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Machine learning for assessing the servicetransformer health using an energy monitor device

Quynh T Tran[1,2], Kevin Davies[1] , Leon Roose[1]
[1] *Hawaii Natural Energy Institute, University of Hawaii at Manoa, USA*
[2] *Institute of Energy science, Vietnam academy of Science and Technology, Vietnam*

Abstract: *This paper proposed an assessing service transformer health model using data that has been collected by a real-time data acquisition and analysis device collocated with the transformer. The online data is provided to the operator in near real-time over the Internet and the operators can evaluate directly the status of the distribution transformer, then giving proper responds. The top oil temperature, vibration and transformer loading are chosen as monitored parameters. The condition of the considered service transformer is determined out using machine learning algorithms. The structure of this algorithm will be presented specifically in the paper. A case study is implemented on a stimulated service transformer to evaluate the effectiveness of the proposed model*

Key Word*: transformer health, machine learning, energy monitoring*

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I. Introduction

A service transformer or distribution transformer is one of the important components of the distribution grid. The distribution transformer is responsible for distributing electricity to low voltage users, therefore the operating condition of the transformer has a great influence on the quality of power supply to consumers[1].When the transformers are operated under rated conditions, their long service life will be guaranteed. However, the majority of these equipment have been in service for many years, errors can occur in distribution transformers due to a number of reasons including overload, oil leakage, over heat, harmonics and unbalanced loads, etc. If one or more of the distribution transformer parameters exceed the design and operational limits, the transformer age may be drastically reduced or an error occurs. This leads to unexpected failures and loss of supply to a large number of customers, affecting the reliability of the system. Currently, a variety of methods are studied to monitor the performance of transformers[2-9]. However, because the cost of installing the sensor equipment is quite high and requires a lot of technical requirements to place the sensors in the transformer, these methods are mainly implemented for transformers with large capacity. The study of methods of monitoring distribution transformers has not really been interesting.

Meanwhile, along with the development of science, the system of measuring equipment for this distribution grid has been more and more modernized. Digital communication and processing applications, integrating digital technology are brought into the grid, thus, the management and evaluation of system parameters are also much easier. Since 2005, Enel (Italy Electric Power Company) has designed and manufactured smart meters. They implemented many projects to integrate power monitoring devices to the network and developed energy management software in Italy, saving up to 500 million euros annually[10]. In the US, since 2003, the city of Austin, Texas has started to build smart grids by replacing one third of conventional meters with smart meters that are communicated through wireless networks, these meters have the function of controlling electrical outlets and smart devices[11]. But for the most part, this collected data source is only used to assess the overall health of the system. Therefore, the study of effective methods for monitoring the health and health of distribution transformers using smart metering devices can leverage the large data resource. The study also helps utilities proactively reduce breakdowns caused by deterioration of transformers, especially for distribution transformers, increase power supply reliability and reduce operating costs.

In this paper, a method for online monitoring of distribution transformers using intelligent measuring equipment will be proposed. The objective of this research is to develop low cost, accurate, and in situ solution for monitoring health condition of remotely located service transformers compatible with power monitor devices integration. The service transformer health will be evaluated by using machine learning algorithms based on selected appropriate system indicators.Top oil temperature, vibration and transformer loading are the parameters that are used to assess transformer health.

II. Structure Of The Online Monitoring System For the Service Transformer Health Assessment Process

The online monitoring program uses data from smart energy monitoring meters installed at the considering service transformer. Data from real time energy monitoring device is transferred continuously every second to other servers or local IP by using a flexible messaging with multiple stages data backup. The basic information including ambient temperature, transformer loading, voltage and current will be collected. Based on these data, a program will be run on the server to calculate transformer loading and estimate the top oil temperature and vibration. After that, the transformer health index will be detected by using Machine learning algorithm. Figure 1 presents structure of the online monitoring system.

