SUPERVISED PREDICTION MODEL IN MONITORING TRANSFORMER HEALTH INDEX

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Supervised Prediction Model In Monitoring Transformer Health Index

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Abstract: *Dissolved Gas Analysis (DGA) enables identification of transformers that operate flawlessly or require maintenance through its analytical techniques. DGA exists to identify properly the various transformer-caused gas problems. Key Gas Method (KGM) analysis stands as a standard method for DGA that uses transformer-produced gases to assess its health index. The prediction models include K-Nearest Neighbors (KNN) and Discriminant Analysis and Principal Component Analysis (PCA) and Support Vector Machine (SVM) that serve for classification decisions about health index status. The produced results undergo comparison with different predictive models to determine the most effective performance levels regarding accuracy rates and precision as well as recall values. Results demonstrate that KNN emerges as the best model since it delivers an accuracy rate of 94.27% along with precision at 94.12% and recall measurement of 92.44%.*

Keywords: transformer; dissolve gas analysis; key gas method

1. INTRODUCTION

Power transformers constitute an important part of the electrical power grid. It constituting one of the biggest capital investments under electricity transmission and distribution systems [1]. They play a critical role and any unprecedented failure may lead to serious operational interruptions and loss of money. To add to this, the plant operators cannot keep on producing power once an outage occurs [1,2]. To curb such risks, reliability of transformers should be maintained by way of planned maintenance. There should be routine inspection as advised in industry practices [1]. Unless the problem of transformer failure is handled in time, it may result in the creation of numerous dangerous conditions. The resultant failure will be on its way to noise pollution, mass outage of power and even fire risks, which can emit toxic fumes and environmental wastes [2].

With the increase in demand of electricity in the world, power transformers are escalating. This hence meant that it had to run at their highest or close to their rated capacities [3]. Potential failures may be as a result of operational stress. This highlights the importance of having powerful monitoring systems. It is necessary to have predictive maintenance strategies. They guarantee the best performance and assist in avoiding disastrous events.

2. LITERATURE REVIEW

2.1. Transformer Health Index (HI)

The transformer HI is a numerical system. It analyzes the transformer performance and condition [3]. The inspection will include inspections on temperature, oil quality condition, insulation, winding resistance, and any test that may be necessary [4]. Based on such elements, researchers can identify HI status of the transformers. This analysis is also useful in predicting the life of the transformer. The evaluation procedure discloses the future maintenance issues. Such information can help the organizations to make the necessary replacement plans before hand [4-5]. With the transformer HI, users can make accurate decisions on asset management. This is done through incorporation of operational observations with field inspection and lab analysis information [5]. According to the source mentioned, this information is used to keep transformers at optimum operating level.

The factors that influence a significant transformer HI measurement have been the subject of research of many researchers [6-7]. The levels of diagnosis and the sources of data are the essential factors to replicate the elements of uncertainty. The current sources of data are subject to uncertainties in measurement that culminate to different forms of errors. Such are the misreading of measurements and quantization problems. Common data sources are available easily but have various flaws. Diagnostic models are also prone to the modeling uncertainty, whether or not the models have precise information or random uncertainty. The principle works in the presence of any sort of uncertainty circumstances.The transformer HI framework is shown in Fig. 1, as well as the implemented version.

The analysis of different sources of uncertainty in transformer subsystems fortifies the transformer HI. This results in improved performance in decision-making and is applicable in systems that have uncertainties in measurement and process [8]. HI index can be successful when it comes to making decisions that need clarification. DGA is used as a common method of assessing power transformers [8-9]. It is important to check the concentration of gases in transformer insulating oil. The sources of these gases include the internal abnormalities in the transformer. DGA is the most common method of diagnosis of transformers [9]. Key gas technique based on IEC 60599 allows detecting developing faults by measuring predominant gasses at various temperatures. The method can be used to detect the type of defects based on the analysis of percentage ratios of combustible gases.

