Generator Thermal Sensitivity Analysis with Support Vector Regression

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Abstract—Generator thermal sensitivity issue is studied in this paper. Currently, thermal sensitivity test is usually adopted in industries to determine if a generator has been experiencing thermal sensitivity problem. However, this kind of tests has its own disadvantages. In this paper, Support Vector Regression is utilized to provide some valuable information regarding thermal sensitivity in a rotating machine based on the normal operational data of the machine. Experimental results on the steam turbine generators show that the proposed method can be used to track the generator condition related to the thermal effects and make a recommendation to the on-site engineers whether or not a thermal sensitivity test should be performed.

I. INTRODUCTION

Electrical machine condition monitoring plays an important role in modern industries and it has been an active research topic. Traditionally, electrical machines are allowed to run until failure then they are either repaired or replaced. Very limited information regarding the machine condition is known before the machine is shutdown and hence resulting in long machine downtime and great economic lost. Recently, predictive maintenance strategy is adopted in many industries. In predictive maintenance, machine condition is monitored continuously, and hence valuable information regarding machine condition can be obtained before the machine is shutdown and repaired and the machine downtime can be greatly reduced.

Predictive maintenance consists of various aspects. For example, fault analysis needs to be performed and classification models can be built with artificial intelligence techniques to classify and identify different machine conditions. In addition, prognosis models can be built to predict the future machine conditions and determine if the machine is experiencing faults related condition degradation. The machine condition trending based on importance machine performance index can be carried out to determine when the machine should be shutdown or a major maintenance/repair should be scheduled. This way the number of unexpected shutdown can be greatly reduced and the reliability is greatly improved.

In this paper, a specific issue, generator rotor thermal sensitivity, is studied. Thermal sensitivity is a phenomenon caused by uneven heat distribution around an axis, e.g. rotor, causing it to bend. Some common causes of generator thermal sensitivity include shorted turns, blocked ventilation or unsymmetrical cooling, insulation variation, wedge fit, distance block fitting, etc. [1]. There are two types of thermal sensitivity, reversible and irreversible. Normally thermal sensitivity is confirmed and the severity is determined through a standard test procedure commonly adopted in industries. However, the thermal sensitivity test is destructive especially when the machine has irreversible thermal sensitivity problem.

Support Vector Regression (SVR) has been widely used in the field of electrical machine condition monitoring. Just to name a few, in [2], a hybrid model is built with SVR to predict the future state of a turbo generator. In [3], the Least-Square Support Vector Machine (LS-SVM) combining with wavelet decomposition is utilized to predict the future vibration of a hydro-turbine generating unit. In this paper, a model for vibration analysis is built with SVR that can be useful in tracking machine conditions. It is applied to analyze the thermal sensitivity issue for a type of steam turbine generators. In this method, only normal machine operational data are used to build the model. The results can be used to recommend whether and when a necessary thermal sensitivity test is needed. The rest of the paper is organized as follows. The basic theory of SVR is reviewed in section II. In section III, the background of generator thermal sensitivity and the procedure of a thermal sensitivity test are introduced. In section IV, after some discussions on the industrial practice regarding thermal sensitivity and the limitations, SVR models are built and the experimental results are presented. Finally, the conclusion is provided in section V.

II. SUPPORT VECTOR REGRESSION

In SVR, the goal is to find a function \( f(x) \), which maps the input to the output, while minimizing the difference between the predicted value \( \hat{y}_i \) and the actual value \( y_i \) based on the loss function [4]. Suppose that there are training data \((x_1, y_1), (x_2, y_2), ..., (x_N, y_N)\), where \( x_i \) is the input and \( y_i \) is the output. In a linear case, \( f(x) \) can be expressed as

\[
\hat{y} = f(x) = wx + b
\]

where \( w \) is the weighted vector and \( b \) is a constant. While trying to minimize the difference between the predicted value and the actual value, in SVR, it is also desirable to keep the function \( f(x) \) as flat as possible [4], which means \( w \) should be as small as possible. One way to find a small \( w \) is to minimize the norm, i.e. \( ||w||^2 =< w, w > \). Thus, the regression problem becomes to

\[
\min_{w,b} \frac{1}{2} \sum_{i=1}^{N} (\hat{y}_i - y_i)^2 + \frac{1}{2} ||w||^2
\]
III. GENERATOR THERMAL SENSITIVITY

A. Causes of thermal sensitivity

As stated in [1], even for a rotor that has thermal sensitivity issue, it is not affected much when the generator is operating with low VAR. On the other hand, when the generator is operating with a power factor lower than 0.85 lagging, a thermal sensitive rotor will be affected and its vibration profile will change. The rotor vibration may increase, decrease, or its phase angle may change. Therefore, even with a thermal sensitive rotor, a generator may not have any issues when operating with low field current; however, its operation may be greatly restricted at high field currents or VAR loads as the rotor vibration exceeds the acceptable limit.

