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Research Article

Evaluating the EEMD-LSTM model for short-term forecasting of industrial power load: A case study in Vietnam

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Abstract. This paper presents the effectiveness of the ensemble empirical mode decomposition-long short-term memory (EEMD-LSTM) model for short term load prediction. The prediction performance of the proposed model is compared to that of three other models (LR, ANN, LSTM). The contribution of this research lay in developing a novel approach that combined the EEMD-LSTM model to enhance the capability of industrial load forecasting. This was a field where there had been limited proposals for improvement, as these hybrid models had primarily been developed for other industries such as solar power, wind power, CO2 emissions, and had not been widely applied in industrial load forecasting before. First, the raw data was preprocessed using the IQR method, serving as the input for all four models. Second, the processed data was then used to train the four models. The performance of each model was evaluated using regression-based metrics such as mean absolute error (MAE) and mean squared error (MSE) to assess their respective output**.** The effectiveness of the EEMD-LSTM model was evaluated using Seojin industrial load data in Vietnam, and the results showed that it outperformed other models in terms of RMSE, n-RMSE, and MAPE errors for both 1-step and 24-step forecasting. This highlighted the model's capability to capture intricate and nonlinear patterns in electricity load data. The study underscored the significance of selecting a suitable model for electricity load forecasting and concluded that the EEMD-LSTM model was a dependable and precise approach for predicting future electricity assets. The model's robust performance and accurate forecasts showcased its potential in assisting decision-making processes in the energy sector.

Keywords: Load forecasting, short-term, hybrid model, decomposition, EEMD, LSTM.

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1. Introduction

According to data from the (*World Energy Outlook 2019 – Analysis*, n.d.), In the year 2040, wind power is anticipated to produce an estimated 8,300 TWh, while solar photovoltaic (PV) is projected to generate around 7,200 TWh, surpassing hydropower which is estimated to be at 6,950 TWh. Furthermore, it is expected that the proportion of heat derived from renewable sources in 2040 will rise to 30% of the total, equivalent to 1,200 Mtoe. One major challenge in developing renewable energy sources such as wind and solar power is the limited generation capacity for consumer loads due to the lack of synchronized development in infrastructure and renewable power plants. This complexity makes integrating renewable energy sources into the existing power grid more difficult and challenging. Furthermore, the stability and forecasting of consumer loads, especially industrial loads, play a crucial role in optimizing the operation of renewable power plants. Accurate information about the electricity consumption of industrial plants in the future allows us to adjust the electricity production from renewable sources to match the actual demand. This improves the operational efficiency of renewable power plants while ensuring that the generated energy is utilized efficiently and cost-effectively. Therefore, the stability and forecasting of industrial consumer loads play a vital role in driving the development and integration of renewable energy sources into the power grid. Advanced technologies and forecasting methods applied in load forecasting enhance prediction capabilities and optimize the operation of renewable power plants, contributing to the creation of a sustainable and efficient electricity system for the future.

According to (Chattopadhyay, 2018), Vietnam's electricity sector is projected to experience significant growth by 2030, with an average annual increase of 8.9 percent in demand and a planned expansion of renewable energy capacity to 20 GW, while coal-fired capacity is expected to quadruple and account for over 40 percent of national generation capacity. In the context of the increasing demand for electricity consumption, the industrial sector always accounts for a high proportion (Duc Luong, 2015) and has a significant impact on the entire national power system. Therefore, accurate short-term industrial load forecasting (STILF) plays a critical role in maintaining the stability and safety of the power system. Inaccurate forecasts can have severe economic and energy security implications, impacting businesses and people's daily lives. Conversely, precise STILF can help optimize electricity usage, reduce

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production costs, and enhance generation capacity. The significance of load forecasting and STILF is particularly relevant in the context of Vietnam's economic and industrial development. With rapid economic growth, the country's industrial sector is experiencing a substantial increase in energy consumption. Consequently, there is a growing demand for accurate and comprehensive STILF to ensure the reliable and efficient integration of new electricity sources into the grid. Nonetheless, accurately predicting industrial demand in Vietnam presents several challenges. These challenges include significant regional variations in energy consumption patterns and the energy efficiency hurdles faced by various industries. Overcoming these obstacles and improving forecast accuracy can be achieved through the development of robust STILF models, leveraging advanced technologies such as data analytics and machine learning. By addressing these challenges and enhancing STILF capabilities, Vietnam can effectively manage its power systems, support sustainable economic growth, and successfully transition towards a greener and more reliable energy future.

In the field of STILF forecasting (Jurado *et al*., 2023; Walser & Sauer, 2021; Zhu *et al*., 2023), researchers have developed various models over the years, which can be categorized into two groups: causal forecasting models that require the identification of influencing factors, and time series-based forecasting models that solely rely on historical data (D. Wang *et al*., 2021; C. Zhang *et al*., 2022). Causal models, such as panel cointegration and support vector regression, attempt to analyze the electricity load by considering specific factors like electricity prices, exchange rates, and meteorological conditions. However, due to the complexity of determining these factors, time series-based approaches have gained popularity for their simplicity and practicality. These approaches include traditional statistical methods, artificial intelligence models, and hybrid models, which have been widely utilized in electricity load forecasting.

These methods can be broadly categorized into statistical methods, machine learning (ML) models, deep learning (DL) models, and hybrid models. Statistical methods, such as Auto Regressive (AR), Auto-Regressive Moving Average (ARMA), and Auto-Regression Integrated Moving Average (ARIMA) models, have been extensively used in STLF. For instance, (J.-F. Chen *et al*., 1995) proposed an adaptive ARMA model that overcomes the limitations of the traditional Box-Jenkins approach by incorporating an adaptive mechanism to update forecasts based on forecast errors. Experimental results demonstrated the superior accuracy of the adaptive algorithm, particularly for 24-hour load forecasting, underscoring the significance of adaptability in enhancing forecasting performance. However, statistical methods have certain drawbacks, including the assumption of historical data patterns persisting into the future, the need for a substantial amount of historical data, difficulty in predicting abrupt and unforeseen changes, sensitivity to outliers, and the quality of input data. Furthermore, statistical models may not perform optimally with non-linear input data, such as industrial loads. In such cases, machine learning-based forecasting methods or deep learning models can be employed to handle non-linear data and improve the accuracy of the forecasts.

