Predicting transmission losses using EEMD – SVR algorithm

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Article Info

Article history:

Received Nov 4, 2024
Revised May 31, 2025
Accepted Jul 23, 2025

Keywords:

Deep learning
EEMD
Java-Bali system
SVR
Transmission losses
Transmission system

ABSTRACT

This work introduces a predictive model for evaluating transmission losses in the Java-Bali electrical system using ensemble empirical mode decomposition (EEMD) and support vector regression (SVR) techniques. Transmission losses, a critical aspect of energy efficiency, are affected by several operational aspects, such as load flow, energy composition, peak load, and meteorological factors such as transmission line temperature. Transmission losses data were decomposed into many intrinsic mode functions (IMFs) by EEMD, effectively capturing both high-frequency (short-term) and low-frequency (long-term) trends. The SVR algorithm, utilizing a radial basis function (RBF) kernel, was subsequently employed to predict the deconstructed IMFs, facilitating accurate predictions of transmission losses. The proposed EEMD-SVR model achieved a mean absolute error (MAE) of 5.43%, with the highest error observed during the period of abrupt load shifts. These results confirm the model's strength in identifying long-term transmission loss patterns, making it suitable for system planning and operational forecasting. While the model exhibited high prediction accuracy, especially in recognizing long-term trends, it faced limitations in accurately predicting abrupt changes in transmission losses. Therefore, future improvements should aim to enhance responsiveness to sudden changes in the system dynamics. The result suggests that the EEMD-SVR model can proficiently assist power system operators in monitoring and mitigating transmission losses.

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1. INTRODUCTION

The largest electricity system in Indonesia is Java – Bali system [1], which is divided into five areas consisting of the Jakarta-Banten area, the West Java area, the Central Java area, the East Java area, and the Bali area. The operation of this system conforms to the basic principles of economy, reliability, quality, and green [2]. Transmission-losses is an economic indicator in the operation of power system because transmission losses show the electrical energy lost when energy is generated until it is transmitted through the transmission network [3]-[5]. The smaller transmission losses show a large level of energy efficiency. Transmission losses typically account about 3-5% of total power generation [6]. However, the small percentage of transmission losses in terms of MW is causing significant concern.

In modern electric power systems, along with increasing loads and the changes in network configuration, it is important to maintain a balance between generation and load so that operation of the electric power system runs reliably, with quality and economically [7]. In addition to load prediction, accurate transmission losses prediction plays a crucial role in the operational strategy and decision making of the system operators [8], [9]. It enables system operators to enhance the reliability of electrical energy supply and implement appropriate mitigation to reduce transmission losses.

Predicting transmission losses presents numerous challenges due to multiple factors such as peak load, voltage, and load flow [10]. It is essential to identify and understand the correlations between these factors and transmission losses to ensure accurate predictions. This analysis is important in optimizing system operations and improving overall energy efficiency [11], [12].

With the advancement of technology, the use of machine learning algorithms has become a method to predict and optimize the performance of the electricity network [13]-[15]. Machine learning can utilize large amounts of operational and historical data to predict transmission losses quickly and accurately [16]. This work aims to develop a predictive model using an appropriate machine learning algorithm, which is not only accurate but also practical to implement in an electric power operating system.

This work aims to develop a predictive model using an appropriate machine learning algorithm, which is not only accurate but also practical to implement in an electric power operating system. To achieve this, we propose a novel hybrid prediction model that combines ensemble empirical mode decomposition (EEMD) with support vector regression (SVR) to forecast transmission losses. Unlike conventional models, the proposed approach decomposes the loss signal into frequency components, enabling the SVR to more effectively capture both short-term fluctuations and long-term trends. To the best of our knowledge, this is the first application of the EEMD-SVR framework for predicting transmission losses in the Java-Bali electricity system, offering both methodological and regional novelty.

2. METHOD

2.1. Data collecting

This work selects Java – Bali transmission system as the research object. The historical data was collected for three years. The data consists of electricity data including daily peak load, production energy, energy composition data for generating plants in each area, and load flow between areas. Meteorological factors such as transmission line temperature are selected [17]. Calendar data was chosen consists of binary weekend-weekday indicator.