Generator rotor thermal sensitivity can be classified into two types: reversible and irreversible. When the thermal sensitivity is reversible, rotor vibration changes as field current varies. That is, when the field current increases, the rotor vibration increases. Later on, when the field current decreases, the rotor vibration will decrease as well. This type of thermal sensitivity usually does not cause major problems in practice and the rotor can be balanced so that its maximum vibration will not exceed the limit. If the rotor vibration does not decrease after the field current is reduced, this type of thermal sensitivity is called irreversible. This type of thermal sensitivity is troublesome since the rotor vibration will keep increasing, and the rotor may have to be taken off-line and repaired in order to reduce the vibration. Readers can refer to [1] for more details on some common causes of generator thermal sensitivity and their thermal sensitivity types.

B. Thermal sensitivity test

A standard procedure for determining generator thermal sensitivity is normally adopted. The purpose of this test is to isolate the machine vibration which is caused by MW (real power) loading from that caused by VAR loading (reactive power). Vibration changing with MW loading does not indicate thermal sensitivity problem. The thermal sensitivity test consists of 3 parts:

1) The thermal sensitivity test is started by loading the generator with small MW and MVAR. 10MW and 0MVAR for example, and then MW gradually increases to about 60% of its rated value and MVAR will be reduced. At each stage, all the important readings, such as the machine vibration, voltage, current, temperature, etc. are recorded.

2) In the second step of the test, the generator MW is kept constant while the field current continuously increases to its rated value, so MVAR increases correspondingly. It is important that the MVAR is high enough so that the generator operates with a power factor lower than 0.85 lagging.

3) The last step of the thermal sensitivity test is the reverse of the first 2 parts. The generator MVAR decreases while the MW is kept constant, and then the MW decreases and MVAR increases so that the final generator MW and MVAR are back to the same
values as when the test is started. The complete process of the thermal sensitivity test is illustrated in Figure 2. If the final machine vibration is similar to the vibration when the test is started, it can be concluded that the thermal sensitivity is reversible. Otherwise, if the final machine vibration remains high, the thermal sensitivity is irreversible and further maintenance actions may need to be taken.

IV. SVR MODEL BASED ON MACHINE VIBRATION TRACKING FOR THERMAL SENSITIVITY ANALYSIS

A. Experimental setup

Two back pressure steam turbine generators (BPSTG) used in a local oil-sand company are investigated in this paper. They are labeled as G1 and G2. Figure 3 shows a typical layout of the BPSTG, which consists of a steam turbine and a generator. They are 4 bearings in total for each generator and two vibration sensors are installed on each bearing along x and y axes of 90 degrees apart. During normal operation, the machines are running at 3600 RPM and the vibration waveform for each bearing is captured and updated every 2 hours.

B. Thermal component

The thermal sensitivity test serves 2 purposes. The first one is to determine if there exists irreversible thermal sensitivity. The other purpose is to determine the ‘size’ of the thermal component, i.e. the difference between the vibration when the generator is operating at the low MW and MVAR loading at the beginning of the test and the vibration when the generator is operating at the highest MW and MVAR during the test. The difference has to be within a certain limit otherwise the generator will not be able to run with its full capacity. The method used to calculate the thermal component is as follows:

\[ V_x = \frac{1}{2} A_x \cos(\theta - \theta_x) \]
\[ V_y = \frac{1}{2} A_y \cos(\theta - \theta_y) \]
\[ 0 \leq \theta < 2\pi \] (11)

where \( A_x, A_y, \theta_x, \) and \( \theta_y \) are the 1X vibration peak-to-peak value and phase angle in the x and y direction, respectively, and they can all be recorded during the thermal sensitivity test.

