Data Mining Techniques for Transformer Failure Prediction Model: A Systematic Literature Review

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Abstract— **Transformer failure may occur in terms of tripping, resulting in an unplanned or unseen failure. Therefore, a good maintenance strategy is an essential component of a power system to prevent unanticipated failures. Routine preventive maintenance programs have traditionally been used in combination with regular tests. However, in recent years, predictive maintenance has become prevalent due to the demanding industrial needs. Due to the increased requirement, utilities are persistently looking for ways to overcome the challenge of power transformer failures. One of the most popular ways for fault prediction is data mining. Data mining techniques can be applied in transformer failure prediction to provide the possibility of failure occurrence. Thus, this study aims to identify the common data mining techniques and algorithms that are implemented in studies related to various transformer failure types. The accuracy of each algorithm is also studied in this paper. A systematic literature review is carried out by identifying 160 articles from four main databases of which 6 articles are chosen in the end. This review found that the most common prediction technique used is classification. Among the classification algorithms, ANN is the prominent algorithm adopted by most of the researchers which has provided the highest accuracy compared to other algorithms. Further research can be done to investigate more on the transformer failures types and fair comparison between multiple algorithms in order to get more precise performance measurement.**

Keywords—transformer failure prediction, data mining, systematic literature review, data mining algorithms, classification.

I. INTRODUCTION

Power transformers are robust and efficient electrical equipment that play a vital role in providing consumers with electricity at sufficient voltage levels. However, over the years, power transformers have undergone changes in their reliability and operational lifetime. This is mainly due to the heavy loading of the equipment, which is driven by the need for higher profits and the hesitancy of power companies to invest in new facilities in a competitive market environment [1]. As a consequence, disruptions in the power system is becoming a major concern to industrial and commercial customers. Utilities are persistently looking for ways to overcome these industrial challenges and to remain relevant in the changing marketplace by adopting different maintenance approaches. Initially traditional maintenance methods were used in combination with regular tests [4,5].

However, in recent years, predictive maintenance (PdM) has become broadly used because it enables improved productivity and save operating costs in diverse industries, such as manufacturing, infrastructure, healthcare and energy. PdM involves using data analysis to predict fault and thus maintain electronic equipment, production machinery and infrastructure systems more effectively and efficiently than conventional approaches, such as corrective maintenance (CM) and preventive maintenance (PM) [2,3]. Failure or fault prediction is where the relevant information on potential defects are analyzed in order to predict the defect dynamically and promptly and to notify the defect prevention mechanism. When an anomalous change in a system resource is detected, the fault prediction mechanism is activated to predict the potential fault. It is not intended to adjust the system, but informs the fault prevention mechanism of the forecast fault in a timely manner. For an instance, the monitoring function noticed that a node is running out of battery. The prediction mechanism is therefore activated to estimate the remaining life of the node's battery.

One of the approaches in developing fault prediction model is through data mining. Data mining is a non - trivial process for extracting hidden, unknown and potentially useful information from large databases [6] where the process involves two fields which are computer science and statistics [7]. Data mining comprises of several techniques that can be applied on varying datasets. According to [8], most commonly used techniques in developing predictive models are classification and regression. Classification is used to classify each item into one of the predefined classes or groups in a set of data [9]. For an example, in power transformer system, a new target class can be set and named as "fault prone" or "non-fault prone", where the classifier assigns the transformers to a target class based on the identified pattern from the given variables. Regression, on the other hand, is very useful to identify the correlation between different variables. For an instance, in a substation transformer system, trip data and defect data are two variables and regression is mainly used to check the relationship between these variables. In simple terms, regression is used when the variables are continuous like numbers whereas classification is used for the categorical variables [10]. Data driven approach is widely used in power systems to detect, classify and diagnose defects using neural networks, decision trees and support vector machines [16,18].

