



## Expert system for predictive maintenance transformer using J48 algorithm

Erna Alimudin\*<sup>1</sup>, Arif Sumardiono<sup>1</sup>, Nur Budi Nugraha<sup>2</sup>

Politeknik Negeri Cilacap, Indonesia<sup>1</sup>

Politeknik Negeri Indramayu, Indonesia<sup>2</sup>

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\*Corresponding author.

Erna Alimudin

E-mail address:

ernaalimudin@pnc.ac.id

### Abstract

Predictive maintenance can reduce the risk of sudden transformer failure which causes the risk of plant to stop operating. One of transformer predictive maintenance technique is the Dissolved Gas Analysis (DGA) Test Oil Transformer. The gas is interpreted and analyzed to find out and get conclusions about the health condition and also possible problems in the transformer based on IEEE Standards and IEC Standards. To facilitate monitoring, a Decision Support System for Interpretation of Test Results of DGA Oil Immersed Transformer was created to form a database containing transformer data with the amount of main gas from the DGA test results. Next, decision tree was made using the J48 algorithm. The decision tree simplifying and speed up the decision-making process for recommended actions that are displayed on the system. The system also displays a trending graph of the last transformer test and quickly displays a dashboard of transformer status, i.e. normal, alarm, or danger. Engineer will get notification email if any transformer is in danger status. In addition, the system is able to provide information on possible fault types for each transformer. The benefits of this system are that the health condition of the transformer can be monitored properly and corrective action can be taken immediately on a problem based on the results of the decision support system. This will reduce the risk of shutdown and support the reliability of plant operations.

## 1. Introduction

Currently in Indonesia there are 33,923 large and medium industrial companies that are still active. This directory is grouped into twenty-four main groups according to the 2015 Indonesian Standard Classification of Business Fields (KBLI). There are 192 industrial products made from coal and petroleum refining products. For operational needs, the refinery has an independent power generation system as well as electricity distribution lines. It aims to increase the reliability and availability of electricity to meet operational needs 24 hours per day. This operational need is certainly one of the keys to the availability of supply of fuel oil (BBM). [1], [2]

One of the critical electrical distribution equipment is the transformer. [3] A transformer is an electrical device that has two windings on an iron core. [4] Transformers change the voltage and current levels and make the transmission of electric power easier. [5] The primary winding of the transformer receives and transmits electrical power, and the secondary winding of the transformer receives electrical power. The primary and secondary voltages of the transformer are related in proportion to the turns ratio. While the primary and secondary winding currents are inversely related to the turns ratio. [6] When a transformer operates, it will generate heat in the iron core and ng as an effect of the flow of electric current. In normal operation, the heat generated can be cooled by transformer oil. [7] However, if there is a disturbance in the transformer, the heat generated will be excessive and this heat will make the transformer oil react to produce some combustible gas (combustible gas) and the failure of the oil insulation system.[8], [9] This dissolved gas concentration will be analyzed and become one of the parameters in the predictive maintenance of the transformer, namely the Dissolved Gas Analysis (DGA) Test. [10]

DGA Test is a test of transformer oil by extracting and calculating the gas content dissolved in transformer oil (oil). [11] The process of extracting gas from transformer oil is regulated by an international standard, namely ASTM D3612-02: Standard Test Method for Analysis of Gases Dissolved in Electrical Insulating Oil by Gas Chromatography. There are 9 main gases that can be analyzed using these standards, namely hydrogen (H<sub>2</sub>), oxygen (O<sub>2</sub>), nitrogen (N<sub>2</sub>), carbon monoxide (CO), carbon dioxide (CO<sub>2</sub>), methane (CH<sub>4</sub>), ethane (C<sub>2</sub>H<sub>6</sub>), ethylene (C<sub>2</sub>H<sub>4</sub>), and acetylene (C<sub>2</sub>H<sub>2</sub>). The result of the DGA Test is the total content of the 9 gases in ppm (parts per million). [5] The results of the DGA Test still need to be interpreted to get conclusions about the health condition and also possible problems with the transformer. The analysis technique of the DGA Test results uses the 2 most commonly used standards in the industry, namely IEEE C57.104TM - 2008 : IEEE Guide for the Interpretation of Gases Generated in Oil-Immersed Transformer

and IEC 60599 : Mineral Oil-impregnated Electrical Equipment in Service - Guide to the Interpretation of Dissolved and Free Gas Analysis. [12], [13]