Machine learning (ML) and deep learning (DL) models have demonstrated their potential in accurately predicting load demand. In recent years, researchers have introduced various algorithms such as artificial neural network (ANNs) (Satish *et al*., 2004), (Carolin Mabel & Fernandez, 2008), random forest (RF) (Lahouar & Ben Hadj Slama, 2015), support vector regression (SVR) (Hong, 2009), (Fan *et al*., 2008), (Y. Chen *et al*., 2017), convolutional neural networks (CNNs) (Imani, 2021), (Cannizzaro *et al*., 2021), (Mustaqeem *et al*., 2022), (Feng *et al*., 2022) recurrent neural networks (RNNs) (Aseeri, 2023; Shi *et al*., 2018), (Haider *et al*., 2022), long short-term memory (LSTM) (Muzaffar & Afshari, 2019), (Pooniwala & Sutar, 2021), (Haider *et al*., 2022), (Azizi *et al*., 2023), (Bui *et al*., 2022) and gated recurrent unit (GRU) (Li *et al*., 2022), (Liu *et al*., 2021), (Ma *et al*., 2022) models for short-term load forecasting. These models have shown improved forecasting results compared to traditional algorithms. For instance, (Fan *et al*., 2008) achieved superior accuracy and efficiency in next-day electricity load prediction using the SVR model. (Lahouar & Ben Hadj Slama, 2015) developed a short-term load prediction model using random forest, incorporating expert feature selection and an online learning process, resulting in high forecasting accuracy for the next 24 hours with an average error rate below 2.3%. (Satish *et al*., 2004) proposed a comprehensive ANN approach considering the impact of temperature on load forecasting. (Shi *et al*., 2018) introduced a novel pooling-based deep RNN to address the issue of overfitting by enhancing data diversity and volume. (Imani, 2021) introduced a load forecasting method, NRE, based on CNN, which surpasses other models by employing load cubes and load-temperature cubes to capture nonlinear load characteristics and load-temperature features, resulting in superior performance across different time periods and datasets. In (Muzaffar & Afshari, 2019), the proposed LSTM network outperformed traditional methods and offers improved accuracy in load forecasting by effectively capturing seasonalities and trends, with potential for further improvement when provided with data spanning more than one year. (Li *et al*., 2022) proposed a GRU model with adaptive temporal dependence that surpassed benchmark methods in multi-horizon load forecasting, achieving improved prediction accuracy (0.22-3.9% MAPE improvement on average), incorporating periodic and nonlinear characteristics, and demonstrating generalization and stability across diverse datasets. Overall, the application of these models can significantly improve load forecasting accuracy and enable better power system planning and operation. However, they also have some disadvantages. One of the main drawbacks of them is that they require a large amount of data to train and validate their models, which may not be available or accessible in some domains. Another drawback is that they may suffer from overfitting or underfitting, which means that they either memorize the training data too well or fail to capture the underlying patterns of the data. Moreover, ML and DL models are often complex and opaque, making it hard to interpret and explain their results and decisions. These disadvantages may limit the applicability and reliability of ML and DL models in some scenarios. Therefore, a hybrid model may be a better alternative.

In recent years, hybrid models that integrate data decomposition and machine learning (ML) methods have gained popularity due to their ability to utilize the strengths of each technique to enhance performance. Energy forecasting often uses decomposition-ensemble hybrid methods, which take advantage of the effectiveness of decomposition methods in handling time-series data. A typical decomposition ensemble method involves breaking down the time series into subseries that are smoother, more regular, and easily recognizable, predicting each subseries separately, and then combining the predictions. To reduce data complexity and reveal data features, decomposition methods are employed in decomposition-ensemble methods. Empirical mode decomposition (EMD) (Jiang *et al*., 2021), (Mounir *et al*., 2023), (Monjoly *et al*., 2017), (L. Zhang *et al*., 2021) variational mode decomposition (VMD) (Q. Zhang *et al*., 2022), (Sivakumar *et al*., 2023), (Ali *et al*., 2021), (Gao *et al*., 2023), (Wu *et al*., 2023) wavelet decomposition (WT) (Aasim *et al.*, 2021; Vijay *et al.*, 2022), (Ahn & Hur, 2023), (Bento *et al.*, 2019) singular spectrum analysis (SSA) (Afshar & Bigdeli, 2011), (Wei *et al.*, 2022), (Adedeji *et al.*, 2019), Seasonal and Trend decomposition using Loess (STL) (Trull *et al.*, 2022), (Nguyen *et al.*, 2021), (Ribeiro *et al.*, 2023) and ensemble empirical mode decomposition (EEMD) (Nguyen *et al.*, 2021),(Nguyen & Phan, 2022),(Ding *et al.*, 2022). For example, in (Mounir *et al.*, 2023), the proposed EMD-Bi-LSTM approach for short-term electrical load forecasting demonstrated high precision with an MAPE of 0.28% and RMSE of 0.31, contributing to improved accuracy and efficiency in energy management systems and smart grid development. (Q. Zhang *et al.*, 2022) proposed a load forecasting method that combined VMD and Stacking model fusion, demonstrating improved accuracy compared to XGBoost, VMD-XGBoost, and KNN methods by decomposing the load series into distinct intrinsic mode functions (IMF) and utilizing ensemble learning to fuse predictions from multiple basic models. The hybrid model proposed by (Aasim *et al.*, 2021), RWT-SVM, integrated WT and SVM features to leverage historical time-series data of electrical load, leading to enhanced forecasting accuracy as evidenced by comparisons with other models and diverse datasets. (Trull *et al.*, 2022) developed the MSTL-DIMS method, a modification of the STL decomposition, which overcomes the limitations of single seasonality and calendar effect by incorporating multiple seasonalities and discrete-interval moving seasonalities, leading to enhanced accuracy in short-term load forecasting for electricity systems. (Nguyen *et al.*, 2021) introduced a hybrid model that combined Ensemble Empirical Mode Decomposition (EEMD) and Bi-LSTM, achieving excellent load forecasting performance with a MAPE slightly above 2% when treating the entire year as a single time series, surpassing traditional models in the power industry. These above studies have highlighted the effectiveness of combining forecasting models with decomposition methods as a superior approach to electric load forecasting compared to using a single forecasting model. However, this method has not been widely applied to STILF, particularly in Vietnam, where data collection and processing pose significant challenges. Therefore, in this research, we proposed a combined approach of data decomposition using EEMD method and the LSTM forecasting model to forecast the industrial load of Seojin Vina installed in Bac Ninh, Vietnam.