In this study, a systematic review of existing literatures is performed to identify the common data mining techniques used in power transformer failure prediction. Various data mining algorithms, failure types and the predictive models' accuracy are presented in this review. The accuracy of prediction model plays a vital role in order to adopt reasonable measures to anticipate and avoid possible internal failures in power transformers. Rest of the paper is organized as follows: Section II discusses on the related works pertaining to the data mining theories and techniques adopted by other researchers. Section III reviews on the methodology used in this study whereas the results and discussion are presented in Section IV and the conclusion is done in Section V.

II. RELATED WORKS

A. Artificial Neural Networks (ANN)

The concept of ANN is basically introduced from the subject of biology where neural network plays an important role in human brain [23]. Neural Network is just a web of inter connected neurons. In the neural network, the most basic information processing unit is the neuron. They are organized in three or more layers, such as the input layer, one or several hidden layers and single output layer [37]. ANN method can be used to recognize the hidden relationships between the dissolved gases and the fault types through training process.

ANN was introduced by [26] in the power systems fault detection in 1996. Reference [22] used ANN to predict the lightning surge and it was found that ANN can be used directly to assess a certain network's risk of failure or indirectly to determine which type of lightning arrester, maximum cable length, or cable insulation level should be used to meet a certain risk of failure. In studies conducted by [11, 15, 16, 23], ANN was vastly used to classify the transformer fault condition based on historical data for dissolved gas analysis. Based on the study conducted by [23], ANN's successful development was able to predict the incipient fault in the power transformer using dissolved gas concentration.

B. Support Vector Machine (SVM)

SVM is defined as a statistical learning concept with an adaptive computational learning method. This learning technique uses input vectors to map nonlinearly into a feature space whose dimension is high [38]. Reference [24] used SVM for estimation of fault type and distance in a long transmission line of the power systems. While SVM gives good accuracy, the time consumed for the training, however makes the task complex and lethargic. Reference [39] mentioned that selection of proper SVM parameters is very important for good generalization performance and high accuracy in fault location and classification of transmission line.

According to [25], SVMs were initially developed to solve the classification problems, however recently they have been extended to the domain of regression problems. This is because SVM is deep rooted in statistical learning which describes the machine learning properties that allow them to generalize the unseen data well whereas SVR's (Support Vector Regression) goal is to find a function that predicts training data's target value with a deviation of at most ε while requiring this function to be as flat as possible.

C. Decision Tree (DT)

The Decision Tree is a tree structure, which is mainly composed of nodes and branches, and the nodes contain leaf nodes and intermediate nodes. The intermediate nodes are used to represent a feature, and leaf nodes are used to represent a class label. The Decision Tree can be used for feature selection [40]. The attributes that appear in the Decision Tree nodes provide important information to promote classification.

Decision tree (DT) based artificial intelligence techniques were already used in transformer fault prediction [29–31]. These studies demonstrate the effectiveness of the DT based algorithms. Moreover, DT based techniques were also used for condition monitoring, assessment, fault diagnosis and repair actions [32, 33]. These studies prove the efficiency of the DT technique in similar areas. Reference [27] applied DT for feature selection and then carried on the bearing fault diagnosis with the kernel neighborhood fractional multiple support vector machine (MSVM). In a study pertaining to fault detection in three phase transformer, [28] explored decision tree using differential protection scheme. Based on the test results, it was found that the decision tree method is the best in classifying fault prediction with higher sensitivity and accuracy as compared with linear model.

D. Naïve Bayes (NB)

Bayesian classifier is a statistical classifier and supervised learning technique. It predicts class membership probabilities. Reference [41] mentioned that NB classifiers show high accuracy and speed when applied to large databases. According to references [42, 43], NB uses not only a small amount of training data, but also works at simple structure, fast calculation speed and high accuracy.