Historical data is divided into two subsets: training data and test data. The training data is used to train the model, while the test data is used to evaluate the model's performance. In this work, data separation was carried out as: training data was 80% while test data was 20%.

2.2. Data preprocessing

Data pre-processing is an important step in the preparation of a dataset prior to its utilization in a machine learning model. The module input in this work were pre-process with data cleansing with interquartile range (IQR) and data normalization with StandardScaler. The IQR technique for data cleaning is designed to identify and remove outliers from the dataset. It is robust estimator for a data set up to 25% outliers [18], [19]. The interquartile range (IQR) quantifies data distribution by determining the interval between the first quartile (Q1) and the third quartile (Q3).

After cleaning the data, we perform data normalization using StandardScaler. This is important because some algorithms, like SVR, are sensitive to differences in feature scaling. StandardScaler transforms the data features to have a mean of 0 and a standard deviation of 1. This ensures that all features are on the same scale, preventing features with large scales from overpowering the model and improving the learning process efficiency.

2.3. Data EEMD decomposition

Ensemble empirical mode decomposition (EEMD) is the improvement of EMD algorithms. It aims to overcome the deficiencies of modal aliasing in EMD methodologies [20]. The decomposition stages that are specific to EEMD are as:

Allow white noise $n_i(t)$ to the original signal $x(t)$. All white noise $n_i(t)$ require that the amplitude value is zero and that the standard deviation remains constant, specifically between 0.1 to 0.4 times the original standard deviation, the equation of $x_i(t)$ is as (1).

$$x_i(t) = x(t) + n_i(t) \tag{1}$$

In which the signal is represented by $x_i(t)$ which is the addition of white noise over time.

The intrinsic modal function (IMF) component $c_{ij}(t)$ and the remainder $r_i(t) \cdot c_{ij}(t)$ can be obtained by decomposing $x_i(t)$ with EEMD. The i^{th} IMF and the Gaussian white noise have been added i times. Repeat the initial two stages N times. Since the statistical average value of an unrelated random sequence is zero, this work will compute the average value of the IMF that was obtained from the first two procedures. The purpose is to eliminate the impact repeatedly by adding white noise on the real IMF. Then IMF finally obtained by EEMD decomposition as (2).

$$c_j(t) = \frac{1}{N}\sum_{i=1}^{N} c_{ij} \tag{2}$$

In which, $c_j(t)$ are j^{th} IMF component which original signal have EEMD decomposed. The results of the EEMD decomposition are as (3).

$$x(t) = \sum_j c_j(t) + r(t) \tag{3}$$

In this work, the target transmission losses variable is decomposed using EEMD. EEMD breaks the target into several IMFs, each of which captures oscillations at different frequencies. This technique reduces the problem of mode mixing by adding random noise to the data before decomposition, which results in a clearer separation of components. After the decomposition process, IMF divided into two groups based on their frequencies. Figures 1 and 2 show transmission losses decompose into IMFs high and IMFs low, with IMFs high represents high frequencies, capturing rapid variations or local noise in the data, and IMFs low represents low frequencies, capturing long-term trends or steady changes in the data.