\( \theta_y \) is subtracted by \( \pi/2 \) (or added by \( 3\pi/2 \) if \( \theta_y - \pi/2 < 0 \)) since the vibration sensor x and y are 90 degree apart. Thus,

\[ \bar{\theta}_y = \theta_y - \pi/2 \]
\[ V_y = \frac{1}{2} A_y \cos(\theta - \bar{\theta}_y) \] (12)

To ensure \( V_x \) and \( V_y \) are larger than 0, constant terms, \( \frac{1}{2} A_x \) and \( \frac{1}{2} A_y \) will be added to \( V_x \) and \( V_y \), respectively. Hence,

\[ \bar{V}_x = \frac{1}{2} A_x + \frac{1}{2} A_x \cos(\theta - \theta_x) \]
\[ \bar{V}_y = \frac{1}{2} A_y + \frac{1}{2} A_y \cos(\theta - \bar{\theta}_y) \] (13)

Finally, by iteration, a \( \theta \) can be found which maximizes the following equation,

\[ V_T = \sqrt{\bar{V}_x^2 + \bar{V}_y^2} \] (14)

The corresponding phase angle can be denoted as \( \theta_T \). At this point, the overall maximum machine vibration can be expressed by a vibration vector with magnitude \( V_T \) and phase angle \( \theta_T \).

The maximum vibration vector can be calculated for the machine vibration at the start of the thermal sensitivity test and at the point when the machine is operating at the highest MW and MVAR during the test, and then the vibration
difference between those 2 conditions can be calculated. Figure 5 is a typical plot of the vibration vector during a thermal sensitivity test indicating the thermal component.

The above analysis is focused on the vibration difference between the lowest load and the highest load of the machine operation during the thermal sensitivity test. However, how the machine vibration changes due to thermal sensitivity in a long term has not been taken into consideration. Also, if the machine thermal sensitivity is irreversible, the thermal sensitivity test can be destructive since the machine vibration may become worse after the test. Moreover, when a machine is undergone a thermal sensitivity test, it has to be removed from the production line, so the productivity is reduced. It is therefore desirable to determine whether or not a machine has been experiencing thermal sensitivity issue by analyzing normal machine operational data. In this paper, the SVR technique is applied to build a model for this purpose. Many different techniques can be used to build a system model, including building a physical model. However, this usually requires an in-depth understanding of the machine structure. Hence, artificial intelligence techniques are often preferred. Based on [8] and [9], SVR seems to be a better choice over Neural Network (NN) and adaptive neuro-fuzzy inference system (ANFIS) and therefore it is selected in this paper. The method is tested on the two BPSTG and some valuable preliminary information about rotor thermal sensitivity problem is obtained.

C. SVR based vibration model

For tracking the machine vibration, a system model is needed. In this case, the inputs of the model are the generator output real power and reactive power, and the output of the model is the machine 1X vibration. Other than the machine output power, many other factors, such as the temperature of the machine operating environment, may also have impacts on the machine vibration. However, machine output power can be directly controlled by the on-site engineers, and this is why they are chosen as the inputs of the model. The model built to predict the machine vibration based on the generator output power can be mathematically expressed as

\[ y = f(P, Q) \]  \hspace{1cm} (15)

where \( P \) and \( Q \) are the machine real and reactive power, respectively, and \( y \) is the output related to machine 1X vibration amplitude. If the model is properly trained and the machine thermal sensitivity is irreversible, the difference between the predicted vibration and the real vibration can be shown in the thermal component analysis. Instead of using the magnitude or phase angle of the vibration vector as the model output, the vibration vector is decomposed into two components by projecting to X and Y axes:

\[ V_{TX} = V_T \cos \theta_T, \quad V_{TY} = V_T \sin \theta_T \]  \hspace{1cm} (16)

Thus, any changes in the magnitude and phase angle of the machine 1X vibration are reflected in \( V_{TX} \) and \( V_{TY} \).

D. Case studies and the analysis results

In this section, SVR models are built for both G1 and G2 and used to track their vibrations. Based on previous thermal sensitivity test results from the plant, it is known that G1 does not have serious problem since the thermal sensitivity is reversible. On the other hand, G2 may have serious thermal sensitivity issue and it is irreversible. Vibrations for both generators are analyzed separately in the following sections.

Fig. 6 shows the plots of \( V_{TX} \) and \( V_{TY} \) of G1. The vibration data is obtained during the period from Jan. to Aug. 2003 on bearing 4 and there are 2761 data points in total. From Fig. 6, no obvious trend can be noticed. \( V_{TX} \) and \( V_{TY} \) do not seem to increase or decrease as time progresses. In order to confirm that the machine condition did not change during that period, SVR models can be built to predict the machine vibration based on the machine output power. If the machine condition indeed did not change during that period, the model predicted vibration should be very close to the real vibration as long as the model is properly trained.