The KGM works by gauging the amount of gas that is produced by paper insulation breaks. This failure causes overheating on power transformers [9]. Defect gases are produced by heating processes and also by electrical processes. The events are breaking chemical bonds and destroying the paper insulation.The detection system also assesses a single gas over a combination of gases to detect defects. Analysis of dominant gases at varying temperatures is possible with the help of the KGM to identify developing defects as described in IEC 60599 [10]. This technique measures the different kinds of defects using the percentages of the combustible gases in electrical insulation surroundings.The KGM has been found to be a good inspection technique [11].

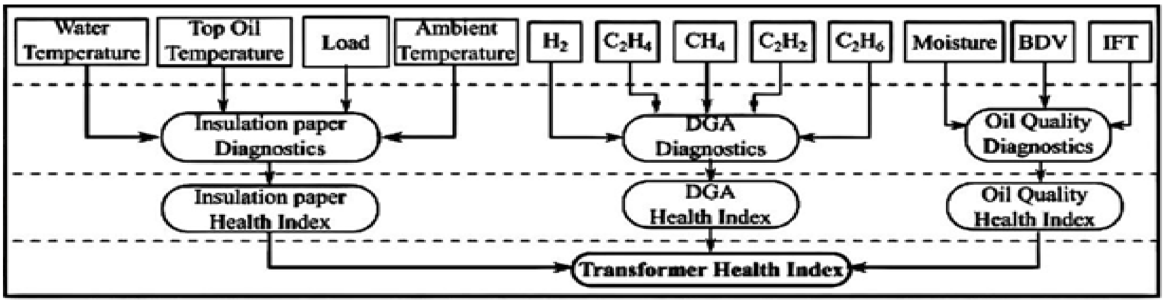

Fig. 1. Transformer HI soft computing framework [10].

2.2. Key Gas Method (KGM)

On the one hand, power transformers play the crucial role in the electrical power system infrastructure. Their failure may create a lot of havoc and may result into a costly repair [8]. In order to maintain proper operation, it is evident that faults should be identified as early as possible using predictive maintenance. One of the methods utilized to achieve this is the KGM where DGA is adopted to determine the overall condition of the transformer. The technique determines gases dissolved in transformer oil, which may signal a possible fault. The important gases of interest in the KGM are hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4) and carbon monoxide (CO). Such gases are generated in a variety of electrical and thermal events in the transformer, including partial discharge, arcing, or overheating. An abnormal gas concentration can be used to detect early signs of trouble in the transformer and mitigation can be effected before the transformer actually failed.

The introduction of KGM to a supervised prediction model involves the training of the latter with the help of the historical records of gas concentrations. The models classify transformers according to the level of healthiness such as healthy transformers, transformers at the risk of failure, and fault transformers, regarding the level of detected gases. The machine learning models such as SVM, KNN, and Random Forest are used to investigate the relationship between the gas concentration and the health of transformers. When trained, these models have the capability to predict future transformer performance and health based on real-time data. This automated predictive technology enables operators to predict the faults and perform the maintenance in time. As an example, the rise of methane emissions can be an indication of early onset of overheating or arcing and thus should be examined further. The KGM helps to decrease the probability of uncontrolled outages, increases the lifespan of the transformers, and reduces the outages.

The performance of the model however depends largely on the quality of data inputted into the supervised prediction model. It is also important to determine the right gases and their levels. Selection of features and model tuning is also necessary to boost the performance of the predictive system. KGM as an element of a supervised prediction model has shown to be beneficial in tracking transformer health. Using machine learning, along with dissolved gas analysis, the utilities will be able to employ better predictive maintenance, thereby making the transformers last longer in the system.

2.3. K-Nearest Neighbours (KNN)

The KNN algorithm is one of the most fundamental and widely adopted techniques in machine learning [11]. It is practically used in numerous fields, such as image recognition, recommendations systems and segmentation of customers. Being a non-parametric, instance based learning algorithm, KNN does not use a predefined model. Rather, it refers to the whole data to make predictions. KNN works by comparing the similarity between the data points which are usually quantified by the Euclidean distance. In the case of a new data point, the algorithm finds the nearest 'K' data points in the training set and then makes a prediction based on it. The K parameter is very important since it defines the number of neighbors that will be involved in decision making. In regression problems, the KNN method calculates the average of the target values of the closest neighbors in order to approximate the outcome. It uses a majority voting scheme in classification problems and classifies the new data point as the most common label amongst its neighbors [12]. Although the Euclidean distance is the most frequently applied metric, other measures of distances, e.g. Manhattan distance or Minkowski distance may also be utilized, depending on the data. These modifications enable the practitioners to customize the algorithm to be more predictive of patterns in particular data sets.