Reference [36] used NB classifier for the transformer fault analysis. The different testing scenarios showed that the NB diagnosis model constructed has a good performance given complete testing data. In a study carried out by [34], few algorithms were used namely Naïve Bayes, Random Forest, J48, Bagging, IBk (KNN in WEKA tool) and Logistic Regression. It was found that the Random Forest algorithm performs better than Naïve Bayes and Naïve Bayes has an advantage over IBk. In another study, [35] employed KNN and Naïve Bayes classifiers for the diagnosis of insulating oil used in power transformers. Based on the evaluation using Duval triangle reports, it was found that the KNN algorithm provides the highest accuracy rate than the Naïve Bayes algorithm.

III. METHODS

This systematic literature review includes 160 papers published between year 2008-2018. Title search is performed based on the keywords: (Transformer AND Failure AND Prediction AND Model). Four main databases are identified for article searching namely IEEExplore, Science Direct, Google Scholar and ACM. Total of 160 articles are identified and these articles are screened through for any duplicates. Total of 41 duplicate records are removed. From the remaining 119 articles, another 96 articles are removed based on the inclusion and exclusion criteria, leaving only 23 eligible full text articles. Further eligibility screening process is done to remove the articles that do not contain sufficient information. Finally, total of 6 eligible articles are selected for this review. These articles are summarized in Table I.

TABLE I. SUMMARY OF ARTICLES

Source	Year	Article type	Citation[a]
[11]	2012	Conference	42
[12]	2013	Journal	14
[13]	2015	Journal	9
[14]	2017	Journal	1
[15]	2012	Conference	36
[16]	2009	Conference	24

a. Taken from Google Scholar as of 14th February 2019

The main inclusion criteria for this study are as follow:

a. studies that adopted data mining technique for developing transformer failure prediction model
b. studies that focused the overall accuracy of the adopted algorithms.

Apart from these criteria, any study would be excluded if the subject matter is not related to transformer failure prediction. For example, smart meter failure prediction, electricity consumption prediction, or any study that gives general reviews are all excluded from the literature review. In addition, any study which compares the algorithms but does not analyze their accuracy are also excluded. This paper follows the guidelines provided by [17] for performing the systematic literature review. Following these guidelines, the systematic literature review is done in four stages as shown in Figure 1.

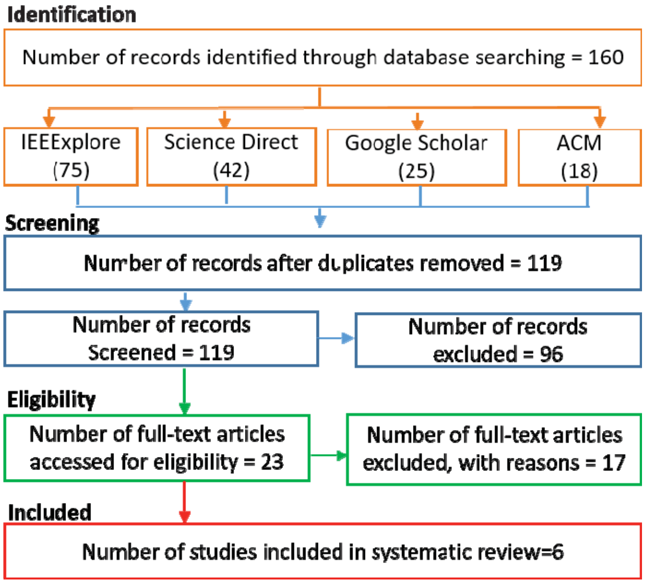

Fig. 1. Systematic literature review flowchart

IV. RESULTS AND DISCUSSION

Based on the systematic literature review performed, it is discovered that the popular data mining technique used for transformer failure prediction is classification. Based on table II , dissolved gas analysis is the most studied failures of transformers by researchers. For more than 30 years, the dissolved gas analysis (DGA) has been used to assess the condition of operating electrical transformers [11,16]. Other types of failure studied include leakages, oil insulation and other anomalies. Based on the review performed, it is found that several algorithms are explored in each study and the models' accuracy is studied. The most frequently used algorithms for predicting failures are artificial neural network (ANN), decision tree (DT), support vector machine (SVM) and Naïve Bayes (NB) where ANN produced the most accurate outputs for most of the studies. In the study conducted by [11], it is found that the majority of the techniques used in transformer failure prediction is neural-network (NN) classifier. This is also confirmed by [19-21].