Based on IEEE C57.104TM–2008, the transformer health condition can be analyzed using two evaluation techniques, namely (1) concentration of individual gases and total dissolved combustible gases (TDCG); (2) determine transformer operating procedures and sample intervals based on the growth of TDCG content in transformer oil. By using these two methods, it takes at least 2 samples of transformer oil and two results of analysis to determine the growth of gas in the oil, then analyze and make decisions regarding the operational procedures of the transformer, whether it can still operate or requires maintenance. After that, an analysis is carried out to determine the disturbances that may occur in the transformer based on the concentration of each gas. There are 4 evaluation techniques used, namely (1) Evaluation based on the key gas method, which divides the disturbance into 4, namely C<sub>2</sub>H<sub>4</sub> for the Thermal-Oil problem, CO for the thermal-cellulose problem, H<sub>2</sub> for the corona problem, and C<sub>2</sub>H<sub>2</sub> for the arcing problem; (2) Evaluation based on Roger Ratio Method; (3) Evaluation based on the Doernenburg ratio method; (4) Evaluation based on CO<sub>2</sub>/CO content to determine the condition of cellulose / solid insulation.[12]

Based on the IEC 60599 standard, it is explained that disturbances in the transformer can cause damage or changes in the structure of the transformer oil and also transformer insulation which is called cellulose insulation. [13] There are 4 types of disturbances reviewed in this standard, namely partial discharge (PD), discharge of low energy (D1), discharge of high energy (D2), and thermal fault. Then after that it is explained in more detail about the evaluation technique to determine the problem in the transformer. The evaluation technique used is the basic gas ratio, CO<sub>2</sub>/CO ratio, O<sub>2</sub>/N<sub>2</sub> ratio, C<sub>2</sub>H<sub>2</sub>/H<sub>2</sub> ratio, and Duval's triangle. [14]

In these two standards, the key to the accuracy of the analysis of DGA Test results is routine and continuous testing so as to produce a database of DGA Test results for each operating transformer unit. [15] With this database, the health condition of the transformer can be monitored properly and if there are signs of a problem, corrective action can be taken immediately. The transformer functions to transfer electrical power and change the voltage according to the needs of the electrical load. [16] Transformer maintenance is one of the important tasks of refinery workers to ensure operational reliability. Transformer maintenance is divided into 3 types, namely preventive, maintenance, corrective maintenance, and predictive maintenance. Predictive maintenance plays the most important role because with the right predictive maintenance, optimization can be achieved between maintenance costs and the life or operation of the transformer, as well as reducing the risk of sudden transformer damage that can cause operational and financial losses. Of course, the main target of predictive maintenance is to reduce corrective maintenance and transformer damage suddenly or unplanned shutdown. The most common predictive maintenance transformer technique and can be an indicator of the health of a transformer is the Dissolved Gas Analysis (DGA) Test. [17],[18] DGA Test is done by extracting and calculating the dissolved gas content in transformer oil. [19] Based on IEC Standard 60599 and IEEE Standard C57.104TM – 2008. [20] The results of the DGA Test are the total content of 7 types of gases, namely carbon monoxide (CO), carbon dioxide (CO<sub>2</sub>), hydrogen (H<sub>2</sub>), methane (CH<sub>4</sub>), acetylene (C<sub>2</sub>H<sub>2</sub>), ethylene (C<sub>2</sub>H<sub>4</sub>), and ethane (C<sub>2</sub>H<sub>6</sub>) which need to be interpreted and analyzed to find out and get conclusions about the health condition and possible problems with the transformer. Based on these two standards, the key to the accuracy of the analysis of DGA Test results is routine and continuous testing so as to produce a database of DGA Test results for each operating transformer unit [12], [13] With this database, the health condition of the transformer can be monitored properly and if there are signs of a problem, corrective action can be taken immediately.