In case of regression tasks, the average value of the target values of the KNNs is used so as to predict the output in the case of KNN. It uses a majority voting scheme in classification problems and classifies the new data point as the most common label amongst its neighbors [12]. Although the most popular distance measure is the Euclidean distance, other distance measures may be used based on the nature of data, e.g. Manhattan and Minkowski distances. These modifications enable the practitioners to customize the algorithm to be more predictive of patterns in particular data sets. The predictive ability of the algorithm is strongly dependent on the value of K, as well as the distance measure used. Too small K can cause over fitting and noise susceptibility, and too large K can cause a smoother, more generalized prediction, which can be inadequate to local behavior. Hence, a close adjustment of these parameters is vital in maximizing the performance of the model. Overall, KNN is an effective and intuitive machine learning algorithm that takes advantage of the closeness of data points to make predictions. It can be successfully applied when the influence of the K value and distance metrics on its performance and results is fully understood [13].

2.4. Discriminant Analysis

The Linear Discriminant Analysis (LDA) statistical method assumes that the covariance matrices of the classes of all groups are the same [14]. The most important evaluation indices of it rely on the average class characteristics and have an assumption of balanced data distribution across classes. LDA establishes linear decision boundaries as a way of effectively classifying more than a single class. The approach takes advantage of data structure to develop a flexible system of information categorization applied in biology, financial, and marketing fields. On the contrary, Quadratic Discriminant Analysis (QDA) is more flexible since any of the classes can have an independent covariance matrix [15]. The basic distinction between these approaches is crucial since QDA is able to identify the intricate correlation among features of different classes. QDA has a better versatility over LDA because it establishes non-linear boundaries of decision when variances between classes are not equal. Nevertheless, this increased flexibility needs more resources to be implemented. Application of QDA technique requires a lot of processing capacity and huge amounts of data to make correct predictions of novel attributes [16].

Classification strategies LDA or QDA are based on data distribution assumptions and the nature of data. The QDA method best fits the dataset in which the difference in class variance is considerable, because it would not be enough to use linear boundaries in such circumstances. Conversely, when data are in line with the equal variance assumption, LDA proves to be computationally fast with better results. LDA and QDA are both supervised classification methods to categorize data points using their own features. KNN is a very common, straightforward classification and regression algorithm. KNN is effective and straightforward, making it a favorite way of solving classification problems that fail to fit the LDA and QDA assumptions.

2.5. Principal Component Ananlysis (PCA)

PCA is one of the most basic approaches to the basis of data science research, machine learning, and statistical operations [17]. With its strong method, PCA converts initial features into principal component features forming a new set of features. The method decreases the dimensions of the data and still retains the important data points, enabling the scientist to view and analyze complex data in a more meaningful way. There are two basic steps that are required to implement PCA and they are mean centering and scaling. These critical processes of the normalization process make the features employ uniform measurements. Mean centering is a transformation of feature values to have zero means, so that scaling operations can normalize all the features to unit variance values. Normalization of the data is inevitable in the proper calculation of the covariance matrix since it is only when the normalization is done that the full picture of interactions of variables will become clear. The covariance matrix can be seen as the pair of relation between features to be both dependent and independent on the level of correlation between variables.

The PCA is computed using eigenvectors as the main components of data relations. Eigenvalues are the ratios of contribution of each component to the total variance [18]. The descending order of arrangement of the eigenvectors and the eigenvalues that they represent can assist the researcher to determine the major components that produce the greatest effects. The selection of principal components lies on the levels of variance that one would like to retain, thus making the analysis customizable. The key elements that are defined using this selection process give a structure to project original datasets into a lower dimensional space. The addition of this enhancement increases the processing abilities without losing critical data points. Use of PCA contributes a lot to the study of complicated systems as it simplifies the data structures and reveals useful patterns which eventually results in improved performance of machine learning.