Nonlinear decision functions, such as NN, SVM with Gaussian kernels, or local linear regression is able to theoretically provide slightly better performance than linear classifiers or regressors [11]. Using real test cases, [12] demonstrated that the trained ANN is able to detect irregularities that could potentially lead to positive results with an accuracy of 97.4 %. While ANN produced more accurate results in [11,12,15,16], however, [11] argues that it is hard to choose between high performing algorithms like SVM and ANN as their performance is comparable, and after conducting few repeated experiments, ANN is found to be the best classifier. The second most popular algorithm adopted by researchers is DT with 85% of accuracy [13]. Interestingly, in the case of power transformers with fluctuations or relatively stable operating conditions, DT achieved better performance [13]. Reference [14] stated that it is however, unclear to identify the best criteria where decision trees or random forests are concerned but then limiting the number of leaves is found to have a positive effect on performance. The study conducted by [14] proved that predictive model with the best performance is SVM which achieved 77% of accuracy compared to DT. While ANN is the prominent algorithm used in many studies, all of these techniques have their own characteristics and researchers are persistently looking ways to achieve highest accuracy to predict the possible failures. New algorithms must therefore be developed using advanced optimization techniques.

TABLE II. DATA MINING (DM) TECHNIQUES AND ALGORITHMS

Source	Transformer failure types	DM Technique	DM Algorithms	Accuracy (%)
[11]	Irregular dissolved gas concentration	Classification	ANN	82
			SVM	80
[12]	Leakage and other anomalies	Classification	ANN	97.4
			NB	95.9
			DT	95.9
[13]	Irregular dissolved gas concentration	Classification	DT	85
			SVM	82
[14]	Irregular dissolved gas concentration, transformer oil insulation	Classification	SVM	77
			DT	70
[15]	Irregular dissolved gas concentration	Classification	ANN	93.5
[16]	Summary on transformer faults (irregular dissolved gas, leakage and loading)	Classification	ANN	96.8

V. CONCLUSION

This paper focused on reviewing data mining techniques and algorithms for developing the transformer failure prediction model. The model's performance is evaluated based on its accuracy. It is found that for dissolved gas failure type, the most prominent technique used is ANN. Whereas for other failure types, there is a requirement for further experiment using different types of input and algorithms in order to have a more reliable prediction. Further research also needs to be carried on to discover more transformer failure types and the best algorithms to predict those failures.

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REFERENCES

[1] Haroldo F. Jr, Joao G. C, Jose L. M, "A review of monitoring methods for predictive maintenance of electric power transformers based on dissolved gas analysis", Renewable and Sustainable Energy Reviews Volume 46, June 2015, Pages 201-209.

[2] B. Lu, D. B. Durocher, P. Stemper, "Predictive maintenance techniques", *IEEE Industry Applications Magazine*, vol. 15.6, pp. 52-60, 2009.

[3] P. Zhao ; M. Kurihara ; J. Tanaka ; T. Noda ; S. Chikuma ; T. Suzuki, "Advanced correlation-based anomaly detection method for predictive maintenance", 2017.

[4] G. Gavrilovs, S. Vitolina, "Identification of power transformer failure and risk source," Proceedings of the 52nd Annual International Scientific Conference of Riga Technical University, 2011.

[5] Mike Gehloff, "Does moving from reactive to proactive maintenance require a change management process," Maintenance Phoenix, January 5, 2014.

[6] Shivam Agarwal, "Data mining concepts and techniques", International Conference on Machine Intelligence Research and Advancement, 2013.