When building the SVR models in this section, different kernel functions have been tried, including linear and polynomial kernel functions with different degrees. By trial and error while taking the model training time into consideration as well, polynomial kernel function with degree 2 is selected. The first 700 data points are used to train the SVR models and the prediction error is simply the difference between the predicted vibration value and the real vibration value:

\[ error = V_{\text{Vibration}_{\text{actual}}} - V_{\text{Vibration}_{\text{predicted}}} \]  \hspace{1cm} (17)
be concluded that there is a direct relationship between the machine output power and the machine 1X vibration. It is possible to build an accurate model with machine real and reactive powers as the model inputs to predict the machine 1X vibration.

Similar analysis can be applied to generator G2. Fig. 10 shows the plots of $V_{TX}$ and $V_{TY}$ of G2. The vibration data is obtained from Jan. to Sep. 2003 on bearing 3 and there are 3123 data points in total. SVR models are built with the same kernel function and parameter for $V_{TX}$ and $V_{TY}$, and again the first 700 data points are used to trained the models. The prediction results and prediction errors are shown on Fig. 11 and 12. From Fig. 11, it can be seen that the prediction results are close to the actual values. The mean and standard deviation of the prediction errors are 0.0114 and 0.2584, respectively. On the other hand, on Fig. 12, starting from data points around 1920, which corresponding to June 23, 2003 in actual date, the actual vibration starts to increase, which causes the prediction error between the predicted $V_{TY}$ and the actual $V_{TY}$ to increase and finally settles down at data points around 2200, which corresponding to July 16, 2003 in actual date. The mean and standard deviation of the prediction errors are 0.5502 and 0.613, respectively. Hence, the mean of the prediction error is much larger than those in the other 3 cases. The prediction error can be further analyzed with the moving window method to show how the mean and standard deviation change more clearly. The results are shown in Fig. 13, with 500 data points as the window size and 100 data points as the moving size. From Fig. 13, it is very clear that the mean of the prediction error starts to increase rapidly after index 15, which is equivalent to index 1900 in the actual data point. If the vibration vectors are plotted during the period from June 23 to July 16, the result would be similar to Fig. 9. $V_{TX}$ did not change too much during that period and it remained at about 2.5 mil, while $V_{TY}$ increased approximately from -1 to 1 mil. Thus, the vibration vector moves from the forth quadrant to the first quadrant.

From the Fig. 12, it is noticed that the model prediction errors are small for the first 1800 data points, it can be confirmed that the SVR model has been trained properly and it should generate outputs accordingly with the changing input power. Therefore the difference shown after the index number 1920, is mainly due to the reason that the machine condition has changed. The machine condition may change due to many mechanical reasons, such as the machine may have been taken off-line and maintenance work have been performed to the machine, or some machine components are worn out. However, it has been confirmed that G2 was continuously running for the whole period and there was not any maintenance work done to the machine. Also, if the machine condition is changed due to components wear out, the process should be slow and the vibration should change slowly instead of increasing abruptly as it is shown in Fig. 12. Another possible cause for the machine condition change is irreversible thermal sensitivity. By checking the generator output powers, it is found out that, from June 23 to 27, the generator was operating with very high MVAR, such as 25MW and 30MVAR, 45MW and 30MVAR, etc. Also, G2 was considered running in the normal condition since its peak-to-peak vibration is under the pre-defined limit and the change of vibration cannot be noticed if the vibration data was not processed by the method described previously in this paper. Thus, considering all the analysis above, it is believed that the vibration change is due to thermal sensitivity. Based on the results, one could then recommend a thermal sensitivity test to be scheduled to confirm this. Since the valuable information about thermal sensitivity can be obtained before the severe machine condition degradation by analyzing past operational data, unexpected shutdowns can be avoided.
CURRENTLY, in practice, a thermal sensitivity test can be performed to determine if a generator has thermal sensitivity issue or not. However, thermal sensitivity test has some disadvantages and it is preferred to determine the thermal sensitivity problem based on the regular machine operational data. In this paper, system model is built with SVR to predict the machine vibration based on the machine output power. The proposed method is applied to analyze the thermal sensitivity in 2 BPSTGs and experimental results show that the proposed method can be used to keep track of the machine condition and provide valuable information on whether the generator has thermal sensitivity issue.

V. CONCLUSION

Generator thermal sensitivity is studied in this paper. Currently, in practice, a thermal sensitivity test can be performed to determine if a generator has thermal sensitivity issue or not. However, thermal sensitivity test has some disadvantages and it is preferred to determine the thermal sensitivity problem based on the regular machine operational data. In this paper, system model is built with SVR to predict the machine vibration based on the machine output power. The proposed method is applied to analyze the thermal sensitivity in 2 BPSTGs and experimental results show that the proposed method can be used to keep track of the machine condition and provide valuable information on whether the generator has thermal sensitivity issue.

REFERENCES