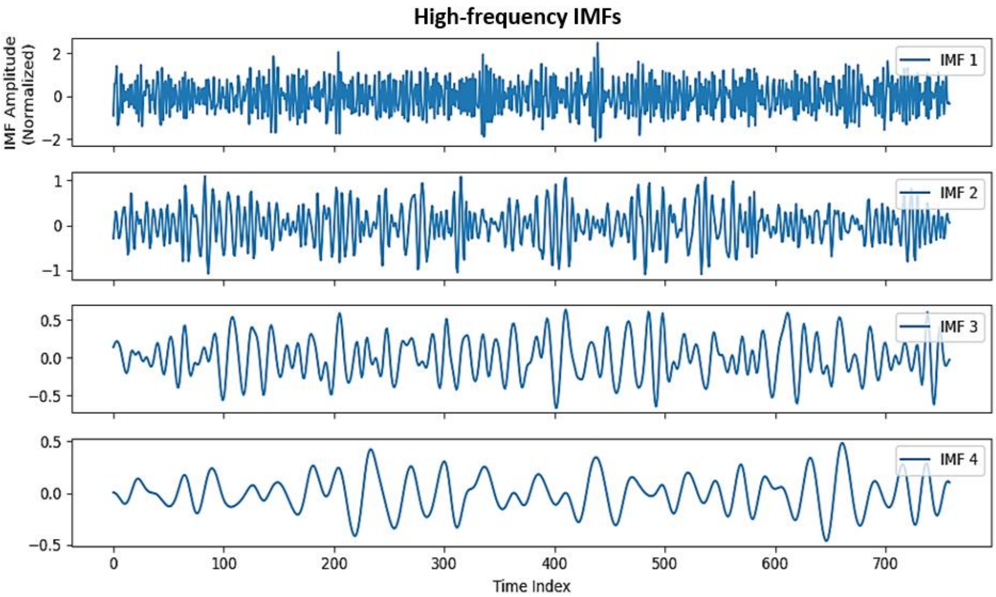

Figure 1. IMFs high component after EEMD decomposition

2.4. Proposed model

The least squares support vector machine (LSSVM) integrates the kernel function with ridge regression and employs the least squares error function to suit the data. However, the quantity of the calculation is the third power of sample, which is not facilitating the model’s simplification and improving calculating speed. Support vector machine regression (SVR) is proposed on this basis, which significantly reduces computational complexity by utilizing support vectors, and has same capacity as LSSVM to match samples with high precision longitude [21], [22].

The SVR regression method is widely used technique in the analysis of time series predicting [23]-[25]. It is adept at generalizing to lightweight, nonlinear, and time-series sample. Nonlinear mapping the input sample data to high dimensional feature space for linear regression, to implement nonlinear fitting in the data space [21]. The predicted regression function in SVR defined as (4).

$$f(x) = \omega \, \phi \, (x) + b \tag{4}$$

Where ω is a weighting matrix, b is the bias term, ϕ (x) is a non-linear mapping of input x into a higher-dimensional feature space using kernel [26]. X represents the input features such as production energy, load flow, transmission line temperature, energy composition for generating plants, daily peak load, and calendar data. SVR minimizes an objective that is composed of two components: i) margin error with tolerance ε, and ii) model regularization to prevent overfitting. The function to be minimized is the objective function.

$$min\ \frac{1}{2}\ ||\omega||^2\ +\ C\ \sum_{i=1}^{n}(\varepsilon_i +\ \varepsilon_i^*) \tag{5}$$

$||\omega||^2$ is the norm weight factor that is reduced to maintain the simplicity of the model, C is a hyperparameter that regulates the balance between minimizing error and regulating model complexity, the variables ε_i and ε_i^* are slack variables that enable data values to fall outside the margin ϵ. The model is subject to the constraint that the error margin should not exceed ϵ for most of the data, but outliers can be allowed outside the margin via slack variables. These constraints are expressed as (6).

$$\begin{aligned} & y_i - (\omega^T\ \phi\ (x_i) + b\ )\ \leq\ \epsilon +\ \varepsilon_i \\ & (\omega^T\ \phi\ (x_i) + b\ ) -\ y_i\ \leq \epsilon + \varepsilon_i^* \\ & \varepsilon_i \varepsilon_i^*\ \geq 0 \end{aligned} \tag{6}$$

Where ϵ controls the margin of tolerance for the error, $\varepsilon_i \varepsilon_i^*$ are slack variables that allow certain data points to exceed the margin with penalty. The radial basis function (RBF) kernel is implemented. SVR can capture non-linear relationships between the input features and the target using the RBF kernel. The kernel is defined as (7).

$$K\ (x_i, x_j)\ =\ exp\ (\ -\gamma\ ||x_i - x_j||^2\ ) \tag{7}$$

Where γ controls the influence of a single training example. We used mean absolute error (MAE) as the loss function as (8).

$$MAE\ =\ \frac{1}{T}\sum_{\tau=1}^{T} |y_\tau -\ y^{\wedge}{}_{\tau}| \tag{8}$$

Where $y^{\wedge}{}_{\tau}$ is the predicted transmission losses, y_τ is the actual transmission losses at time τ. We chose the MAE because it is less sensitive to possible outliers [11].