The main contributions of this paper were in proposing a hybrid Short-Term Industrial Load Forecasting (STILF) method that combined the LSTM network with the EEMD data decomposition technique, leading to enhanced forecasting accuracy. This novel approach involved decomposing the original load data into random frequency components using the EEMD method and then dividing it into training and testing sets. The LSTM model was then utilized to forecast the load based on these sets, and the predicted values of the components were aggregated to generate the final forecast result. The successful application of the proposed method in industrial load forecasting in Vietnam was particularly noteworthy, considering the challenges and limitations in data collection that were prevalent in the region. By incorporating the EEMD and LSTM techniques into the forecasting process, the study overcame some of the difficulties related to data availability at the local level. This demonstration of feasibility and potential for industrial load forecasting, especially in scenarios with limited and incomplete data, underscored the practicality of the proposed method. Furthermore, this research significantly contributed to the field of industrial load forecasting and management by introducing an effective and novel approach. Given the critical importance of accurate load forecasting in ensuring the reliable and efficient operation of electrical systems, the combination of EEMD data decomposition and LSTM network offered promising prospects for improving forecasting accuracy. The findings of this study could serve as valuable guidance for future research and practical applications in the domain of industrial load forecasting, enabling more efficient planning and management of energy resources. The remaining part of the study consisted of the following: Section 2 presented the relevant techniques and the proposed forecasting framework. Section 3 detailed the experiments and analysis conducted. Finally, in Section 4, conclusions and suggestions for future research were provided.

2. Methodology

The proposed model in the study aimed to enhance the accuracy of load forecasting by integrating two techniques and developing a data decomposition technique with a deep learning model. The method consisted of two main components: decomposition and forecasting. Firstly, the initial data is collected by receiving signals from measuring devices, then forwarded to the data management system and pushed to the server. The measuring devices perform data sampling approximately every minute, however, the time for sending data to the server is not synchronized and may not be fixed. Therefore, the data needed to be time-synchronized, and a sampling frequency of once per hour was selected. This hourly sampled data was treated as the raw input for the model before undergoing preprocessing and forecasting steps. Then the data needed to be pre-processed then was decomposed into random frequency components using the EEMD method, which separated a signal into intrinsic mode functions (IMFs) based on the local characteristic timescale of the data. The details of pre-processing and the decomposition technique were presented in Section A and B, respectively. After the decomposition process, the data was split into training and testing sets, and the LSTM model was utilized for prediction. LSTM is a type of recurrent neural network that is well-suited for modeling time series data because of its ability to maintain a memory of past inputs. The details of the LSTM model were described in Section C. The LSTM model was trained on the decomposed data to predict the IMFs' values for the testing dataset. Finally, the predicted values of the IMFs were combined to generate the final forecast result. The model's structure was presented in Figure.1.

2.1 Dataset pre-processing

The raw unstructured dataset is transformed into a structured one. This step involves several important tasks to prepare the data for accurate electrical load forecasting. Firstly, the data is cleansed by handling any missing or irrelevant data and then data was removed outliers by using IQR method. IQR, or

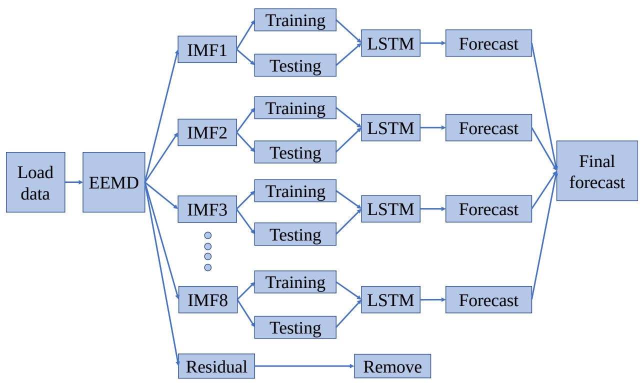

Figure 1. The structure of the proposed model

Interquartile Range, is a commonly used method for detecting outliers in data. Outliers are values that deviate significantly from the overall pattern of the data. There are various methods for identifying outliers, such as Z-score, density-based clustering, and isolation-forest. However, IQR is a popular univariate method that uses the median to locate different data points. The choice of statistical measures, such as median, mean, or mode, depends on the type of variability and presence of outliers. If there is less variability and no outliers, mean and standard deviation are preferred, but if there is much variability and outliers, median and IQR are preferred. The IQR method involves dividing the data into quartiles, namely Q1, Q2, and Q3, which represent the first, second, and third quartiles, respectively. These quartiles divide the data into four approximately equal-sized quarters. The IQR itself is calculated as the difference between Q3 and Q1. To further identify potential outliers, lower and upper bounds can be established using the (1), (2), (3):

$$IQR = Q3 - Q1 \tag{1}$$

$$Lower\ bound = Q1 - 1.5 * IQR \tag{2}$$

$$Upper\ bound = Q3 + 1.5 * IQR \tag{3}$$

Outliers are data points that fall below the lower bound or exceed the upper bound, indicating values that significantly deviate from the overall pattern of the dataset. It is important to note that the choice of statistical measures, such as median, mean, or mode, depends on the data's variability and the presence of outliers. In cases with higher variability and the existence of outliers, using the median and IQR is preferable to the mean and standard deviation.