Currently, the DGA Test database does not yet exist. This makes it difficult to monitor the health condition of a transformer and it is difficult to determine corrective actions. The impact is the risk of sudden transformer damage which can result in an unplanned shutdown. The unplanned shutdown has fatal consequences for refinery operations. An unplanned shutdown could result in a refinery shutting down and causing huge financial losses. [21] Therefore, it is necessary to conduct research to build a DGA Test Oil Immersed Transformer Result Interpretation system.

Previous research, had compared traditional methods with computer learning methods when used to analyze the results of the DGA Test. There were several cases of errors when the diagnosis was made by traditional methods due to limitations in the ability to diagnose with traditional methods. To overcome the shortcomings of traditional methods in diagnosing errors, it was tried to use intelligent methods. Intelligent methods were able to overcome the limitations of diagnostic capabilities in traditional methods. The values of precision, recall, and F1 scores obtained from the SVM (Support Vector Machine), KNN (K-Nearest Neighbour), and Decision Tree methods were tried to get a score close to one. [22]

Some of machine learning algorithms or artificial intelligent methods had been used to classifying transformer condition by DGA Test result. even several methods have been compared to find out which method gives the highest accuracy. [11] J48 algorithms had the highest accuracy in classifying 347 labeled data, i.e. 54 normal cases and 293 defective cases were considered. [23]

Another previous research used Analytical Incremental Learning to build an analysis model based on 167 data from the IEC TC10 dataset. The data will be classified into 5 fault conditions and 1 Normal condition. The trials have been conducted to 5 different DGA models and the result has been recorded. SVM has the lowest testing accuracy at 65.00% followed by J48 at 72.73% and Naive Bayes at 75.76%. The shortcoming in this study was that it only used public data, but did not test with actual field data. In addition, this research has not focused on building a database system, trending, and reporting on the evaluation of the DGA test results. J48 algorithms had the highest accuracy in classifying 347 labeled data, i.e. 54 normal cases and 293 defective cases were considered. [24] Based on previous research, it is known that the shortcomings of traditional methods can be overcome by using machine learning algorithms. Some of the algorithms that can be used in classifying transformer conditions based on the results of the DGA Test is SVM, J48, and Naive Bayes. In this study, these methods will be tried to determine the highest accuracy when used to analyze DGA Test data.

In previous studies, classification testing used secondary data. Meanwhile, in this study, primary data will be used. The primary data here is the data from the DGA Test Transformer which has been labeled by the engineer based on the IEEE standard and IEC standard. This data will then be used to form a decision tree that is applied to the expert system created. So, when new data is entered, the expert system will assist the engineer in making a decision whether the transformer needs maintenance or not.

Some of previous studies had used Internet of Things (IoT) for getting data of DGA Test, but the data DGA Test only processed by using data processing software tools. That means, only programmers can work on the program and know the results. Meanwhile, the direct users who need results quickly to analyze the condition of the transformer will find it difficult. Therefore, in this research the processing DGA Test for predictive maintenance transformer expressed in the form of a system by using Graphical User Interface (GUI). GUI is a system that allows users to interact with a computer device used by the user. [25] The expert system will be friendly used to the direct user. Thus, the direct user can get the result of predictive maintenance transformer quickly.

