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RESEARCH ARTICLE

Feature Importance in Predicting Generator Rotor Thermal Sensitivity: A Random Forest-LSTM Approach

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Abstract

Thermal sensitivity incidents on generator rotors at Muara Tawar Power Plant have increased over the past five years, which will have an impact on the overall performance of the power plant. The general method of conducting thermal sensitivity testing requires the generating unit to be in a certain operating pattern, thus limiting the analysis of anticipating events in real time. Correlation analysis between excitation current variables, reactive power, vibration, and temperature needs to be carried out periodically. The acquisition of these operating parameters was carried out on three generator rotors for 14 days per minute and will be implemented into a machine learning model. This study uses the Random Forest model to predict vibrations on the rotor and determine feature importance values, with the addition of Long Short-Term Memory (LSTM) modeling to predict future trends based on feature importance. The results show that the Random Forest model can predict vibrations in the rotor and determining the importance of the features used, with an average evaluation metric RMSE of 0.92% and R^2 of 81.62% on the exciter side, and RMSE of 2.75% and R^2 of 61.42% on the turbine side. The LSTM model also demonstrates good capability in predicting future trends in thermal sensitivity identification based on exciter current features with an RMSE of 7.29% and for reactive power features of 6.52%, indicating that the proposed modeling implementation allows a better understanding of the variables relevant to thermal sensitivity, thus predicting them in the future can produce comprehensive operation and maintenance strategies.

Keywords: thermal sensitivity, feature importance,random forest, long short term memory

1. Introduction

In a Combined Cycle Power Plant (CCPP), the Gas Turbine (GT) normally operates in simple cycle mode during peak load hours, while in combined cycle mode, the plant frequently functions as a base load generator. This transition is being pushed by constraints on coal-fired power facilities due to emissions concerns[1]. As these plants become more reliant on transitioning between operational modes, the thermal sensitivity of the generator rotors has emerged as a critical factor in maintaining reliable and efficient performance[2].

Thermal sensitivity is a phenomenon that has emerged in the power plant environment of UP Muara Tawar Blocks 3 and 4 over the past five years. Generator 3.2 experienced this phenomenon in September 2018, where the following month maintenance in the form of testing alone was required as visualized in Fig 1, necessitating an outage permit for the substation. The test results indicated that there was an increase in vibration values when the field current on the generator rotor was increased, supported by the indication of the appearance of abnormal hot spots that disrupted the rotor's heat balance. A similar incident was found on Generator 4.1 in October 2018, where additional tests were also conducted, such as insulation resistance, winding resistance, rotor impedance, oscilloscope repetitive surge, and rotor ventilation. The rotor ventilation test results indicated that some ventilation was blocked, causing the rotor's heat balance to be disturbed and resulting in vibration.

Thermal sensitivity is of critical importance as it can lead to unplanned outages, reduced efficiency, and, in extreme cases, rotor failure[3]. Consequently, understanding the key factors that drive thermal sensitivity is of great interest to plant operators and maintenance teams. Reliably forecasting the thermal sensitivity of generator rotors is essential to improve the effectiveness of operation and maintenance procedures in power plants. Few researchers use different methods to predict thermal sensitivity; research using Support Vector Regression (SVR) was performed utilizing several operating parameters such as Active and Reactive Power, resulting in predicted values for changes in magnitude and phase angle[4]. Another research study utilized Multiple Linear Regression, where the study analyzes the relationship between generator vibrations and process parameters such as field current, reactive power, and hydrogen temperature[5]. However, the prediction of thermal sensitivity cannot be solely determined by the results of vibration predictions due to the dynamics of the electrical and mechanical systems on the rotor[6], as vibrations can occur for various reasons. Therefore, the Feature Importance of Random Forest will calculate the level of influence of a variable on the prediction[7] [8]; this result will show an indication of thermal sensitivity but cannot predict it in time series. In exploring the detection of bearing faults within electrical machinery a paper have demonstrated the effectiveness of a hybrid model that combines LSTM networks, Random Forest classifiers, and Grey Wolf Optimization to achieve high accuracy in fault classification where this approach underscores the potential of integrating advanced machine learning techniques to enhance predictive maintenance strategies [9].

Building on this foundation, we present an integration of Random Forest that leverages historical operating data from three generators to predict the vibration of the generator rotor in Block 3 of the UP Muara Tawar power plant and analyze features indicating thermal sensitivity, with Long Short Term Memory used to estimate future feature importance.