2.6. Support Vector Machine

SVM are very influential and broadly used supervised learning algorithms which work well in regression and classification [19]. Their mathematical strength and flexibility have contributed to the popularity of SVM in many areas such as bioinformatics, text classification and image recognition. The major objective of SVM is to obtain the most suitable decision boundary also termed as hyperplane that is best in separating data points of differing classes. This division rests on the idea of the maximization of the margin, which means the distance between the hyperplane and the nearest points of each of the classes. Such closest data points are called support vectors. The SVM model heavily relies on support vectors since they directly determine the orientation and location of the hyperplane. Such key data points alone specify the ideal separating boundary, so SVM is a sparse and efficient model, which can generalize well to new data.

The margin maximization property does not only lower the risk of overfitting but also increases the capacity of the model to work with data that is high dimensional, which is a typical feature of real-world machine learning issues [20]. This margin answer makes sure that even in the case where data is not linearly separable in perfect sense, SVM is still effective. In non-linearly separable data, SVM uses the kernel trick, a mathematical trick to map input data to a higher dimensional feature space where the data is linearly separable. Examples of common kernel functions are the polynomial, radial basis function (RBF) and sigmoid kernels. This strategy allows SVM to represent complicated decision boundaries without any direct computation of transformations and, hence, is computationally effective. SVM has been developed by incorporating margin maximization, support vector reliance, and kernel-based flexibility and thus has been shown to be a flexible and excellent performing classifier. It finds especially good application in those areas where generalization and precision are at a premium [21].

3. METHODOLOGY

3.1. Data Collection

The KGM integration provides a logical approach to design and management of complex systems, especially in the area of power transformer condition monitoring. This system is devoted to the analysis of the data received as a result of the usage of DGA as a diagnostic method to discover the developing faults in transformers. DGA functions based on the determination of transformer oil dissolved gas concentration. The system has a structured data organization procedure to guarantee a standard and substantial analysis. This is performed by means of the framework presented in Table 1 that is used to categorize the DGA data and to prepare it to be processed. One of the most important part of this process is the calculation of the Total Dissolved Gas Concentration (TDCG) which is one of the parameters that are taken into account to evaluate the total level of gas and also identify abnormal operating conditions.

The figures in Table 2 are the threshold levels of concentrations of each gas, including hydrogen (H_2), methane (CH_4), ethylene (C_2H_4), and others. These values are required in order to compute the TDCG. Being computed, the TDCG serves as an indicator, converting the raw data on the gas concentrations into normalized parameters. Transformer health and operating condition classification could be determined by these parameters. After the TDCG calculation, the database is then processed and arranged according to these parameters obtained. This sorting makes the information to be organized in such a way that it can be analyzed further, modeled or even used in making decisions. These can be alarm activation, maintenance initiation or feeding the data into the machine learning algorithms to predict transformer's HI.

3.2. Pre Processing Dataset

As indicated in Table 2, the TDCG limit values, are used as the standard when determining the condition of the power transformers depending on the gas concentrations that is identified during the DGA. Such set thresholds enable the system to classify each of the transformers into definite conditions such that an easy interpretation of the health status of the equipment can be obtained by assigning a transformer to a particular condition as indicated in Table 2 when the gas concentrations of the transformer fall within the most desirable ranges. This type of classification means that the transformer is functioning within all the operational parameters as required and has no sign of abnormal gas formation, which means that it is performing ideally. The transformer in this state is good and in a good condition with no need of immediate maintenance or action.