[7] J. Srivastava, A.K Srivastava, "Understanding the linkage between data mining and statistics", International Journal of Engineering Technology, Management and Applied Sciences, 2015.

[8] Yue Jiang, Bojan Cukic, Yan Ma, "Techniques for evaluating fault prediction models", Empir Software Eng (2008) 13:561–595

[9] G. Kesavaraj ; S. Sukumaran, "A study on classification techniques in data mining", Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT), 2013.

[10] Sagar.P, "Analysis of prediction techniques based on classification and regression", Int. J. Comput. Appl. 163(7), 975-8887, 2017.

[11] Piotr Mirowski, Yann LeCun, "Statistical machine learning and dissolved gas analysis: a review", IEEE Transactions On Power Delivery, VOL. 27, NO. 4, OCTOBER 2012

[12] Lin Zhao, SH Goh, et al., "Prediction of electrical and physical failure analysis success using artificial neural networks", 2013

[13] Ke Deng, Weihong Xiong, Liming Zhu, Hongzhi Zhang, "Prediction of dissolved gas in power transformer oil based on random forests algorithm", Electric Utility Deregulation and Restructuring and Power Technologies, November 26-29, 2015.

[14] Eduardo e Oliveira1, Vera L. Migueis, Luis Guimaraes, José Borges, "Power Transformer Failure Prediction: Classification in Imbalanced Time Series", U. Porto Journal of Engineering, 3:2 (2017) 34-48

[15] Huo-Ching Suna, Yann-Chang Huang, Chao-Ming Huang, "Fault Diagnosis of Power Transformers Using Computational Intelligence: A Review", 2nd International Conference on Advances in Energy Engineering (ICAEE), 2012

[16] Morais J, Pires Y, Cardoso C, Klautau A, "An overview of data mining techniques applied to power systems", 2018.

[17] Alessandro Liberati, Douglas G Altman, et al., "The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate healthcare interventions: explanation and elaboration", BMJ 2009;339:b2700

[18] Al Karim M, Chenine M, Zhu K, Nordstrom L, Nordstrom L, "Synchro phasor-based data mining for power system fault analysis", 2012 3rd IEEE PES innovative smart grid technologies Europe (ISGT Europe). IEEE; 2012. p. 1–8.

[19] V. Miranda and A. R. G. Castro, "Improving the IEC table for transformer failure diagnosis with knowledge extraction from neural networks," IEEE Trans. Power Del., vol. 20, no. 4, pp. 2509–2516, 2008.

[20] R. Naresh, V. Sharma, and M. Vashisth, "An integrated neural fuzzy approach for fault diagnosis of transformers," IEEE Trans. Power Del., vol. 23, no. 4, pp. 2017–2024, Oct. 2008.

[21] W. Chen, C. Pan, Y. Yun, and Y. Liu, "Wavelet networks in power transformers diagnosis using dissolved gas analysis," IEEE Trans. Power Del., vol. 24, no. 1, pp. 187–194, Jan. 2009.

[22] Ángel L. Orille-Fernández, Nabil Khalil, Santiago Bogarra Rodríguez, "Failure risk prediction using Artificial Neural Networks for lightning surge protection of underground MV cables", IEEE Transactions on Power Delivery, Vol. 21, No. 3, JULY 2008.

[23] Dipali D. Dhonge , P. S. Swami , Dr. A. G. Thosar, "Developing Artificial Neural Network (ANN) model for fault diagnosis of power transformer using Dissolved Gas Analysis (DGA)", International Journal of Scientific & Engineering Research, Vol 6, Issue 7, July 2015.

[24] Papia Ray, Debani Prasad Mishra, "Support Vector Machine based fault classification and location of a long transmission line", Engineering Science and Technology, an International Journal 19, 2016.

[25] M.F.Faisal, A.Mohamed, "Support Vector Regression based s-transform for prediction of distribution network failure", 2009.