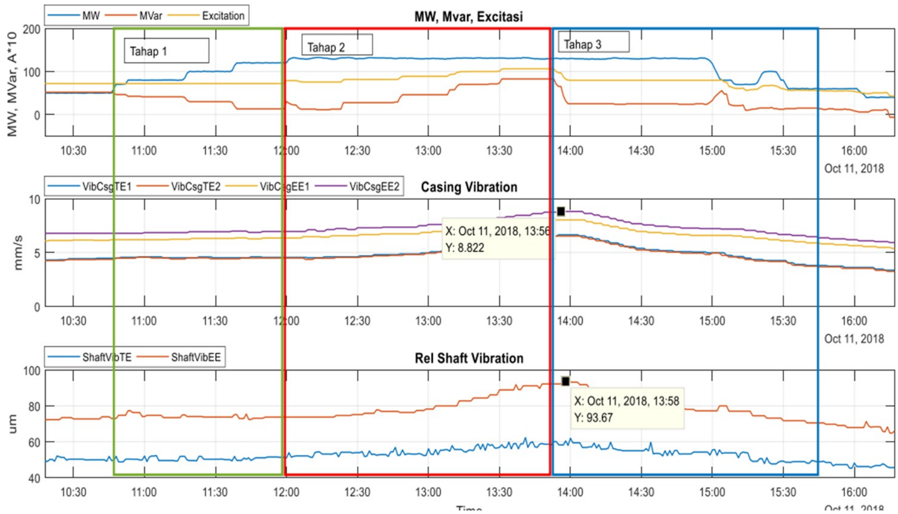

Figure 1. Thermal Sensitivity Test Profile

2. Generator Thermal Sensitivity

Thermal sensitivity in generator rotors is a typical phenomenon in which the rotor's vibration intensity varies with increasing field current[10]. This is a common occurrence with generators from all manufacturers. Thermal sensitivity can be induced by an uneven temperature distribution around the rotor or axial stresses that are not evenly distributed circumferentially. The main reason for the latter is a large differential in the thermal expansion coefficient between the rotor's copper coils and steel components[11]. If the rotor windings are not electrically or mechanically balanced in the circumferential direction, the generator rotor will be unevenly loaded, resulting in rotor bending and changes in vibration. In most cases, a thermally sensitive rotor will not actually prevent the generator from operating, but it can limit operation at high field currents or VAR loads due to the excessive rotor vibration that occurs[12].

There are two types of thermal sensitivity: reversible and irreversible[13]. Both types vary with the field current; however, the reversible type follows the field current as it increases and decreases, while the irreversible type does not. The Thermal Sensitivity test requires three stages. The first stage of testing is to hold the field current and then vary the active power on the generator. The second stage is to hold the active power on the generator and then increase the field current, while the third stage is to keep the active power constant while the field current is reduced. If there is a significant change in vibration or phase angle in response to changes in field current in stages 2 and 3, the incident must be recorded and can be described as a Thermal Sensitivity phenomenon [12]. In long-term generator operation, damage occurs to the rotor windings, such as blockage of ventilation channels and short circuits in the rotor windings, as a result of which the heating of the rotor windings increases significantly both in stable conditions, measured operating mode, and when the excitation current is forced in dynamic operating mode[14] [15]. Therefore, it can be concluded that to predict the occurrence of Thermal Sensitivity, operational data besides exciter current and output power from the generator rotor are needed. This is to analyze how additional variables would behave in the prediction model for different generators and in what manner those variables reflect their importance to the Thermal Sensitivity phenomenon.

3. Proposed Random Forest-LSTM Algorithm

Random Forest is a sophisticated ensemble learning technique that is known for its accuracy and robustness across a wide range of applications, especially in complex regression and classification tasks[16]. It is an ensemble model because it is made up of many decision trees and when combined they create a strong model for learning complex, nonlinear datasets. In this part, the Random Forest model is discussed, which is used for our vibration prediction of power plant generator rotors. Random Forest builds each tree node by node, recursively splitting the training data. For regression tasks, the criteria to choose where to split the data is based on the reduction of variance[17].

$$\Delta Variance = Var(S) - \left(\frac{n_{left}}{n_{total}} Var(S_{left}) + \frac{n_{right}}{n_{total}} Var(S_{right}) \right) \tag{1}$$

Where:

- S denotes the set of data points at the current node.
- S_{left} and S_{right} are the datasets of the left and right child nodes, respectively.
- n_{left}, n_{right}, n_{total} are the numbers of samples in the left, right, and at the parent node.
- Var(S) represents the variance of the target values in set S.

This criteria grows each tree well by making sure that the largest variance reduction splits ends up making a split in a particular node, thereby aiding greatly in terms of the reduction in error and the accuracy of the model. After constructing the forest of trees predictions on the new data points can be made by averaging the predictions of all the trees. So for regression models, this is usually the average of all the trees predictions.

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} t_i(X) \tag{2}$$

Where:

- N is the number of trees in the forest.
- $t_i(X)$ is the prediction of the i-th tree for input X.

By aggregating its predictions over branches, the model is able to decrease its variance while preserving bias, leading to a more accurate and robust prediction. To assess the performance of the Random Forest model, several metrics are used, including the Root Mean Squared Error (RMSE) and the Coefficient of Determination (R^2)[18]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

$$R^2 = 1 - \frac{\Sigma_{i=1}^{n}(y_i - \hat{y}_i)^2}{\Sigma_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{4}$$

One of the most valuable outputs of the Random Forest algorithm is the feature importance metric, which quantifies the contribution of each feature to the prediction accuracy of the model[19]. In a Random Forest with N trees, the importance of feature f is the total variance reduction across all trees and To make the feature importance comparable, they are normalized so that they sum to 1 where f represents all features in the dataset.

$$I(f) = \sum_{t=1}^{N}\sum_{s\epsilon S_t(f)} \Delta Var(s) \tag{5}$$

$$I_{normalized}(f) = \frac{I(f)}{\Sigma_f I(f)} \tag{6}$$

Where:

- $S_t(f)$ includes all splits in tree t where feature f is used.
- $\Delta Var(s)$ is the reduction in variance achieved by each split s.

