecasting models for the Open RAN," in *IEEE INFOCOM 2024-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, May 2024, pp. 1–6, doi: 10.1109/INFOCOMWKSHPS61880.2024.10620742.
- [23] P. F. Perez, C. Fiandrino, M. Fiore, and J. Widmer, "Dissecting advanced time series forecasting models with AICHRONOLENS," in *IEEE INFOCOM 2024-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, May 2024, pp. 01–02, doi: 10.1109/INFOCOMWKSHPS61880.2024.10620847.
- [24] A. H. Ardakani, S. A. Abdollahian, and F. Abdollahi, "NARX transformer: a dynamic model for leveraging multicycle data in long-term battery state of health estimation," *IEEE Transactions on Instrumentation and Measurement*, vol. 73, pp. 1–8, 2024, doi: 10.1109/TIM.2024.3460947.
- [25] M. R. Fauzi, N. Yudistira, and W. F. Mahmudy, "State-of-health prediction of lithium-ion batteries using exponential smoothing transformer with seasonal and growth embedding," *IEEE Access*, vol. 12, pp. 14659–14670, 2024, doi: 10.1109/ACCESS.2024.3357736.
- [26] Q. Wu, Y. Ma, B. Zhang, F. Guo, W.-A. Zhang, and X. Qiu, "Privacy-preserving cross-silo federated learning for remaining useful life estimation of distribution transformers," *IEEE Sensors Journal*, vol. 25, no. 22, pp. 41594–41602, Nov. 2025, doi: 10.1109/JSEN.2025.3613334.
- [27] S. Zhu, X. Zhang, and Y. Wang, "Hybrid neural networks for lithium-ion batteries state of health estimation and remaining useful life prediction," *Journal of The Electrochemical Society*, vol. 172, no. 10, Oct. 2025, doi: 10.1149/1945-7111/ae0feb.
- [28] W. Zhang, J. Jia, X. Pang, J. Wen, Y. Shi, and J. Zeng, "An improved transformer model for remaining useful life prediction of lithium-ion batteries under random charging and discharging," *Electronics*, vol. 13, no. 8, 2024, doi: 10.3390/electronics13081423.
- [29] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.
- [30] H. Zhou *et al.*, "Informer: beyond efficient transformer for long sequence time-series forecasting," in *Proceedings of the AAAI Conference on Artificial Intelligence*, May 2021, pp. 11106–11115, doi: 10.1609/aaai.v35i12.17325.
- [31] F. Alpsalaz, Y. Özüpak, E. Aslan, and H. Uzel, "Hybrid machine learning approach for enhanced fault detection and power estimation in photovoltaic systems," *IET Renewable Power Generation*, vol. 20, no. 1, Jan. 2026, doi: 10.1049/rpg2.70153.
- [32] Y. Özüpak and E. Aslan, "Using artificial neural networks to improve the efficiency of transformers used in wireless power transmission systems for different coil positions," *Revue Roumaine Des Sciences Techniques—Série Électrotechnique Et Énergétique*, vol. 69, no. 2, pp. 195–200, Jul. 2024, doi: 10.59277/RRST-EE.2024.2.13.
- [33] S. M. Lundberg *et al.*, "From local explanations to global understanding with explainable AI for trees," *Nature Machine Intelligence*, vol. 2, no. 1, pp. 56–67, Jan. 2020, doi: 10.1038/s42256-019-0138-9.

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