## 2. Method

The data used was the data from the DGA Test Oil Immersed Transformer which had been labeled based on the IEEE standard. This means that each data will contain the attribute key gas values and recommended action classes. This data is then divided into two to build decision support system as an expert system for predictive maintenance transformer, namely training data and test data. The training data is used to build rules with classification. In this research, three different methods were tried by using WEKA Classifier and then the results were compared. The methods were Naive Bayes, SVM, and J48 algorithm. The highest result will be used as rules in the system created. The result of accuracy comparison can be seen in Table 1.

*Table 1. The Result of Accuracy Comparison*

Method	Accuracy Percentage (%)
Naive Bayes	85.84
SVM	85.04
J48	92.92

After tried these three methods, found that the highest accuracy was obtained from J48 algorithm. Therefore, an expert system will be created that determines the health condition of the transformer using the j48 algorithm. The expert system created aims to make it easier for engineers in an industry to determine whether the transformer used needs maintenance or not. This determination is based on the health condition of the transformer which is known from the DGA Test Results.

Testing data was used to test the success of the classification. Testing data was not taken from training data, but new data was taken as testing data. The training data is made up more than the testing data. This is done to get more accurate classification results. The training data used amounted to 113 data and the testing data used amounted 20 data. The decision of testing result will be divided into two classification, normal or alarm. The recommended action is maintenance or test samples again within the specified time span. The steps of the research work can be seen in Figure 1.

The decision tree that will be built in this research is based on the steps of the C4.5 algorithm which called as J48 in WEKA Classifier. The first step is to calculate the entropy value of each attribute to the possible values. The attribute with the smallest entropy value will be selected as the root node. Next, select the leaf node from the remaining attributes. Again, the entropy value of each remaining attribute is calculated against the possible values. The attribute with the smallest entropy value will be selected as the leaf node. And so on until there are no remaining attributes that have not been selected as nodes in the decision tree. Entropy calculated by using formula in Equation 1.

$$\text{Average entropy} = \sum b \left( \frac{n_b}{n_t} \right) \times \left[ \sum c - \left( \frac{n_{bc}}{n_b} \right) \log_2 \left( \frac{n_{bc}}{n_b} \right) \right] \quad (1)$$

$P_b$  = probability of a thing or parameter on branch  $b$  that is positive

$n_{bc}$  = the number of items or parameters on branch  $b$  that have positive values

$n_b$  = total number of items or parameters on branch

$$P_b = \frac{n_{bc}}{n_b}$$

The tree that is successfully built from the calculation of the entropy of the training data will be used as a reference for the classification of the test data. The classification stage will be evaluated based on accuracy, sensitivity and specificity. Success for the overall classification level can be measured by calculating the number of correct classifications divided by the total number of classifications as shown in Equation 2. Sensitivity is a measure of the predictive ability to select an instance of a class from a set of data sets. Sensitivity is defined in Equation 2. Specificity is particularity. Specificity is usually used in two-class problems where something is more interesting in a particular class. Specificity is defined in Equation 3.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \times 100\% \quad (2)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \times 100\% \quad (3)$$

$$\text{Specificity} = \frac{TN}{FP + TN} \times 100\% \quad (4)$$

TP = true positive (positive classified as positive)

TN = true negative (negative classified as negative)

FP = false positive (negative classified as positive)

FN = false negative (positive classified as negative)

In finding the values of accuracy, sensitivity, and specificity, the TP, TN, FP, and FN values were used. Positive is meant in this case is a positive transformer that needs maintenance and negative is a transformer whose condition is ok in the DGA Test test. Then, what is meant by classified maintenance is when the system in this study states the transformer needs maintenance or needs maintenance and is classified as ok, namely when the system in this study states the transformer is ok or does not need maintenance and will be retested periodically on the specified schedule. [26]

After obtaining the appropriate decision tree using the J48 algorithm, a decision support system will be created for predictive maintenance of transformers. Applications are made using the Hypertext Preprocessor (PHP) programming language, My Structured Query Language (MySQL) database, XAMPP server, and Bootstrap as interfaces. PHP is a programming language that is used widely for handling, creating, and developing a website and is commonly used on HTML. MySQL is a relational database management system (RDBMS) system that is able to work quickly and is easy to use. MySQL is also a database access program that is networked, so it can be used for multi-user applications. XAMPP functions as a server that stands from several stand-alone programs, which consist of the Apache PHP programming program. Bootstrap is a medium for making web interfaces and web-based applications.