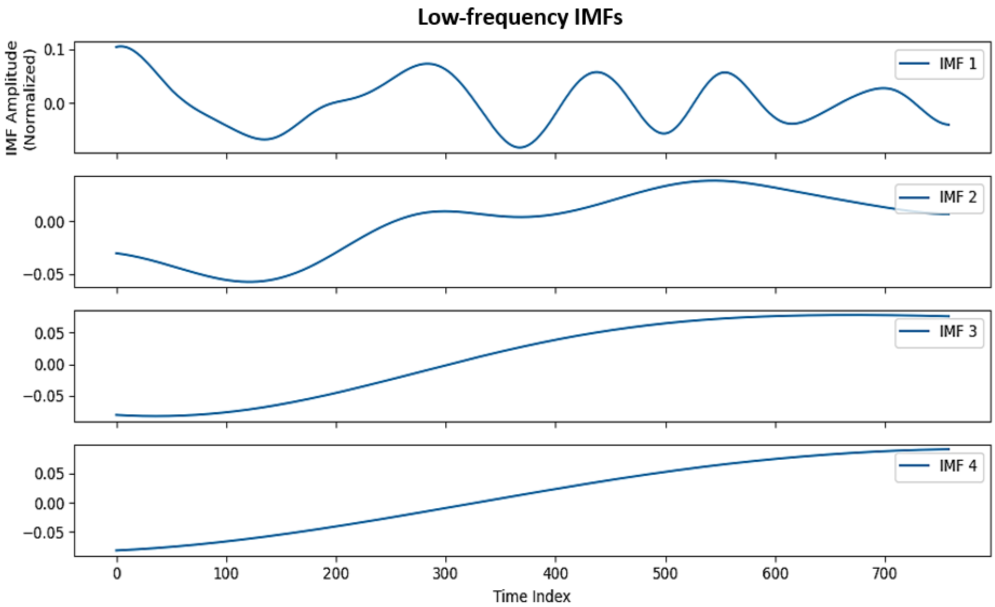

Figure 2. IMFs low component after EEMD decomposition

3. RESULTS AND DISCUSSION

In this work we implemented the EEMD method with SVR to predict transmission losses in the Java-Bali system. The EEMD-SVR model effectively captured both short-term variations and long-term trends in transmission losses data by decomposing the signal into several IMFs. In (8) IMFs were obtained because of the decomposition of the target variable, transmission losses (kWh), using EEMD. These IMFs are oscillations that occur at varying frequencies. The EEMD decomposition was followed by the training of two distinct SVR models using the high-frequency and low-frequency IMFs. Based on Figure 1, high-frequency IMFs are responsible for documenting rapid, temporary changes in the losses, which may be linked to grid disruptions, weather conditions, or load imbalances in the power system. Figure 2 shows low-frequency IMFs identifying the underlying trends in the transmission losses data that may be indicative of long-term shifts in grid performance and production energy patterns. The RBF kernel was chosen to cope with the non-linear relationships present in the data. Comparison of the results between EEMD-SVR model and actual transmission losses in Java-Bali system is shown in Figure 3.