Table 1. Gasses invalved in KGM

Type of gas	Formula
Hydrogen	H_2
Methane	CH_4
Acetylene	C_2H_2
Ethylene	C_2H_4
Ethane	C_2H_6
Carbon Monoxide	CO
Carbon Dioxide	CO_2

Transformers categorized under "Condition 2" can also be functional and they can be considered to continue service. Nevertheless, they also show premature evidence of deterioration or small abnormalities, like somewhat increased gas levels. Although these signs do not have a considerable impact on the performance of the transformer yet, they can be considered as a reason to monitor it more closely. This situation might be an indication of the early development of certain problems like thermal stress or partial discharge that might increase over time in case it is not prevented. Transformers with additional degradation belong to the category of Condition 3. In such a condition, there are maintenance issues whose level of severity takes a period of six months to correct.Transformers under the critical Condition 4 require immediate attention because of large-scale issues that must be corrected immediately. These issues of major concern must be promptly addressed as soon as possible and preferably within three months, to maintain safe and effective operation of transformers.

Table 2. Limit assigned as input

TDCG limit (ppm)	Condition
720	1
721-1920	2
1921-4630	3
>4630	4

4. RESULT & DISCUSSION

The study is aimed at laying down an effective execution methodology in order to facilitate the implementation of DGA that will be experienced in the nearest future. In the course of pursuing this objective, the study employs the parameter morphology to assess the effectiveness of different training algorithms [22-23]. Several measures of performance will be used to evaluate the network in the research, and they will focus on precision, accuracy, and recall measurements. The analysis examines various diagnostic strategies and implementation methods of DGA. Table 3 shows the statistics of recall, accuracy, and precision of KNN, SVM, PCA, LDA, and QDA models [24-25]. The proposed study is intended to choose the most efficient prediction model that can be able to classify cardiac anomalies based on the analysis of KNN, SVM, PCA, LDA, and QDA methods.

Table 3 illustrates the performance of various models so that they can be evaluated. Evaluation of the accuracy, precision and recall values determines how effective each model is in diagnosing the cardiac anomalies.

Table 3. Performance of prediction model

Training algorithm	Accuracy performance (%)		
	Overall	Training	Testing
SVM	94.12	94.64	93.68
KNN	93.28	94.12	92.44
PCA	91.32	91.89	90.75
LDA	90.24	90.42	90.06
QDA	87.42	88.12	86.72

In Table 3 of this study, the SVM model was better than other models as they had a rate of overall accuracy of 94.12%. This outstanding predictive performance demonstrates the effectiveness of SVM model in effective predictions. The accuracy results were high with the training rate being 94.64% and testing rate being 93.68 percent. These measures show that the model performs well in terms of making right predictions and recognizing the significant cases. KNN model ranked second in the list of classifiers, with the overall accuracy rate of 93.28%. It was performing well but could not be compared to that of SVM model. The classifier gave training and testing results of 94.12% and 92.44% respectively. These strong findings notwithstanding, the decision tree classifier unable to outperform the SVM model performance levels. The PCA model was the third-best performing model, achieving the training of 91.89% and testing rates of 90.75% as well as the overall of 91.32%. Although PCA is effective, it does not have the best performance outcomes as compared to the best models. Transformer HI classification of overall accuracy of LDA model is 90.24%, training is 90.42% and testing is 90.06%. LDA model yielded much better results than QDA but lower than the rest of the other prediction models. The QDA model had an overall accuracy of 87.42% although it is not as accurate as compared to other models. The QDA model was evaluated with a training of 88.12% and the testing of 86.72%. On the whole, the study findings point out that the predictive models have shown an impressive performance, but they have not yielded results that are better than those of predictive methods developed in the domain in the past.

5. CONCLUSION

To sum up, the assessment of classification models to predict health indices of transformers shows the necessity of machine learning in monitoring. The predictive performance of all models was high, but effectiveness was different. KNN model was most accurate, precise, and recalling, thus it would be useful in diagnostics. Conversely, QDA model fared the worst demonstrating a shortcoming in processing intricate patterns in real-world data.This disparity underlines the importance of selecting models that are applicable to the nature of datasets. On the whole, the results verify the idea that data-driven methods are effective to assist preventive maintenance in the electrical asset management. In the effort to boost the accuracy of prediction, the research recommends the consideration of the state-of-the-art models such as Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks [26]. These are able to learn complex patterns and have the advantage of bigger and high-quality training sets. Increasing the size of training data and the model architecture may result in improved classification of transformer health index to enhance power system reliability and efficiency.

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