### 3. Results and Discussion

In this study, 113 DGA test data labeled as training data were used. The training data comes from the data from the DGA Test (Dissolved Gas Analysis) from an oil-immersed transformer consisting of 7 gases, namely hydrogen (H<sub>2</sub>), carbon monoxide (CO), carbon dioxide (CO<sub>2</sub>), methane (CH<sub>4</sub>), ethane (C<sub>2</sub>H<sub>6</sub>), ethylene (C<sub>2</sub>H<sub>4</sub>), and acetylene (C<sub>2</sub>H<sub>2</sub>). Each gas has been given a condition label 1, 2, 3, or 4. Each data is labeled as normal or alarm, according to the interpretation based on the IEEE C57.104 standard and the operational conditions of the transformer in the field. The training data is then evaluated using the J48 algorithm in WEKA Classifier, to produce a decision tree as shown in Figure 1.

After the decision tree has been formed, then proceed with the system testing stage. Unlabeled testing data will be used as system input. The testing data was new data taken, different from training data. The testing data comes from the data analysis of the DGA test which is done manually by a transformer expert. The data resume from the analysis of the DGA Test 20 samples of the transformer oil in Table 2. Then the data is converted into unlabeled data

in Table 3. Unlabeled data means, the data used as testing data without the result, just only the attributes. The attributes used are CO, CO<sub>2</sub>, H<sub>2</sub>, CH<sub>4</sub>, C<sub>2</sub>H<sub>2</sub>, C<sub>2</sub>H<sub>4</sub>, and C<sub>2</sub>H<sub>6</sub>. The ppm value of each attributes has been converted by engineer into number 1-4 as IEEE standard dn IEC standard.