Selected feature metrics will form a dataset to be used as input for the LSTM algorithm. In this research, LSTM is employed to model and predict the behavior of generator rotor vibrations using sequentially derived feature importance values from the Random Forest algorithm.Long Short-Term Memory (LSTM) networks, introduced by Hochreiter and Schmidhuber, are a special kind of recurrent neural network (RNN) capable of learning long-term dependencies[20]. They address the vanishing gradient problem in traditional RNNs by introducing memory cells with carefully designed mechanisms for remembering and forgetting information.

LSTM computations for each time step t are as follows step 1 is a Forget Gate that determines which information to discard from the cell state $f_t = \sigma(W_{fxt} + U_{fht-1} + b_f)$, step 2 is an Input Gate that controls how much new information to add to the cell state $f_t = \sigma(W_{xit} + U_{iht-1} + b_i)$ and $\tilde{C}_t = \tanh(W_{Cxt} + U_{Cht-1} + b_C)$, step 3 is a Cell State Update that combines the retained previous state and new candidate values $C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$, and step 4 is an Output Gate that determines what part of the cell state to output: $\sigma t = (W_o xt + U_o h_{t-1} + b_o)$, $h_t = o_t \odot tanh(C_t)$.Where: x_t is the input at time t, h_t is the hidden state, C_t is the cell state, σ is the sigmoid activation function, tanh is the hyperbolic tangent activation function, f_t , i_t , o_t are the forget, input, and output gate activations, $\tilde{C}_t$ is the candidate cell state, W_f, W_i, W_C, W_o, U_f, U_i, U_C, U_o are weight matrices, b_f , b_i , b_C, b_o are biases, and $\odot$ denotes element-wise multiplication.This aggregation method effectively reduces the model's variance without increasing bias, resulting in a more accurate and stable prediction.

Algorithm 1 Random Forest and LSTM Integration Algorithm

Require: Training data X, target variable y, number of trees N, sliding window size w, sequence length l, hyperparameter grid param_grid

Ensure: Predicted feature importance trends and performance metrics

Step 1: Random Forest Regression and Feature Importance
Train a Random Forest model with N trees
for each decision tree in the Random Forest do
    Compute feature importance using variance reduction.
end for
Step 2: Dynamic Feature Importance Tracking
for each sliding window of size ω in the data do
    Train a Random Forest model on the windowed data.
    Record feature importances for key variables.
end for
Convert the recorded feature importance trends into sequential data.
Step 3: LSTM Training and Prediction
Split sequential feature importance data into training and testing sets.
Initialize an LSTM model and define MSE as the loss function.
for each parameter set in param_grid do
    Train the LSTM model and evaluate using MSE.
    if current MSE is the best so far then
        Update the best model and parameters
    end if
end for
Use the best LSTM model to Predict future trends for feature importance.

The integration of the Random Forest with LSTM, as described, forms the core theoretical model that will be tested using real-world data, which is detailed in the following section on research methodology.

4. Research Methodology

In this section is focused on how to implement and test the theoretical model presented in the previous section. It relies on the empirical approaches, detailing data collection, pre-processing, experimental setup, and the evaluation process to effectively apply the proposed Random Forest-LSTM algorithm. General research flowchart is explained visually in Figure 2.

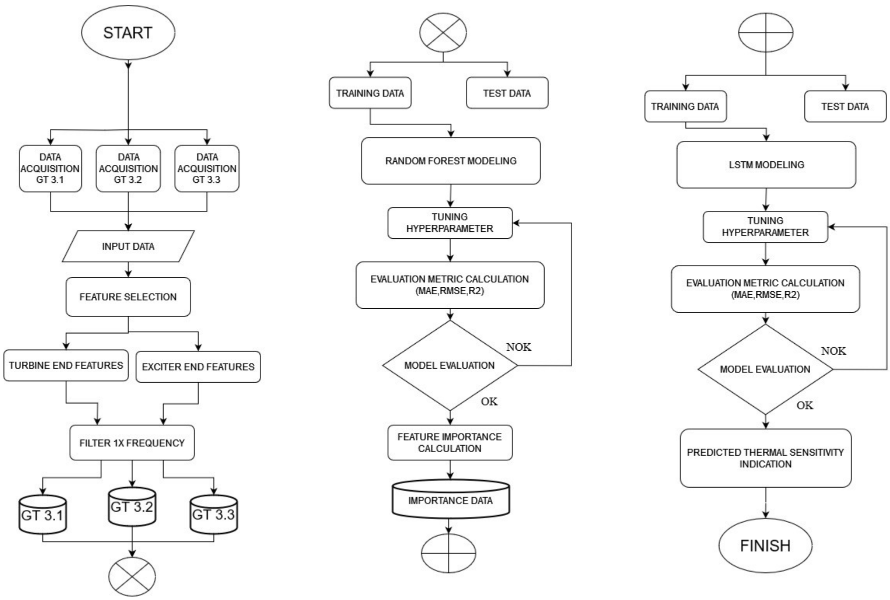

Figure 2. Research Flow Chart

4.1 Data Acquisition & Processing

Collecting continuous operational data from a Combine Cycle Power Plant (Gas - Steam Powered) is quite a challenging activity, due to the unpredictable operating pattern. The data obtained is operational data from 3 gas turbines which will vary depending on the dispatcher's request. The operating parameters selected for use in the model are shown in the table below, where sampling data per minute was collected from 3 generators in the time span from 07 March 2024 to 21 March 2024.

Bearing casing vibration variables from each end were chosen because there is a correlation between the friction event of the rotor shaft against the bearing which will cause the bearing to vibrate, but in some cases the opposite can also occur[21].