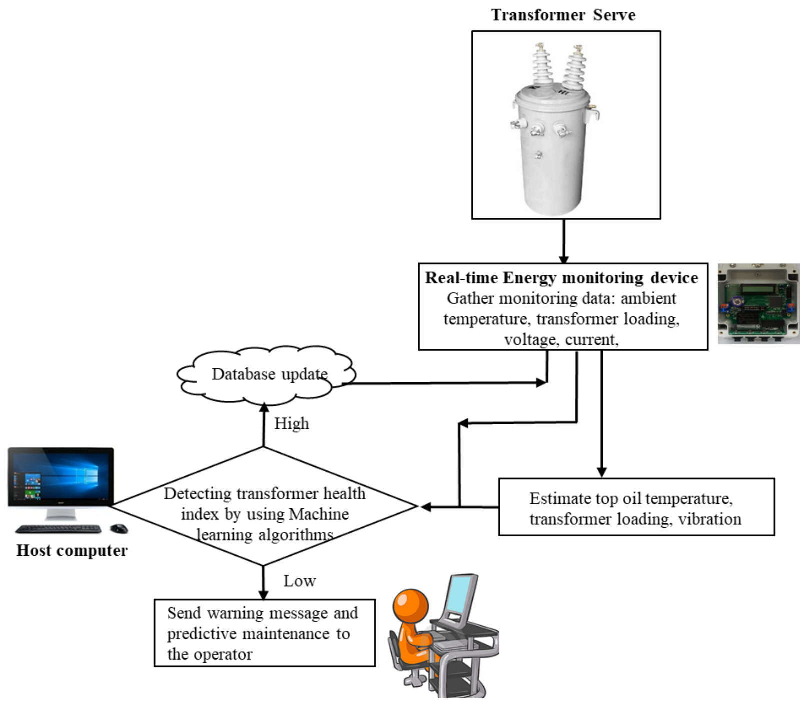


Figure 1. Structure of the online monitoring system

Because transformer loading, top oil temperature and vibration can be estimated from the measured current and voltage, they are selected as inputs in this problem. Transformer health condition is the final output.

-Transformer loading (TL) calculation

Transformer loading is chosen as an important parameter to evaluate the transformer health. TL is determined based on the ratio of the load to the nameplate power of the service transformer as shown in the equation (1)

$$TL = \frac{P_{load}}{P_{nameplate}} * 100\% \quad (1)$$

The risk of unexpected fault is evaluated if TL is larger than 100%. This failure can break the thermal insulation of the transformer or damage the transformer coil.

- Top oil temperature estimation

Top oil temperature is the one of significant parameter that effects on the transformer health. The top oil temperature usually fluctuates following the abnormal conditions of transformer such as partial discharge, internal fault and etc [12]. The deterioration of the insulation system will raise the heat inside the transformer and therefore, the top oil temperature will rise as well. The transformer health is in good condition when top-oil temperature is low. When the temperature is high, the transformer's condition is poor. To save the cost of installing the thermal sensor inside the transformer, which are usually expensive, the top oil temperature will be estimated by using the following dynamic equation contained in IEEE load guide [13]:

$$\left[\frac{K^2 R + 1}{R + 1}\right]^n . \Delta\theta_{oil,R} = \tau_{TO} . \frac{d\Delta\theta_{oil}}{dt} + \Delta\theta_{oil} \quad (2)$$

Where: K is the load factor which is

R is the ratio of the heat generation in the winding to the heat generation in the core at rated load

$\tau_{TO,}$ is the top- oil time constant

$\Delta\theta_{oil,R}$ is the top oil temperature increasing under rated conditions, °C

- Vibration estimation

Vibration is generated by electrodynamic forces and magnetic forces at the winding and the core of transformer. It also is one of the important parameters to assess the condition of transformer. The electrodynamic forces are proportional with the current squared and the magnetic forces are proportional to the voltage squared [14]. In [15], the vibration is estimated based on the relation between top oil temperature, voltage and current at the corresponding operating frequency. Equation (3) is the estimation of the vibration:

$$v_{tank} = (\alpha+\beta\theta_{top\ oil}).i^2 + (\gamma+\delta\theta_{top\ oil}).u^2 \quad (3)$$

Where: α, β, γ, and δ are coefficients that depend on transformer geometry

i and u are the current and voltage of the transformer, respectively

The condition of each parameter is defined based on the estimated values and its limits. The limitation is identified following the IEEE standard [13, 16].