[26] Aravena JL, Chowdhury FN. "A new approach to fast fault detection in power systems", Int Conf Intell Syst Appl Power Syst, Florida, USA; 1996. p. 328–32.

[27] Sugumaran. V, Sabareesh. G.R, Ramachandran. K.I, "Fault diagnostics of roller bearing using kernel based neighborhood score multi-class support vector machine", Expert Syst. Appl. 2008, 34, 3090–3098.

[28] Ravi Shankar Chauhan, Dr.Amrita Sinha, "Fault detection in three phase transformer using Decision Tree", Int. Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 2015.

[29] Georgilakis, P.S., Paparigas, D, "AI helps reduce transformer iron losses", IEEE Comput. Appl. Power, 1999a, 12, (4), pp. 41–46

[30] Georgilakis, P.S., Doulamis, N.D., Doulamis, A.D., Hatziargyriou, N. D., Kollias, S.D, "A novel iron loss reduction technique for distribution transformers based on a combined genetic algorithm neural network approach", IEEE Trans. Syst. Man Cybern., Part C: Appl. Rev., 2001, 31, (1), pp. 16–34

[31] Georgilakis, P.S, "Spotlight on modern transformer design", (Springer, London, UK, 2009)

[32] Georgilakis, P.S, "Book review: condition monitoring and assessment of power transformers using computational intelligence", Int. J. Electr. Power Energy Syst., 2011, 33, (10), pp. 1784–1785

[33] Georgilakis, P.S., Katsigiannis, J.A., Valavanis, K.P., Souflaris, A.T, "A systematic stochastic petri net based methodology for transformer fault diagnosis and repair actions", J. Intell. Robot. Syst., 2008, 45, (2), pp. 181–201

[34] Yue Jiang, Bojan Cukic, Yan Ma, "Techniques for evaluating fault prediction models", Empir Software Eng (2008) 13:561–595.

[35] Y. Benmahamed, Y. Kemari, M. Teguar, A. Boubakeur, "Diagnosis of power transformer oil using KNN and Naïve Bayes classifiers", IEEE 2nd International Conference on Dielectrics (ICD), 2018.

[36] Zhu Yong Li, Wang fang, Geng Lan Qin, "Transformer fault diagnosis based on Naive Bayesian classifier and SVR", TENCON 2008.

[37] Balint Nemeth, Csaba Voros, Richard Cselko, Gabor Gocsei, "New Method for Improving the Reliability Of Dissolved Gas Analysis", International Journal of Scientific & Engineering Research, Volume 6, Issue 7, July-2015

[38] U.B. Parikh, B. Das, R. Maheshwari, "Fault classification technique for series compensated transmission line using support vector machine", Int. J. Electr. Power Energy Syst. 32 (6) (2010) 629–636.

[39] K. Schittkowski, "Optimal parameter selection in support vector machines", J. Ind. Manage. Optim. 1 (4) (2008) 465–476.

[40] Sugumaran, V.; Muralidharan, V.; Ramachandran, K.I, "Feature selection using decision tree and classification through Proximal Support Vector Machine for fault diagnostics of roller bearing", Mech. Syst. Signal Process. 2008, 21, 930–942.

[41] Chintan Shah, Anjali G. Jivani, "Comparison of data mining classification algorithms for breast cancer prediction", 4th ICCCNT 2013.

[42] Sharma, R.K.; Sugumaran, V.; Kumar, H.; Amarnath, M. "A comparative study of NB classifier and Bayes net classifier for fault diagnosis of roller bearing using sound signal", Decis. Support Syst. 2015, 1, 115.

[43] Mccallum, A.; Nigam, K. "A Comparison of Event Models for NB Text Classification", In Proceedings of the AAAI-98Workshop on Learning for Text Categorization, Madison, WI, USA, 26–27 July 1998; Volume 62, pp. 41–48.