After cleansing, the raw dataset is divided into two subsets: training and testing. To ensure the impact of all relevant input features, regardless of their actual range, the dataset is transformed using min-max scaling within a specified range or through normalization. This step not only enhances the runtime efficiency but also helps to improve the accuracy of the forecasting results.

2.2 Ensemble Emperical Mode Decompostion (EEMD)

EMD is a data processing technique that can handle non-linear and non-stationary time series by decomposing them into a finite number of oscillatory modes called intrinsic mode functions (IMFs). IMFs have specific properties such as the same or one more zero-crossing than extrema and a zero mean around the local average. EMD iteratively shifts the signal to obtain a set of IMFs and a residual. However, EMD suffers from mode-mixing, where one IMF may contain signals of different scales, or one signal may appear in different IMFs. To overcome this issue, EEMD enhances EMD by adding white noise to the signal and performing EMD on multiple noisy versions of the signal. It then averages the results to obtain the final IMFs. EEMD creates a uniform background in the time-frequency space, which assigns the signals to their proper scales. The steps of EEMD involve adding white noise, decomposing the signal into IMFs, repeating the process with different noise realizations, and finally, averaging the obtained IMFs to obtain the final IMFs.

Step 1: Input the original signal $x_0(t)$

Step 2: Given the amplitude of the white noise ε and the number of realizations I, and initialize the number of realizations $i = 1$;

Step 3: Generate the white noise $n_i(t)$ and reconstruct the signal using Eq 4.

$$x_i = x_{i-1}(t) + n_i(t) \tag{4}$$

Step 4: Decompose $x_i(t)$ into n IMFs $c_{j,i}(t)$ ($j = 1, 2, \ldots, n$) and one residue $r_i(t)$ using EMD

Step 5: If the maximum number of realizations is achieved, go to Step 6; otherwise, $i = i + 1$ and return to Step 3.

Step 6: Calculate the final IMFs using Eq…

$$c_j(t)=\sum_{i=1}^{I} c_{j,i}(t) \tag{5}$$

The original signal can be decomposed into n IMFs and one residue:

$$x_0(t)=\sum_{j=1}^{n} c_j(t) + r(t) \tag{6}$$

Where is the j_{th} IMF and is the residue which can be calculated using (6).

2.3 Long short-term memory network (LSTM)

LSTM is a type of Recurrent Neural Network (RNN) that overcomes the limitations of short-term memory and difficult training. It is well-suited for tasks such as time series classification and prediction and has numerous applications in natural language processing. Each LSTM unit includes a cell state, which is responsible for memory, and is denoted as c_t at time t. The LSTM unit receives the current input x_t, the previous hidden state h_{t-1}, and the cell state c_{t-1} through three gates: the input gate i_t, forget gate f_t, and output gate o_t. The gates perform internal calculations to determine whether to activate or deactivate the cell state based on the input information. The input gate applies a nonlinear function to the input signal and adds it to the cell state, multiplied by the forget gate. This creates a new cell state c_t, which produces the output h_t by applying a nonlinear function and multiplying it by the output gate. The equations for each variable are provided.

$$i_t = \sigma.(W_i.[h_{t-1}, x_t] + b_i) \tag{7}$$
$$f_t = \sigma.\left(W_f.[h_{t-1}, x_t] + b_f\right) \tag{8}$$
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{9}$$
$$o_t = \sigma.(W_o.[h_{t-1}, x_t] + b_o) \tag{10}$$
$$h_t = o_t.\tanh(C_t) \tag{11}$$

In the equations, the weight matrices for each layer are labeled as W_i, W_f, W_o, W_c. The hidden layer states are represented as h_{t-1} and h_t, while the cell states at time t-1 and t are represented by C_{t-1} and C_t. The biases of each gate are b_f, b_i and b_o, and the output bias is b_y. The sigmoid function and the hyperbolic tangent function are denoted by σ(...) and tanh(...), respectively. The process of LSTM is visualized in Figure. 2.

2.4 Evaluation criteria

To assess the performance of a forecasting system, various evaluation criteria are used to determine its effectiveness. This paper focuses on point forecasting criteria, which are used to evaluate the accuracy of individual predictions. The criteria used in this study include the root mean squared error (RMSE),

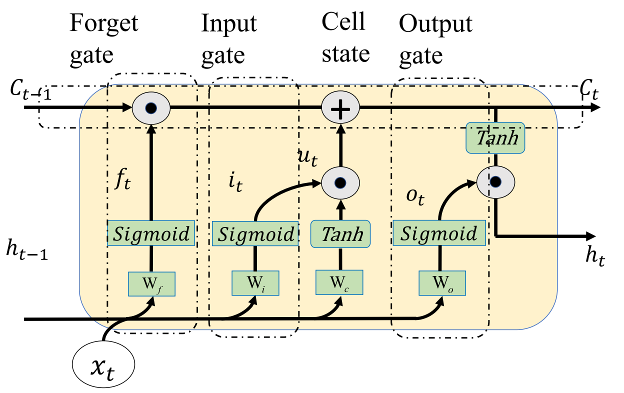

Figure 2. The architecture of LSTM model

which measures the average difference between predicted and actual values, the mean absolute percentage error (MAPE), which calculates the average percentage difference between predicted and actual values, and the normalized root mean squared error (n-RMSE), which provides a normalized measure of the RMSE. These criteria serve as benchmarks for evaluating the forecasting system's accuracy and reliability. The formula off these criteria was shown in (12), (13), (14)

$$RMSE = \sqrt{\frac{1}{n} * \sum\left(y_{true} - y_{pred}\right)^2} \quad (12)$$

$$n\text{-}RMSE = \frac{RMSE}{\max(y_{true}) - \min(y_{true})} * 100\% \quad (13)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_{true} - y_{pred}}{y_{true}}\right| \quad (14)$$

When y_{true} is the true values, y_{pred} is the forecasting values, n is the number of sample data.