III. Machine Leanring For Transformer Health Assessment Process

Machine learning (ML) is the study of computer algorithms that improve automatically through experience. It is seen as a subset of artificial intelligence or a mathematical model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed. Machine learning algorithms are used in a wide variety of applications that difficult or infeasible to develop conventional algorithms to perform the needed tasks. In this paper, four useful ML algorithms that will be used to determine Transformer Health are introduced below:

- Support Vector Machine (SVM): SVM is applied for classification and regression analysis problem. SVM arranges each sample data as a point in space and the model will map the sample data into separate categories, which are divided with a clear gap. Then, the new sample data will be mapped into the same space and the new output's category will be predicted depend on the side of the gap where the new sample data fall.

- Decision trees: Decision trees is a simple classification or regression algorithm. The sample data will be mapped in no-overlapping regions and easy to visualize the results. Decision trees can handle the missing data in the input space and can continues to create trained system for predict.

- Random forest: Random forest is an ensemble learning algorithm for classification, regression problem and other tasks. It can construct multiple decision at training data and give the mean prediction of the individual trees. Each individual tree will received a random train-test data set and then predict the category. The most voted category will be the predicted output.

- K-Nearest Neighbors (kNN): kNN is a supervised algorithm for classification or regression problems. This ML algorithm will map the inputs into the feature spaces. Each input will be assigned to the class that is most common among its nearest neighbors.

To assess Transformer health by using machine learning algorithms, a dataset that represent for investigated transformer and measured variables is required. This paper presents a method which is based on pattern classification for evaluate transformer health. Classification is a method that used to assign labels to inputs. In this paper, class labels for transformer health are four classes: Good, Fair, Poor and Very poor. The process will include 4 step: Summarizing the training dataset; Visualizing the training dataset; Create 4 ML models then pick the best accuracy algorithm; Make predictions on the validation dataset. Figure 3 shows the 4-step machine learning process.

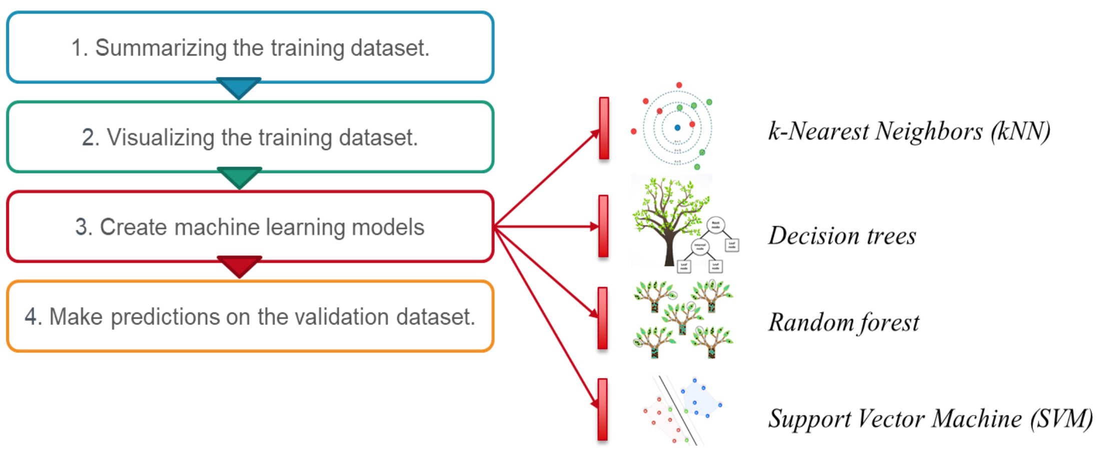


Figure 3. The 4-step machine learning process

The proposed method is applied on a simulated 50kVA- 7.2/0.208kV distribution transformer to show the effectiveness of proposed model to check the transformer health in real-time. The electrical conditions on the transformer were measured by a real-time energy monitoring device. Figure 4 - Figure 6 present respectively the real-time profile of top-oil temperature, vibration and transformer loading which are estimated from real-time measured current and voltage. The considering transformer is known that it is in Good condition.