Table 1. Example of Generator Data

Time Stamp	Reactive Power (MVAR)	Exciter Current (A)	Bearing Temp TE(*C)	Bearing Casing Vib TE (mm/s)	Shaft Vib TE (mm)	Bearing Temp EE (*C)	Bearing Casing Vib EE (mm/s)	Shaft Vib EE (mm)
03-07 10:02:44	6,195	476,55	67,1	5,434	53,3	70,4	3,004	34,675
03-07 10:02:44	6,195	483,57	67,1	5,434	52,15	70,4	3,004	34,675
....	......	......	......	......	......	......	......	......
03-21 23:58:44	4,944	521,1	66	4,67	52,875	69,52	1,704	31,825
03-21 23:58:44	4,944		66	4,67	52,875	69,52	1,704	31,825

Table note
a TE = Turbine End
b EE = Exciter End

Likewise with the bearing temperature from each side, based on historical data explained by the related power plant operator, there was an increase in bearing temperature before the trend of increasing vibration, the relationship between temperature, vibration and excitation current can be seen in Fig 3, for simplicity graphical representation of correlation will only be shown for GT 3.3, for two other generators they have similar correlation. Feature dividing of the data that has been taken will be divided into turbine side and excitation side data, this is to study and analyze how the characteristics of the two different sides differ. Rotor Thermal Sensitivity is generally a phenomenon that result vibrations at natural frequency, where sorting data at this frequency becomes very important as the final step before implementing it to the algorithm[22].

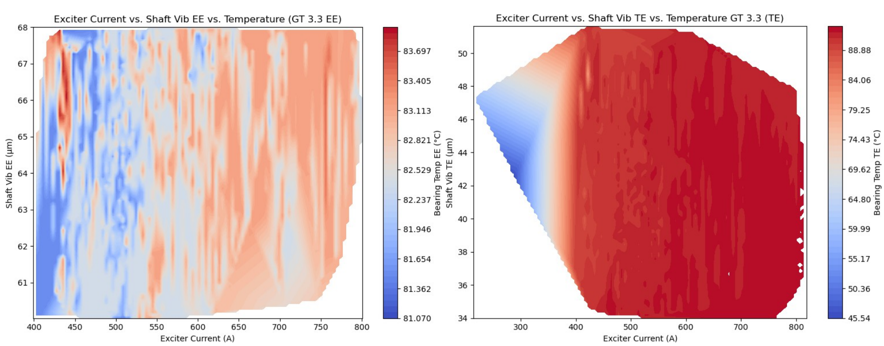

Figure 3. Correlation of Exciter Current, Shaft Vibration, and Bearing Temperature

4.2 Algorithm Implementation

The processed data will be aggregated to hourly intervals from the original minute-level data to reduce computational complexity and divided into 80% training data and 20% testing data in Random Forest modeling to ensure that the model has the opportunity to learn from various operational scenarios before being tested on unseen data. Hyperparameter tuning is done using the Grid Search CV method, and will be done on the parameters Number of estimators (50, 100, 200), Maximum depth (None, 10, 20), Minimum samples split (2, 5, 10), and Minimum samples leaf (1, 2, 4). The best parameters will be optimized through iterations of the Mean Squared Error (MSE) evaluation metric calculation. After the best model is found, the next stage is to carry out predictions on the test data.

The results of this prediction will then be used to calculate Feature Importance, which is a metric that describes the contribution of each feature to the accuracy of the model's prediction. Feature Importance is obtained through statistical analysis in a 24-hour rolling window where the data will be processed per hour and the results averaged per day. The results will be analyzed qualitatively through graphs to be able to compare the differences in importance values of each variable and conclude the indication of Thermal Sensitivity. Although Thermal Sensitivity is not indicated by one of the generators, the Feature Importance values of the Exciter Current and Reactive Power variables will still be used in LSTM modeling to predict the indication of Thermal Sensitivity in the future. LSTM modeling will change the Feature Importance data into data whose values are in a uniform range and divided into a series of historical data using data from the last 24 hours to predict the next value. From here, the data is divided into 80% training data and 20% testing data.

An iterative process will be initiated where various combinations of parameters such as Units (32, 50, 64), Batch size (16, 32, 64), Learning rate (0.001, 0.0005), Epochs (20, 30). The model is learned with these settings and then evaluated to see how well it predicts the test data. During training, if the model does not show improvement in its predictions after a few iterations, the training will be stopped early to avoid wasting time. Once all combinations of settings are tested, the combination that gives the lowest prediction error is selected as the best. This process helps ensure that the selected model is the most effective in making accurate predictions, based on historical data, and can be used to make further predictions with higher confidence in its accuracy

5. Result and Discussion

This section provides explanation about comparing the result of 3 generators with each turbine side and exciter side that implements Random Forest prediction and it's feature importance and the result of LSTM feature importance prediction.

5.1 Random Forest Prediction and Feature Importance Result

Prediction result of the model has successfully achieve estimating based on the test data, comparison between predicted and actual data of Shaft Vibration Exciter End of 3 generators is shown in Fig 4. As expected the range value of vibration between 3 rotors is different.The duration of non-operation of GT 3.1 and GT 3.2 for approximately 2 days had little effect on the prediction results. Where GT 3.1,3.2, and 3.3 exciter end vibration prediction RMSE are 0.89%, 0.49% and 1.39% in average of 0.92% with R2 in order are 89.78%,85.59%, and 81.62% in average of 85.66%.It can be concluded that the modeling successfully predicted vibrations with the features used.