3. Result and discussions

3.1 Data description

To verify the effectiveness of the proposed method, we used a load dataset from Seojin Industrial - an investment corporation in the field of manufacturing of wireless communication equipment, both domestically and internationally, and electronic components for Samsung Corporation in Vietnam with 2 transformers SUB1 and SUB2. Specifically, the SUB1 and SUB2 data sequences are divided with a data measurement time interval of 60 minutes, starting from July 30th, 2021 to February 10th, 2023. The raw dataset of two transformer was shown in Figure. 3.

In the context of load data, which is a type of nonlinear data, it is evident that the presence of linear trends in the raw dataset indicates abnormal or missing data in the time series. To ensure the reliability of the data for prediction models, it becomes crucial to eliminate such anomalies. The procedure for handling missing data in this particular scenario is categorized into two cases. In the first case, where data is missing within a single day, the author employs a loop to identify the two nearest time points surrounding the missing value. Subsequently, an Imputation algorithm is applied to calculate the average value of these adjacent data points, which is then used to replace the missing value. This process is iteratively carried out for the remaining hours. For the second case, which involves missing data spanning multiple consecutive days, the author treats these missing values as NaN (not a number) and removes them from the dataset to ensure data integrity and accuracy. Figure. 4 showed the pre-processed dataset.

3.2 Extracting signal components with the EEMD

This section presented the outcomes of the EEMD process applied to the electric load data. The decomposition results were discussed in terms of their components and their relevance to the analysis of the load data. Then, to validate it, a signal reconstruction was performed to determine the error between this signal and the original signal.

In the case of Seojin power data, EEMD decomposed it into 11 IMF components and a residual component, which represented the different scales at which influencing variables impacted the power load sequence, from high to low frequency in the SUB1 and SUB2 datasets. The residual component showed the long-term changing tendency of the load data sequence.

By de composing the time series into its constituent IMFs, EEMD provided a way to analyze the signal at different time scales and extract meaningful information about the underlying