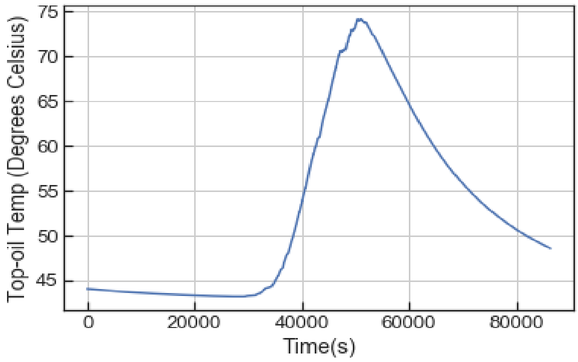


Figure 4. Estimated top oil temperature profile

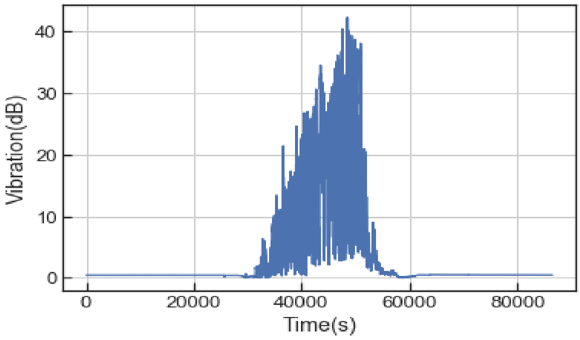


Figure 5. Estimated vibration profile

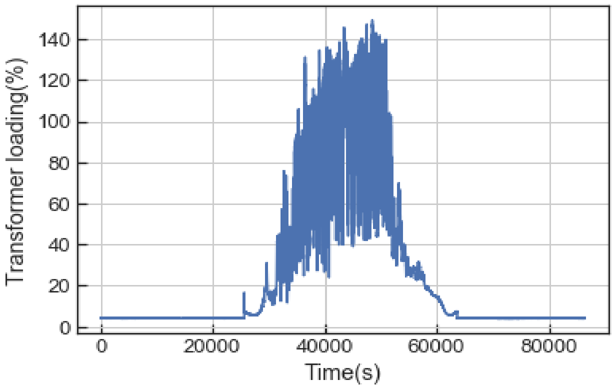
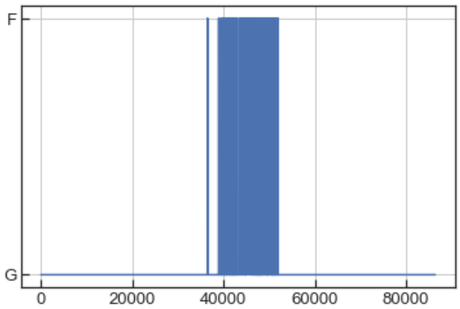


Figure 6. Calculated transformer loading profile

It can be seen that the values of all three input parameters increase at the peak hours from second 40000 to second 60000. The changing of these parameters will effect on the transformer health index as well. The prediction results are shown in Figure7 - Figure 10.