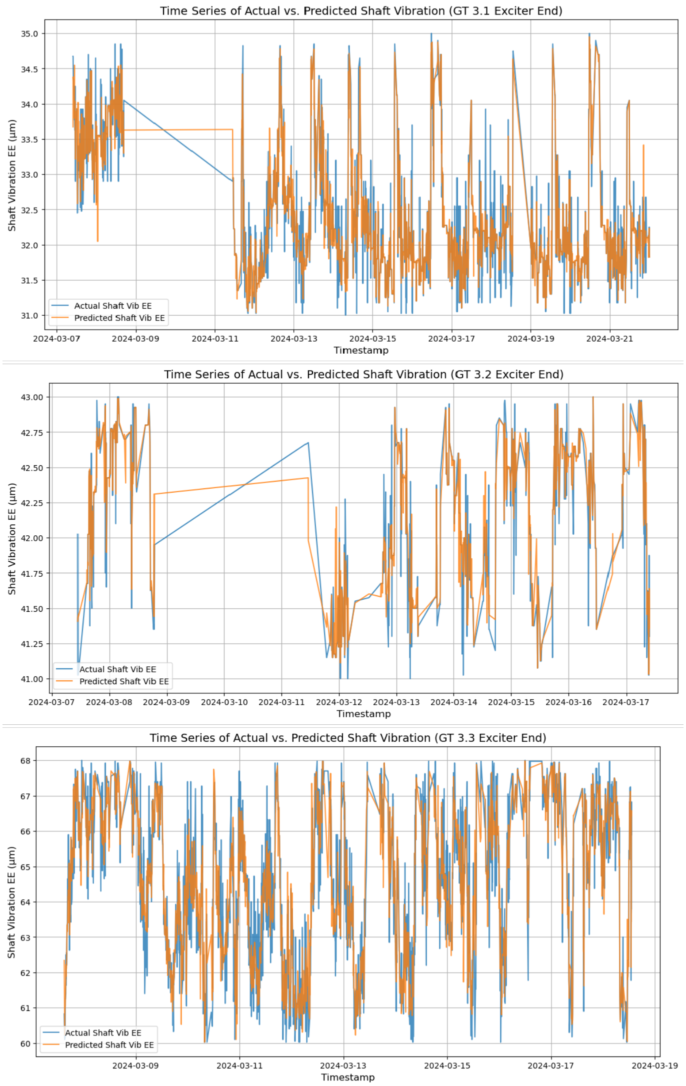

Figure 4. Actual and Predicted Value of Shaft Vibration Exciter End

Likewise with the prediction results in the Turbine End section which can be seen in Fig 5. Vibration in the part closest to the purely mechanical side, namely the turbine, has also been successfully predicted using a model with evaluation metrics RMSE are 2.14%, 2.05% and 4.06% in average of 2.75% with R2 in order are 50.34%,61.58%, and 72.33% in average of 61.42% .Comparing metric results between each end, it can be concluded that exciter end does a better job to predict shaft vibration in its respective end, this is due to the need of additional variables and data that correlates to predicting shaft vibration in turbine end. The magnitude of the vibration value cannot be concluded solely due to the Thermal Sensitivity event, thus predicting values of vibration in the upcoming time is useless, unless it is used solely to study the trend of vibration. Therefore the Feature Importance calculation is carried out and the comparative value is shown in the Table 2.