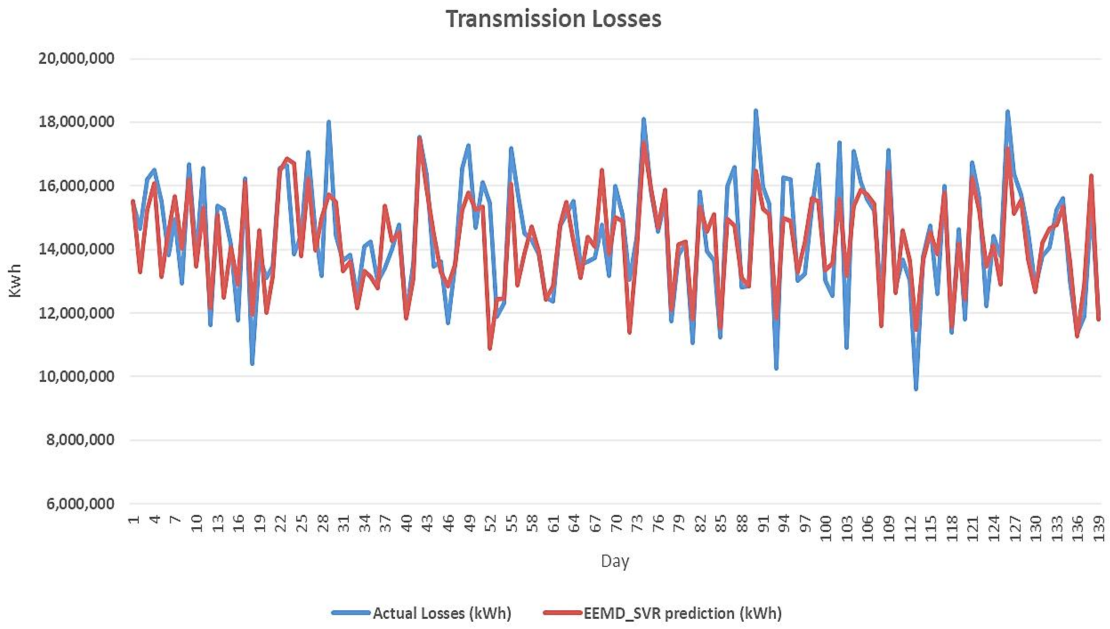

Figure 3. Comparison between EEMD_SVR model and actual transmission losses

The EEMD-SVR prediction line (in red) closely follows the actual losses line (in blue) for most of the graph, suggesting that the model accurately depicts the general pattern of transmission losses. The general trend of both lines is similar, with regular peaks and valleys. This shows that the model has learned both the short-term changes and the longer-term trends in the data. The EEMD-SVR model does not consistently capture spikes or abrupt increases in actual losses. The model frequently underestimates the abrupt surges in losses, shown when the blue line exceeds the red line. The model also not as accurately predict sudden declines in the actual losses. The model has a propensity to overestimate the extent of the dip, like the spike issue. This is evident in the instances where the red line remains above the blue line during such declines.

The EEMD decomposition process is likely to be a contributing factor to this smoothing effect. The model can capture the general trends and patterns; however, the sharp, sudden changes (spikes and declines) in the actual losses data may be attenuated during the decomposition process, particularly in the high-frequency components. The test data displayed a MAE because of the combined predictions from both SVR models, which suggests a high degree of accuracy in accurately predicting transmission losses. From this proposed model MAE range between 0.04% - 29.62%, the average MAE typically around 5.43%. Largest MAE values, in terms of both kWh and percentage, are observed during periods of substantial change or increases in the actual transmission losses. It is possible that the model is unable to accurately capture sudden changes or fluctuations in the data, which could be a result of either insufficient training data for those periods or an incapacity of the model to capture high variability in the underlying system. Figure 4 shows that MAE from EEMD-SVR model.