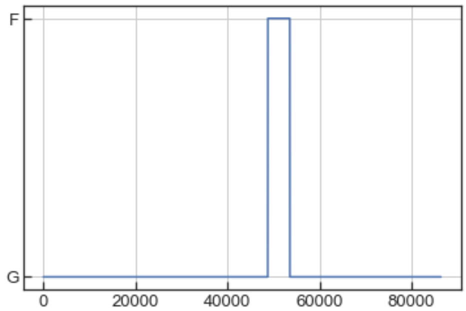


Figure 7. Predictions by using KNN algorithmFigure 8. Predictions by using Decision tree algorithm

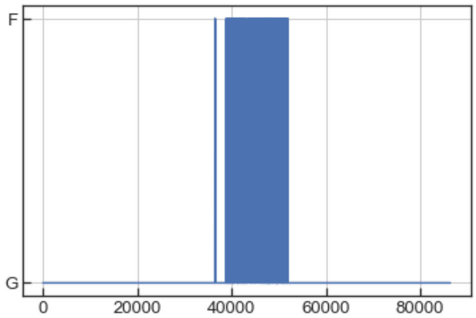


Figure 9. Predictions by using Random forest algorithm

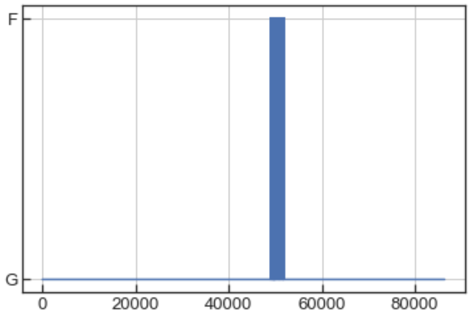


Figure 10. Predictions by using SVM algorithm

Because the assessment process was implemented in real-time, the prediction results are changing in real-time as well so that the system will send warning messages to the operator when the index of transformer health is in poor condition. Although four assessment algorithms give slightly different results, the final result is shown that the transformer is currently operating in good condition, in accordance with the condition that was previously evaluated. The results also show the relationship between the algorithm's assessment results and the input parameters. While the Decision tree algorithm and SVM algorithm display results curves corresponding to the profile curves of top oil temperature and vibration, the results curves of the kNN algorithm and Random forest algorithm display corresponding the change of transformer loading as well. The statistical evaluation results of each method were also compared in Figure 11

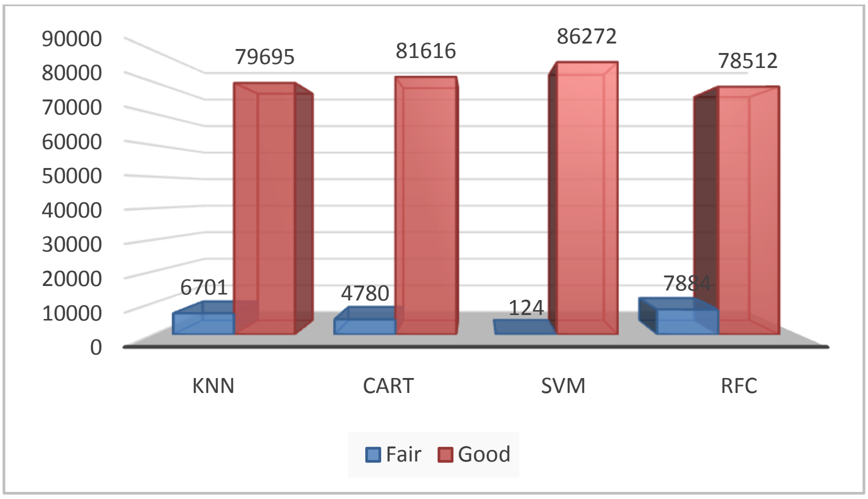


Figure 11. predictions on the validation dataset

The results indicate that transformer maintenance is not required. It can be observed that the value of HI varies proportionally with the fluctuation of transformer loading. Therefore, a plan is required to regulate the load of the transformer to avoid overload and potential breakdown.

IV. Conclusion

In this paper, an online method of monitoring distribution transformer health using machine learning algorithms at low cost and with minimal disruption were presented that uses advanced real-time grid energy monitor system. An application on 50kVA service transformer was performed to show the effectiveness of the proposed methodologies. In further work, this monitoring model will be applied on the a bigger transformers to evaluate the effect of the input parameters in different scenarios and to provide the overall validation.

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