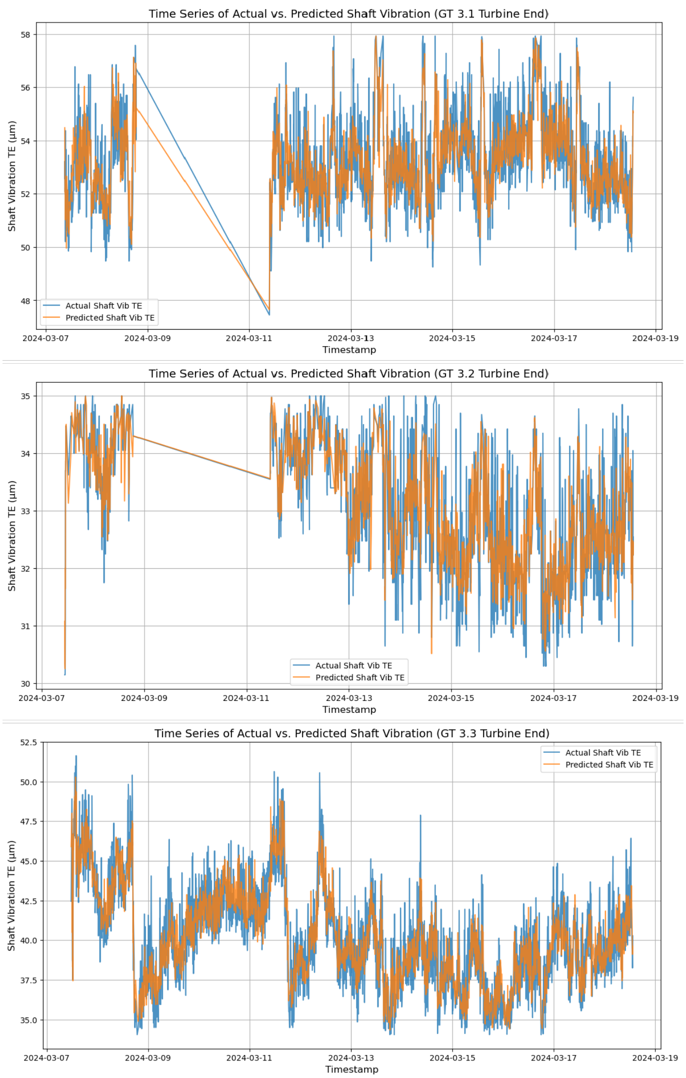

Figure 5. Actual and Predicted Value of Shaft Vibration Turbine End

GT 3.1 excitation side is dominated by excitation features and followed by vibration features on the bearing, almost similar dominance in GT 3.3 also occurs when dominated by reactive power and vibration features on the bearing. This can be an early indication that Thermal Sensitivity is one of the causes of vibration. However, in contrast to what happened in GT 3.2 where the dominance of vibration features on the bearing was very high and caused other features to be less relevant. The turbine side also experienced the same value sequence as the excitation side on all its generators. GT 3.2 has a new generator rotor, the first time the generator rotor was commissioned was in 2022 which indicates that the vibration on the rotor is purely from vibration on the bearing side only. The effect of temperature can be concluded that it does not have too much effect on the prediction model, except for GT 3.1 which is in third place, this can be caused by excessive friction on the bearing which increases the temperature value or uneven temperature distribution along the rotor which is also an indication of Thermal Sensitivity. From those values, maintenance and planning engineer could implement better strategy about resources and scheduling of maintenance regarding the condition of the rotor.

Table 2. Feature Importance Result

Feature	GT 3.1 EE	GT 3.2 EE	GT 3.3 EE	GT 3.1 TE	GT 3.2 TE	GT 3.3 TE
Reactive Power	0.122	0.183	0.33	0.207	0.18	0.44
Exciter Current	0.329	0.188	0.24	0.351	0.204	0.183
Bearing Temp EE	0.222	0.072	0.132	NotUsed	NotUsed	NotUsed
Bearing Casing Vib EE	0.324	0.555	0.296	NotUsed	NotUsed	NotUsed
Bearing Temp TE	NotUsed	NotUsed	NotUsed	0.162	0.089	0.079
Bearing Casing Vib TE	NotUsed	NotUsed	NotUsed	0.278	0.526	0.296

Table note
a Feature Importance Range (0–1)

5.2 Feature Importance Prediction with LSTM

In this subsection mentioned Feature Importances from previous subsection will be used as a data to predict in hourly manner as long as 3 days ahead of future values using LSTM and results will be discussed. The choice to limit LSTM's future predictions to a 3-day horizon is primarily dictated by the dataset used for training the model, which spans only between ten to fourteen days. This relatively short duration constrains the model's ability to reliably extend its forecasting further without risking significant decreases in accuracy. Due to the Feature Importance results in GT 3.2 which are really dominated by the bearing vibration feature, the prediction results of the LSTM model on the generator will not be discussed further here but the model is still applied. The dominance of the excitation current and reactive power features that occur in GT 3.1 and GT 3.3 will be the main prediction topic here, the prediction of the vibration feature on the bearing will not be discussed further but will still be applied.