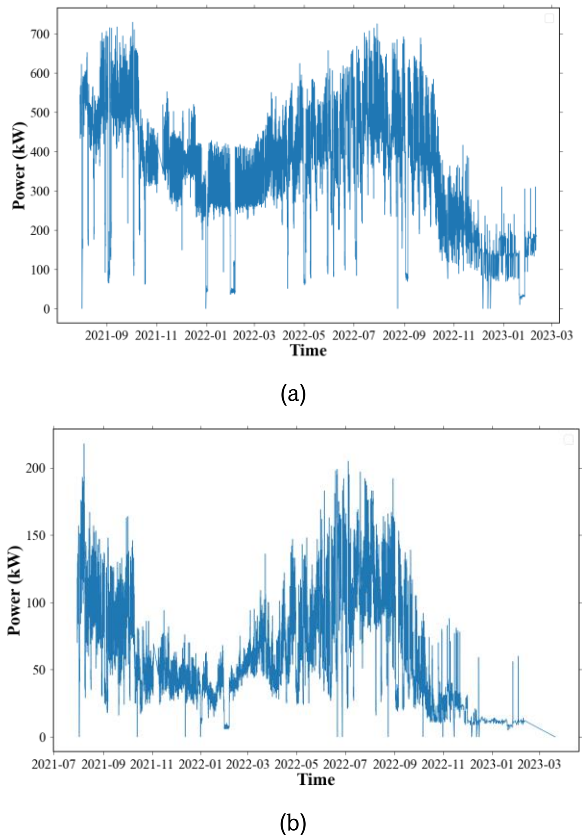

Figure 3. The raw dataset (a) SUB1; (b) SUB2

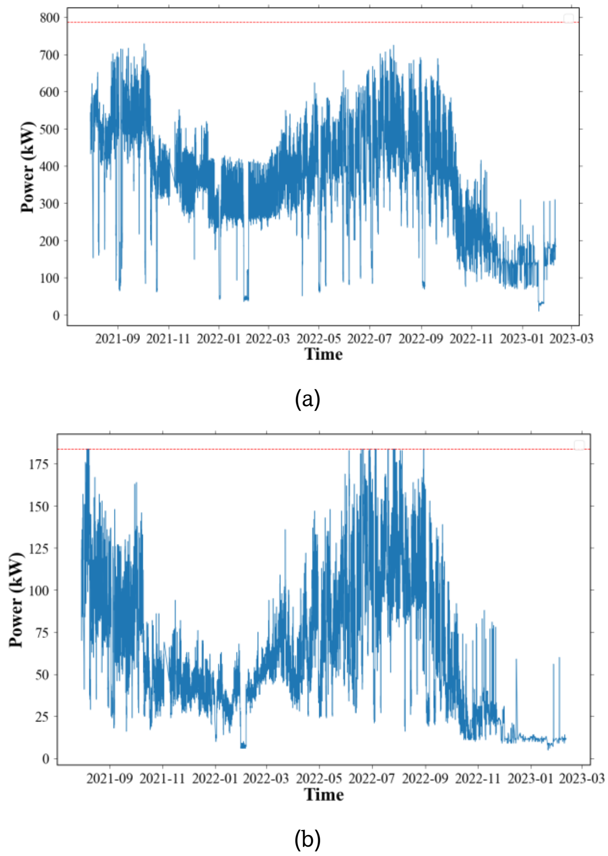

Figure 4. Processed data with IQR method. (a) SUB1; (b) SUB2

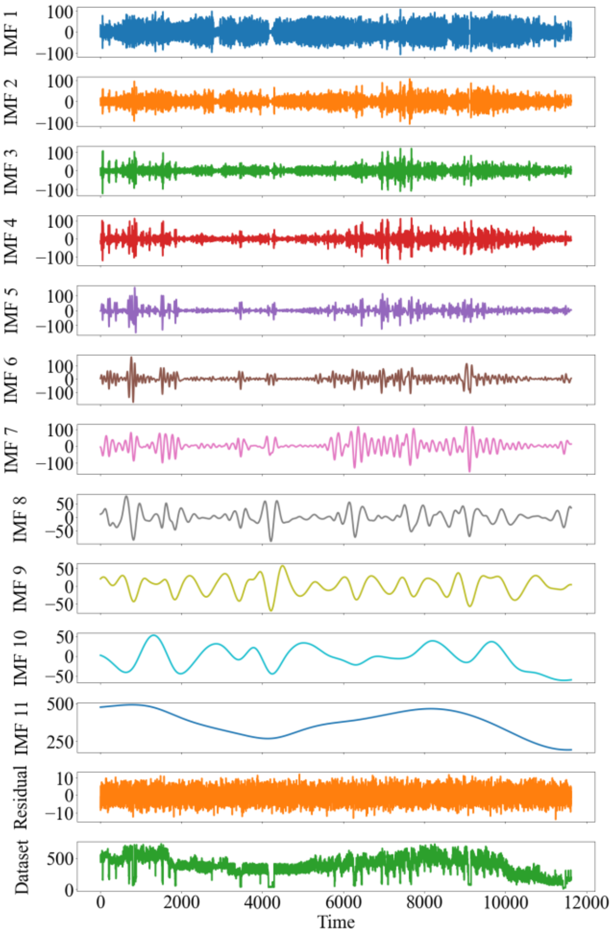

Figure 5. The result of EEMD method for SUB1

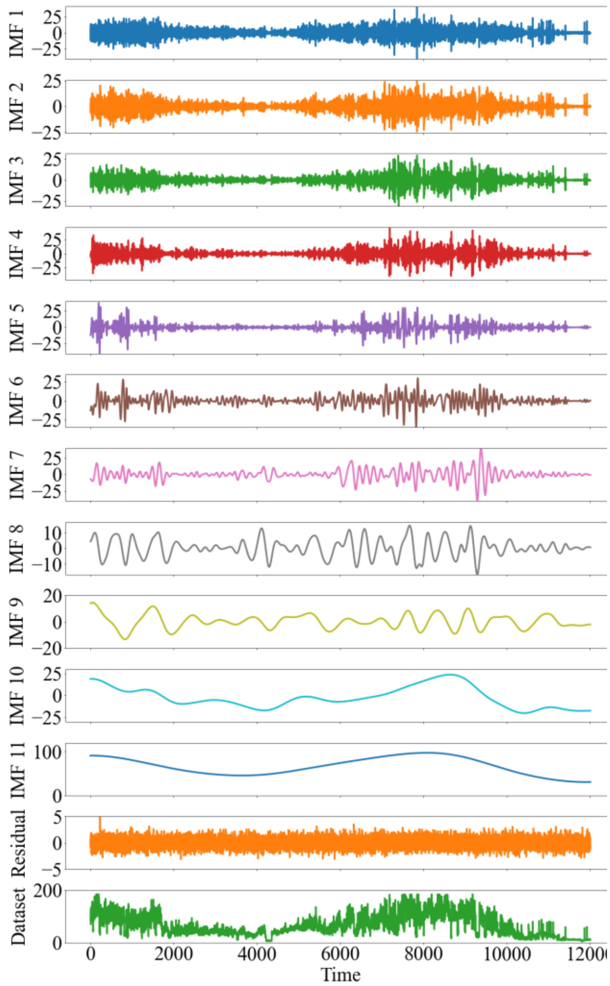

Figure 6. The result of EEMD method for SUB2

processes that affected the power load. Each IMF captured a different frequency band of the signal, and together they provided a comprehensive representation of the signal's temporal and spectral characteristics. Moreover, the decomposed IMFs were often more stable than the original power load sequence, making them useful for forecasting and modeling applications. Figure. 5 and Figure. 6 illustrated the decomposition results and highlighted the contribution of each IMF component to the overall signal of SUB1 and SUB2, respectively.

3.3 Forescasting results and discussions

To highlight the performance of the proposed model, representative models from statistical, machine learning, and deep learning domains, namely LR (Linear Regression), ANN(Artificial Neural Network), and LSTM (Long Short-Term Memory), were employed. These models were utilized to benchmark and compare the performance of the proposed model. In this study, the forecasting was divided into two types: 1-step forecasting and 24-steps ahead forecasting for both SUB1 and SUB2 datasets. Both datasets were split into training and testing sets with a ratio of 70/30 and served as inputs for the forecasting models. The results were depicted in Figure. 7 and Figure. 8, showing the visualization of a random day from the test set.

The similarity between both SUB1 and SUB2 objects was evident from the 1-step forecasting results. The proposed model was able to capture patterns and improve upon the single models, as it closely followed the actual values even during sudden changes. The LSTM and ANN models showed comparable performance, with a slight edge for the LSTM model. The LR model, however, performed poorly, especially during abrupt changes where its forecasts deviated significantly from the actual values. This was consistent with the theory that LR was not suitable for nonlinear and highly fluctuating data, su ch as the power load data used in this study.

The proposed model demonstrated superior performance in terms of accuracy compared to the comparative models in both the SUB1 and SUB2 datasets when forecasting the next 24 steps. Although the forecast results of the proposed model were relatively close to the actual data, they did not achieve the same level of accuracy as the 1-step forecast. Both the ANN, LSTM, and LR models had significant errors compared to the 1-step forecast. The ANN and LSTM models were capable of capturing rapid changes in the data; however, their accuracy remained high. On the other hand, the LR model could only predict the trend of data changes without capturing its abrupt fluctuations. To provide further clarity on the forecasting results, Table 1 presented the error metrics of the various models.