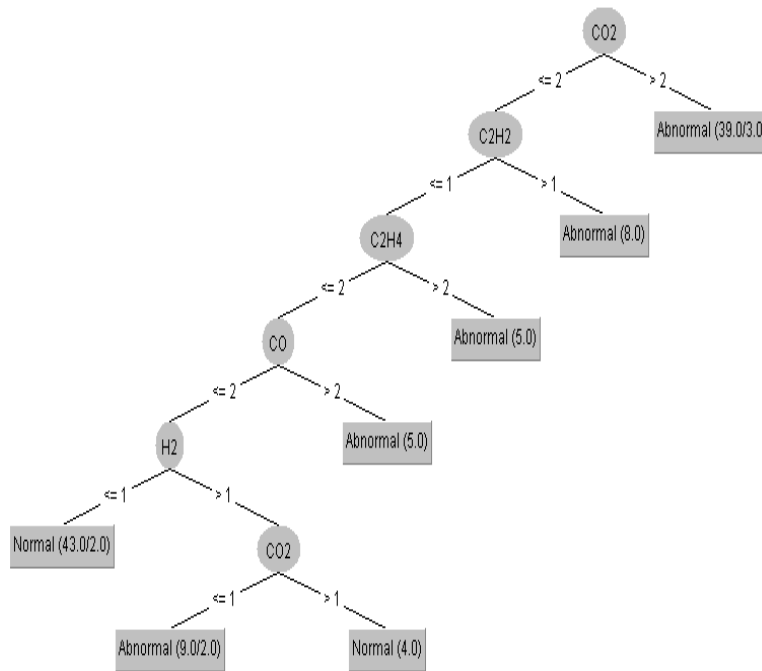


Figure 1. Decision Tree based on 113 Training Data of DGA Test Result

Table 2. 20 Testing Data of DGA Test Result

No	Tag Number	Sample Taken (DD/MM/YYYY)	CO (ppm)	CO <sub>2</sub> (ppm)	H <sub>2</sub> (ppm)	CH <sub>4</sub> (ppm)	C <sub>2</sub> H <sub>2</sub> (ppm)	C <sub>2</sub> H <sub>4</sub> (ppm)	C <sub>2</sub> H <sub>6</sub> (ppm)	Result
1	T1-1	1/8/2022	61	1282	0	0	0	0	2	Normal
2	T1-3	19/7/2022	824	15959	55	0	0	23	5	Alarm
3	T2-1	1/8/2022	56	1257	592	2	0	7	0	Normal
4	T2-4	8/8/2022	193	2655	296	11	0	26	3	Normal
5	T2-12	22/7/2022	344	4438	50	32	0	221	25	Normal
6	T3-4	8/8/2022	483	3724	19	1	0	21	0	Normal
7	T3-11	1/8/2022	318	673	0	4	0	3	4	Normal
8	T3-12	22/7/2022	32	4143	0	0	0	1	0	Normal
9	T3-12	1/8/2022	42	4458	0	0	0	0	0	Normal
10	T3-13	19/7/2022	179	3044	341	4	0	0	0	Normal
11	T4-4	8/8/2022	209	3202	0	0	0	11	0	Normal
12	T4-11	1/8/2022	547	9057	0	4	0	23	5	Normal
13	T5-4	8/8/2022	132	2159	31	52	1	206	27	Alarm
14	T5-12	22/7/2022	179	2330	0	0	0	16	0	Normal
15	T5-13	19/7/2022	161	2013	765	0	0	0	0	Alarm
16	T6-12	22/7/2022	182	2760	0	17	0	107	39	Alarm
17	T6-13	19/7/2022	246	3559	273	2	0	0	0	Normal
18	T7-12	22/7/2022	581	7443	70	4	0	3	0	Normal
19	T10-1	1/8/2022	27	859	347	0	1	0	2	Normal
20	T11-1	1/8/2022	1008	2611	0	6	0	0	0	Alarm



Table 3. 20 Unlabeled Testing Data with Seven Key Gas of DGA Test Result as Attributes

ID	CO	CO2	H2	CH4	C2H2	C2H4	C2H6
1	1	1	1	1	1	1	1
2	3	4	1	1	1	1	1
3	1	1	2	1	1	1	1
4	1	2	2	1	1	1	1
5	1	3	1	1	1	4	1
6	2	2	1	1	1	1	1
7	1	1	1	1	1	1	1
8	1	3	1	1	1	1	1
9	1	3	1	1	1	1	1
10	1	2	2	1	1	1	1
11	1	2	1	1	1	1	1
12	2	3	1	1	1	1	1
13	1	1	1	1	1	4	1
14	1	1	1	1	1	1	1
15	1	1	3	1	1	1	1
16	1	2	1	1	1	3	1
17	1	2	2	1	1	1	1
18	3	3	1	1	1	1	1
19	1	1	2	1	1	1	1
20	3	2	1	1	1	1	1

This unlabeled data will be the input to the system with the decision tree that has been built. The system will process this data and the results will be compared with the results of manual analysis and also the previous training data. The decision tree obtained becomes a reference for the system to determine the decision on the condition of the monitored transformer. To test the accuracy of the system, 20 labeled test data were used. The result is 16 data in normal conditions and 4 data in alarm conditions. The testing stage will be evaluated based on accuracy, sensitivity and specificity on Table 4.