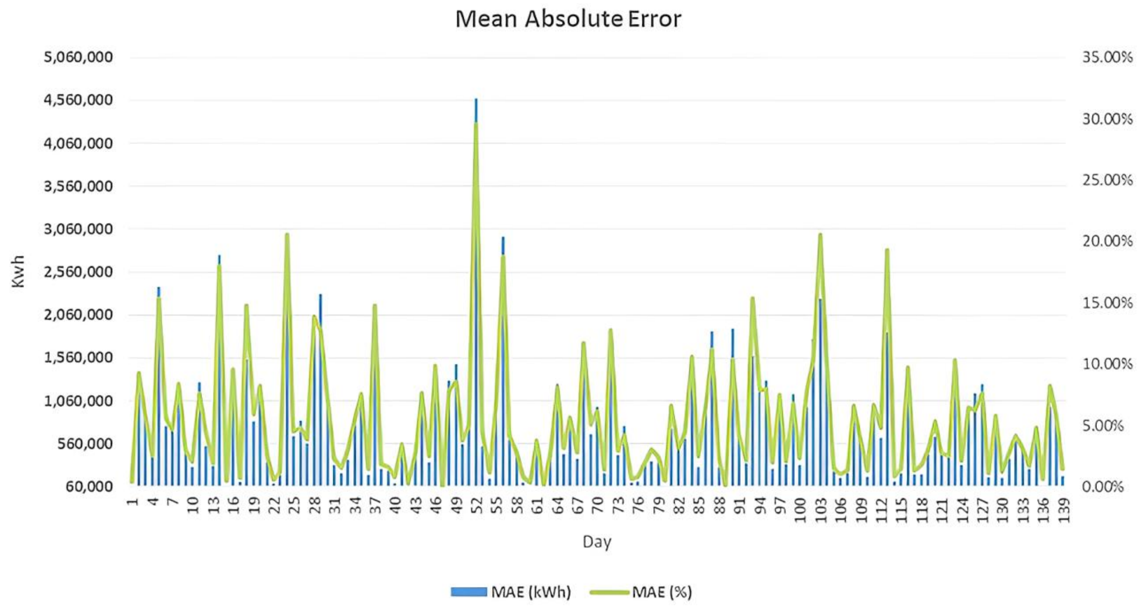

Figure 4. Mean absolute error from EEMD-SVR model

4. CONCLUSION

The Java-Bali electricity system in Indonesia’s largest electricity network, covering five regions: Jakarta-Banten, West Java, Central Java, East Java, and Bali. The system aims to achieve economic, environmental sustainability, quality, and reliability objectives. Among these objectives, economic efficiency is crucial, and one key aspect is reducing transmission losses, which significantly impact the overall efficiency and effectiveness of the system.

In our study, we proposed an EEMD-SVR model to predict transmission losses in Java-Bali electricity system. This model exhibits the capacity to identify non-linear relationships between input and target variables, utilizing the RBF kernel to manage data complexity. The proposed model achieved a MAE of approximately 5.43%, with prediction accuracy ranging from 0.04% to 29.62% depending on load variation. The model effectively captures both short-term fluctuations and long-term patterns in transmission losses.

From a practical standpoint, the predictive output of the model can assist system operators and planners in optimizing operational strategies. For instance, predictions can be integrated into load dispatch planning, helping operators reroute power flow through more efficient transmission corridors or schedule generation more economically to reduce marginal losses. The model enables proactive mitigation during periods of predicted high losses by supporting decisions such as reactive power compensation, generator dispatch reallocations, and demand response coordination. Additionally, planners can use the forecast to justify infrastructure reinforcement in high-loss areas to improve long-term system efficiency. These applications demonstrate the model’s potential not only for monitoring but also for guiding policy and operational decisions to reduce transmission losses across the Java-Bali grid.

While the model performs effectively under normal conditions, limitations remain in responding to abrupt spikes or dips in losses. Therefore, future work should focus on improving the sensitivity of the model to rapid power system changes, possibly through the integration of adaptive decomposition or hybrid models with real-time data processing capabilities. This work has successfully developed a predictive model to aid power system operators in monitoring and mitigating transmission losses, while enhancements are needed to address abrupt variations in loss data.

FUNDING INFORMATION

Authors state there is no funding involved in this research.

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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Karel Octavianus Bachri	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors hereby declare there is no conflict of interests.

DATA AVAILABILITY

The data that support the findings of this work are available on request from the first author and the corresponding author by the permission of State Electric Company of Indonesia. The data, which contain information that could compromise the privacy of research participants, is not publicly available due to certain restrictions.

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