In the analysis of forecast errors for SUB1, the proposed model outperformed the LR, ANN, and LSTM models in terms of accuracy when forecasting the next 24 steps. The 1-step forecasts demonstrated that the proposed model achieved the lowest values of RMSE, n-RMSE, and MAPE, significantly lower than the compared models. Among the 1-step forecast models, the LR model exhibited the highest RMSE (48.52 kW), n-RMSE (6.79%), and MAPE (8.61%). The ANN and LSTM models

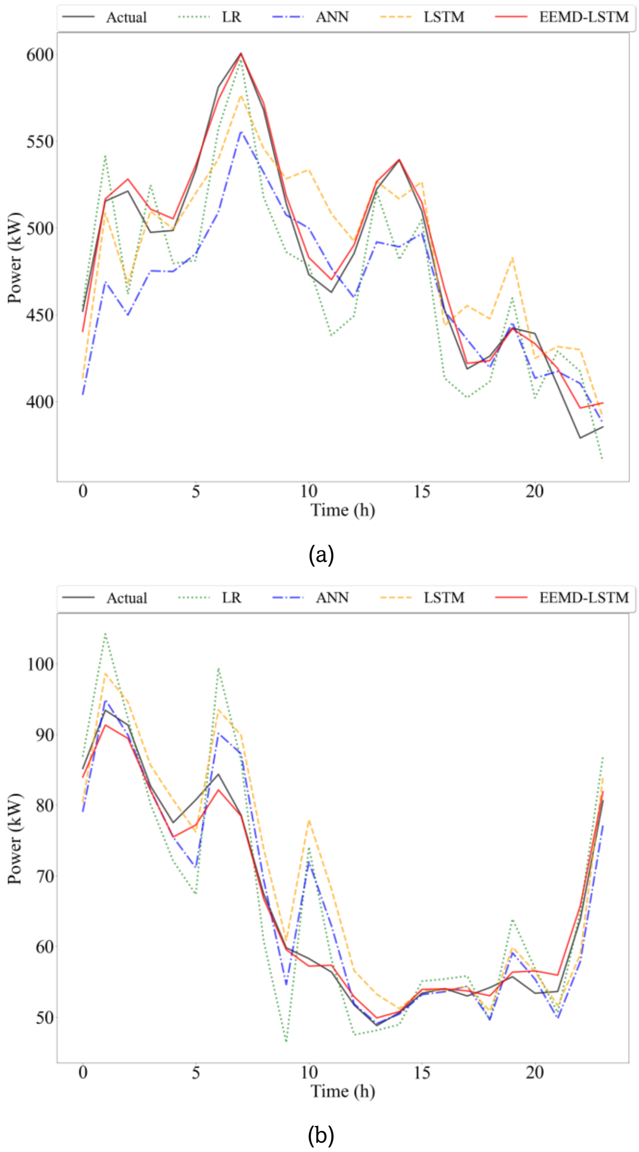

Figure 7. Forecasting results for 1-step ahead in one day random. (a) SUB1; (b) SUB2

showed slightly better performance with lower values of RMSE, n-RMSE, and MAPE. Similar trends were observed for the 24-steps forecasts in SUB1. The EEMD-LSTM model showed superior performance with the lowest RMSE (39.26 kW), n-RMSE (5.49%), and MAPE (7.63%) compared to the LR, ANN, and LSTM models. The LR model exhibited the highest RMSE (152.35 kW), n-RMSE (21.31%), and MAPE (29.44%), indicating its poorer accuracy in longer-term forecasts. Although the ANN and LSTM models achieved lower values of RMSE, n-RMSE, and MAPE compared to the LR model, they still fell short of the performance of the EEMD-LSTM model.

Turning to SUB2, the 1-step forecasts highlighted the superior performance of the proposed model, which achieved the lowest values of RMSE (0.82 kW), n-RMSE (0.46%), and MAPE (1.44%). The LR, ANN, and LSTM models showed slightly higher values of RMSE, n-RMSE, and MAPE, with the LR model exhibiting the highest errors among the three models. In the 24-steps forecasts for SUB2, the EEMD-LSTM model once again demonstrated the best performance, achieving the lowest RMSE (7.6 kW), n-RMSE (4.25%), and MAPE (6.8%). The LR model exhibited the highest values of RMSE (29.08 kW), n-RMSE (16.26%), and MAPE (21.83%) compared to the ANN and LSTM models, indicating its inferior accuracy in longer-term predictions. Although the ANN and LSTM models showed better performance with lower values of RMSE, n-RMSE, and MAPE compared to the LR model, the EEMD-LSTM model consistently outperformed them. This further confirmed the superiority of combining the strengths of the data separation method and the LSTM deep learning model compared to single models.

In ref (Song *et al.*, 2021), the authors proposed a CNN-LSTM model that yielded the best forecasting results when applied to 4 heat exchange stations, with error indices of RMSE, CVRMSE, MAE, and MAPE being 0.026, 0.050, 0.011, and 3.6%, respectively, for station No.1, and similar conclusions were drawn for the other 3 stations. According to (Y. Wang *et al.*, 2021), the authors forecasted using the combined SVMD-XGBoost model for two industrial entities, China and Ireland, and obtained forecasting results with MAPE of 3.63% and 4.96%, respectively. In the study (Chiu *et al.*, 2023), the authors proposed a combined CNN-GRU model for forecasting building load. The forecasting results showed that the proposed model outperformed other models, achieving the lowest mean absolute percentage error (MAPE) of 1.5071%, specifically for household 3. From the above cited results, the proposed model in this paper yields better performance with the lowest MAPE