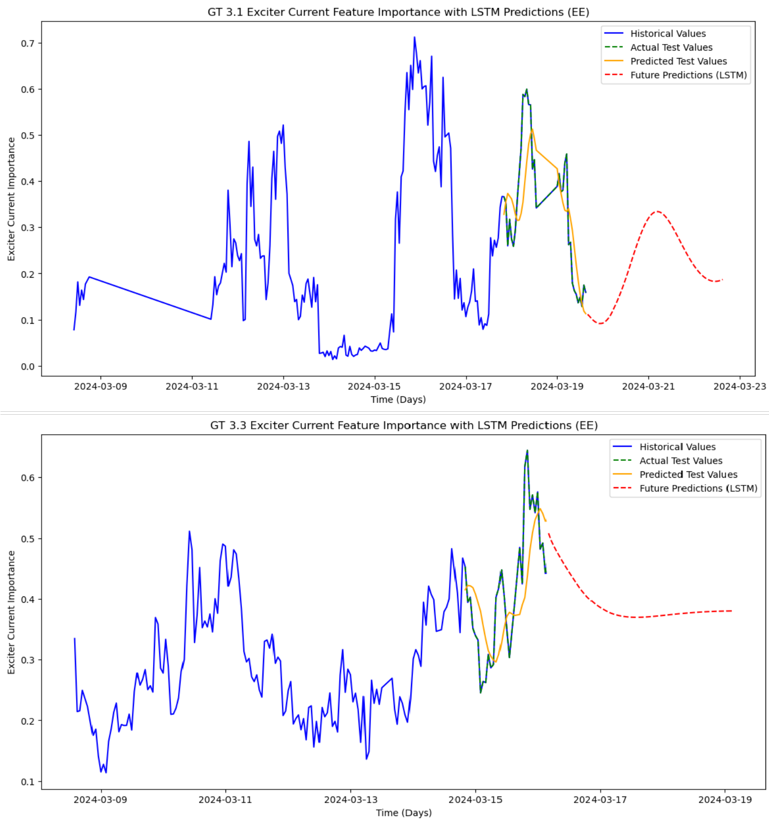

Figure 6. GT 3.1 and GT 3.3 EE Exciter Current Feature Importance Prediction

5.2.1 Prediction at Exciter End

In both graphs in Figure 6, the historical values are plotted as the solid blue line, the actual test values as the green dashed line, the predicted test values as the solid yellow line, and the future prediction using LSTM is depicted as the red dashed line. It can be seen that the excitation current shows significant fluctuations reflecting its strong influence on shaft vibration. For GT 3.1, an intensive fluctuation pattern with a peak value of 0.7 can be seen reflecting a higher variability in the effect of the excitation current on shaft vibration. Similar to GT 3.3, the actual test values and the predicted test values are close together, indicating the accuracy of the model in mapping the actual operating conditions with the results of the RMSE evaluation metrics for GT 3.1 being 9.34% and GT 3.3 being 9.44% percent. The LSTM prediction for the next 3 days shows that the excitation current value will experience a temporary increase before decreasing again, indicating a change in the operating pattern or machine conditions that affect the shaft vibration on the excitation side.

Significant difference can be seen in Figure 7 where there is a steep increase fluctuation pattern shown in GT 3.1, this can occur due to the integrated operation pattern with the electricity network system where the loading pattern is determined by the dispatcher, such as variations in electricity demand or network configuration can affect the reactive power generated for the same excitation current. An example case is a change in impedance in the network due to changes in configuration or component failure can change the distribution of reactive power[23] [24]. The UP Muara Tawar generator at some range of time is functioned to absorb MVAR so that the modeling results show a low Feature Importance. In GT 3.3, there can be a high average Feature Importance for reactive power accompanied by a downward trend according to the operation pattern. The results of the RMSE metric evaluation on this feature in GT 3.1 is 5.91% percent and GT 3.3 is 8.88% percent.

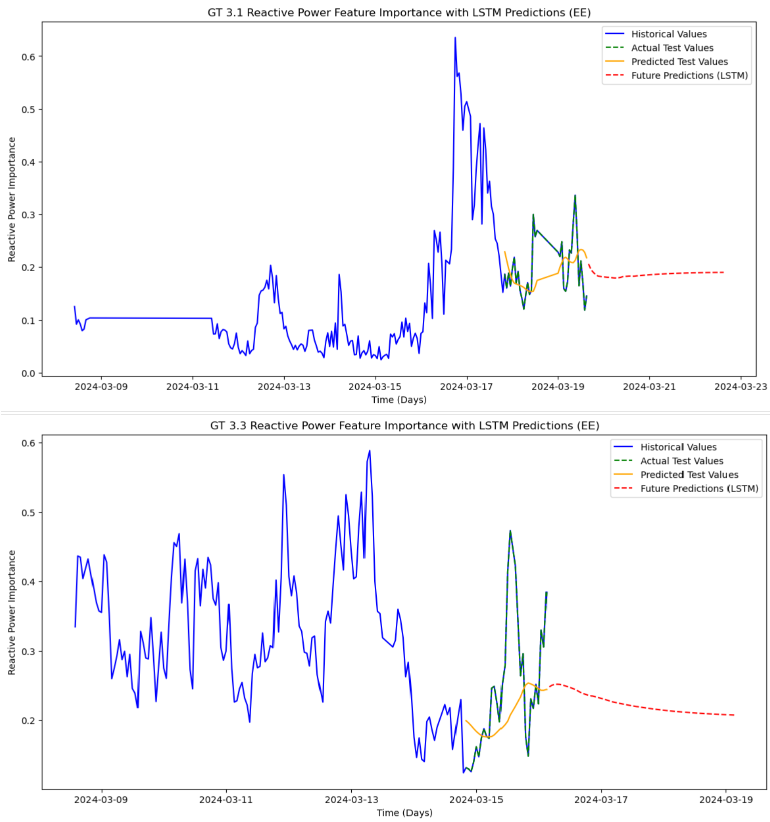

Figure 7. GT 3.1 and GT 3.3 Reactive Power Feature Importance Prediction

5.2.2 Prediction at Turbine End

Feature Importance prediction of reactive power on the turbine side can be shown in the figure 9, the average value of Feature Importance from both shows that this feature is indeed selected as a feature that will predict vibration on the turbine side, the size of the value is influenced by the operating pattern with the network, in GT 3.1 a small average value is obtained due to the influence of the mechanical side indicated by the Feature Importance value of bearing vibration in the previous discussion. However, in GT 3.3 reactive power shows an increasing trend and an average that is significant enough to identify potential Thermal Sensitivity events.The results of the RMSE metric evaluation on this feature in GT 3.1 is 9.66% and GT 3.3 is 1.66% percent.