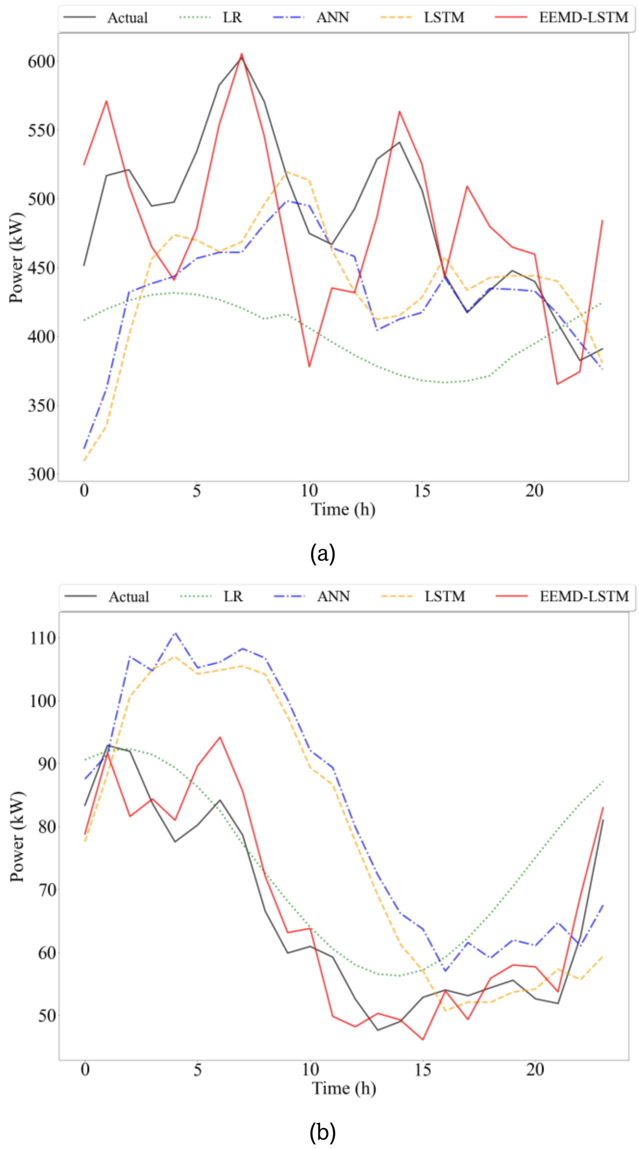

Figure 8. Forecasting results for 24-steps ahead in one day random. (a) SUB1; (b) SUB2

Table 1.
The error metrics of forecasting models

			RMSE (kW)	n-RMSE (%)	MAPE (%)
SUB1	1-step	LR	48.52	6.79	8.61
		ANN	37.56	5.25	6.93
		LSTM	37.07	5.18	6.51
		EEMD-LSTM	6.92	0.97	1.3
	24-steps	LR	152.35	21.31	29.44
		ANN	92.71	12.97	15.78
		LSTM	91.13	12.75	15.38
		EEMD-LSTM	39.26	5.49	7.63
SUB2	1-step	LR	6.81	3.81	11.34
		ANN	6.25	3.49	10.29
		LSTM	6.16	3.44	10.42
		EEMD-LSTM	0.82	0.46	1.44
	24-steps	LR	29.08	16.26	21.83
		ANN	18.6	10.4	17.12
		LSTM	18.58	10.39	16.68
		EEMD-LSTM	7.6	4.25	6.8

error of only 1.3%. Some notable findings of the proposed model in this study are as follows:

- The application of power generation data to industrial areas is divided into two transformer substations, SUB1 and SUB2. This is an area that has not received much attention, with many missing data points.
- A novel idea for the time series model was proposed, by decomposing and reconstructing the pre-processed industrial load data. Multiple component series were obtained, and they were predicted using the LSTM neural network. The prediction results of these component series were aggregated to obtain the final prediction.
- The load data was decomposed using the EEMD method, resulting in seven IMF component series for both SUB1 and SUB2. These component series were then predicted using the LSTM neural network, and their prediction results were summed to obtain the final prediction.
- The prediction accuracies of LR, single-prediction ANN, LSTM, and EEMD-LSTM were analyzed. Comparing modern time series models with the classical LR method, modern methods showed an improvement of approximately 10-30% over LR, while the proposed model achieved an impressive 780% improvement over LR.

In addition to the outstanding advancements mentioned earlier, the proposed method also had some limitations:

- One of the main limitations was the increased training time due to the complexity of the method. If applied in real-time scenarios, the data decomposition and forecasting process would have required significant computation time, making it challenging to meet the demands of very short-term forecasting where quick responses were needed.
- Another crucial aspect to consider was the need for careful hyperparameter optimization to achieve optimal results. As shown in this report, all hyperparameters were manually selected based on trial-and-error, without employing sophisticated optimization algorithms. Introducing such optimization algorithms could potentially have increased the model's complexity and training time even further.

4. Conclusion

In this study, an innovative approach called EEMD-LSTM was introduced for the purpose of predicting Seojin load using the SUB1 and SUB2 datasets. A meticulous and systematic data pre-processing procedure was conducted to adequately prepare the data for the subsequent utilization of the proposed model, as well as comparative models such as LR, ANN, and LSTM. The outcomes obtained from the comprehensive analysis undeniably validated the remarkable superiority exhibited by the EEMD-LSTM method, as it consistently demonstrated the most favourable results in terms of minimized error rates in both 1-step and 24-steps forecasting. Specifically, with respect to 1-step forecasting, the EEMD-LSTM method showcased exceptional performance with remarkably low MAPE and n-RMSE errors, amounting to approximately 1% and 1.4% respectively. Similarly, in the context of 24-steps forecasting, the EEMD-LSTM method impressively maintained its superiority, attaining MAPE and n-RMSE errors that hovered around the 5% and 7% mark, respectively. These error rates distinctly outperformed those exhibited by alternative models. Consequently, this noteworthy finding successfully substantiated the efficacy of incorporating data decomposition techniques into the forecasting process. In addition to its potential in forecasting industrial load, the EEMD-LSTM model holds broader applicability to various renewable energy sources such as solar, wind, and other renewables worldwide. Emphasizing the potential impact of these research findings in optimizing and enhancing the performance of renewable energy systems, we believe that the EEMD-LSTM method can make significant contributions to the global energy industry. However, it is important to acknowledge that, similar to any other research methodology, the EEMD-LSTM method did possess certain inherent limitations. Factors such as increased training time due to the method's inherent complexity, potential challenges associated with real-time data application, and the necessity for meticulous hyperparameter optimization to achieve optimal results were worth considering. To address these limitations, future research could have explored strategies to reduce the computational burden, such as optimizing the data decomposition process and employing more efficient algorithms for hyperparameter tuning. Additionally, investigating the use of parallel processing or distributed computing techniques might have helped expedite the training time of the proposed method, enabling its application in real-time forecasting scenarios. Overall, despite these limitations, the proposed method remained a promising approach in industrial load forecasting and offered valuable insights for further advancements in the field.

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