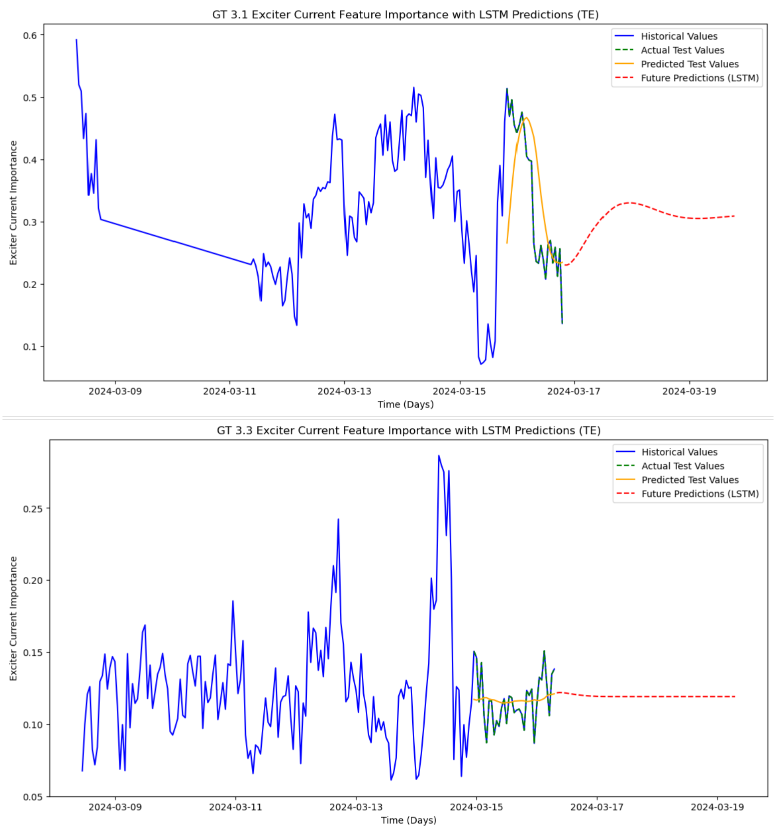

Figure 8. GT 3.1 and GT 3.3 TE Exciter Current Feature Importance Prediction

Feature Importance prediction of excitation current on the turbine side can be shown in the figure 8, according to expectations that the value ranges between 0 to 0.6 only with a smaller average compared to the excitation side. GT 3.1 shows a higher trend compared to GT 3.3 which indicates an indication of the influence of Thermal Sensitivity on the entire generator rotor shaft with an increasing prediction trend.

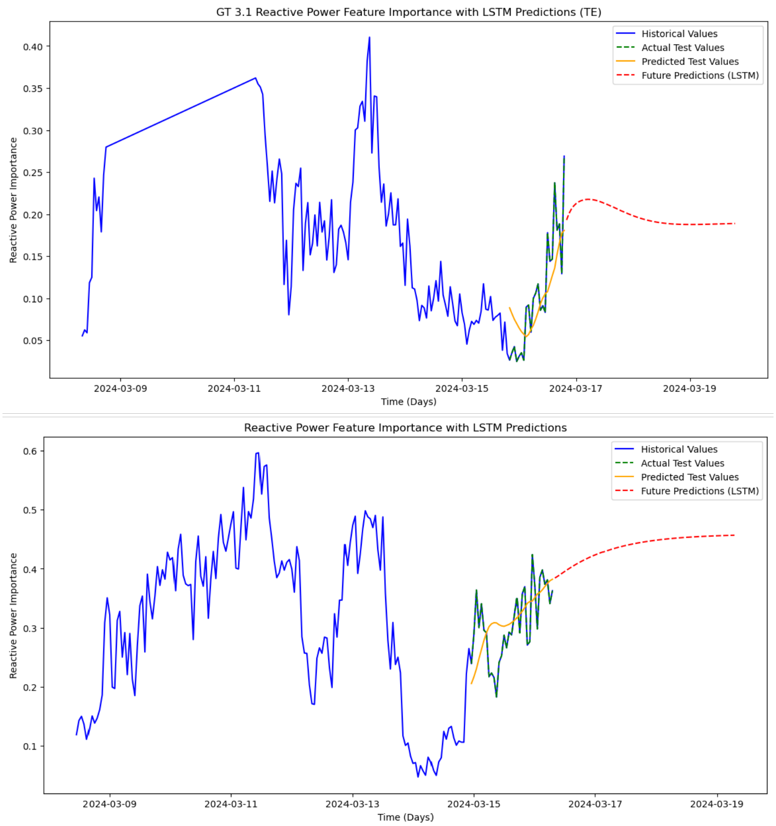

Figure 9. GT 3.1 and GT 3.3 TE Reactive Power Feature Importance Prediction

The RMSE metric evaluation value of this modeling is 4.8% for GT 3.1 and 5.6% for GT 3.3. For simplicity of representation of evaluation metrics, average values of exciter current feature RMSE and reactive power feature will be calculated, which are 7.29% and 6.52%. The differences between what was predicted and what actually happened at the Exciter End can be explained by a few things. Firstly, the operating conditions are always changing, like sudden jumps in the load, and the model cannot always keep up with that unpredictability. Secondly, the way the model updates the importance of the features might not be fast enough to catch quick changes, which leads to errors in the short-term predictions.The differences between predicted and actual values at the Turbine End could be because of the complicated relationship between the mechanical condition and the operating parameters. If there is mechanical wear and tear or unexpected mechanical issues, that can suddenly change the vibration patterns and make the predictions less accurate.

6. Conclusion

This research presents a new approach to predict indications of the Thermal Sensitivity phenomenon by utilizing modeling integration from Random Forest and LSTM. Through analysis of historical generator data, the Random Forest model is able to predict vibrations on the rotor to determine feature importance used, with the results of average evaluation metrics RMSE 0.92% and R2 81.62% on the excitation side and 2.75% and R2 61.42% on the turbine side and also with the very useful addition for analyzing the occurrence of Thermal Sensitivity, the values of Feature Importance have been successfully calculated. In addition, Long Short Term Memory (LSTM) modeling is able to predict future trends of Thermal Sensitivity identification based on excitation current feature with RMSE value of 7.29% and reactive power feature of 6.52%. The success of this predictive model offers promising insights to improve operational and maintenance strategies in power plants.

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