Table 4. Accuracy, Sensitivity and Specificity Percentage Value of 20 Data on Testing Stage

TP	FP	FN	TN	Accuracy (%)	Sensitivity (%)	Specificity (%)
16	0	0	4	100	100	100

Information :

- TP (True Positive) = Normal Transformer Condition is classified as Normal
- TN (True Negative) = Alarm Transformer Condition classified Alarm
- FP (False Positive) = Normal Transformer Condition classified Alarm
- FN (False Negative) = Alarm Transformer Condition is classified as Normal

Based on the test results, obtained 100 percent accuracy, 100 percent sensitivity, and 100 percent specificity. From 20 transformer condition data, 16 normal condition transformers were classified as normal, 4 alarm condition transformers were classified as alarms, 0 normal condition transformers were classified as alarms, and 0 alarm condition transformers were classified as normal by the system. This indicates that the system is ready to be used as a Decision Support System for Transformer conditions.

The application is made using the Hypertext Preprocessor (PHP) programming language, My Structured Query Language (MySQL) database, XAMPP server, and Bootstrap as an interface. The view of menu input transformer data shown in Figure 2.

Data transformer input can only be accessed at operator & engineer level. Operator/engineer can add transformer data and fill in the specifications, then click "submit". "Reset" button is used to empty specifications. List of transformers can access all levels. User can use the "search" feature. To find tag number transformer "edit" u/ change the transformer data "change status" transformer operation or not operation. Transformers that had status do not operated will not show in the "report". "Delete" menu used to delete the transformer data "report" user can show report each transformers. After all data are inputted, user can quick interpretation to see the analyze result of transformer condition. The quick interpretation result shown in Figure 3. All of transformer data that had been tested by quick interpretation will be shown in report menu. The report menu view shown in Figure 4.

Figure 2. View of Input Transformer's Data Menu



Figure 3. Quick Interpretation Result

NO	TAG NUMBER	TOL SAMPLE	OPERATOR	ALAT TEST	RESULT	TDCG	CONDITION	SAMPLING INTERVAL	NEXT SAMPLING DATE	OPERATING PROCEDURE	KEY GAS
1	T2-301	2019-10-02	Azz Fahren	Mytica	Normal	205	1	Annual	2020-10-18	Continue normal operation	
2	T7-302	2019-10-02	Azz Fahren	Mytica	Normal	842	2	Quarterly	2020-01-18	Exercise caution, analyze for individual gases. Determine load dependence	THF
2	T7-302	2019-07-02	Ashen RUC	Mytica	Normal	789	2	Quarterly	2019-10-18	Exercise caution, analyze for individual gases. Determine load dependence	THF
2	T7-302	2018-01-02	Ashen RUC	MYRVDG	Normal	1512	2	Quarterly	2018-04-02	Exercise caution, analyze for individual gases. Determine load dependence	THF
2	T7-302	2017-12-14	Ashen RUC	MYRVDG	Normal	1782	2	Quarterly	2018-03-14	Exercise caution, analyze for individual gases. Determine load dependence	THF

Figure 4. Report Menu View

#### 4. Conclusion

The transformer predictive maintenance technique that can be an indicator of the health of a transformer is the Dissolved Gas Analysis (DGA) Test Oil Transformer. DGA Test is done by extracting and calculating the gas content dissolved in transformer oil. There are 7 key gases which are interpreted using IEEE standards and IEC standards in this study, namely CO, CO<sub>2</sub>, H<sub>2</sub>, CH<sub>4</sub>, C<sub>2</sub>H<sub>2</sub>, C<sub>2</sub>H<sub>4</sub>, and C<sub>2</sub>H<sub>6</sub>. These seven key gases are used as attributes for training data. There are 113 training data, which have been labeled normal or alarm by the engineer. This data is then

trained to get a decision tree using the J48 algorithm. The decision tree obtained was then tested using 20 test data. The results obtained a value of 100% for accuracy, specificity, and sensitivity. This decision tree is then applied to the Expert System for Predictive Maintenance Transformer. The expert system created can be accessed by users to enter new data in the form of transformer DGA Test Results for interpretation quickly and provide output decisions regarding the condition of the transformer, namely normal or alarm. The benefits of this system are that the health condition of the transformer can be monitored properly and corrective action can be taken immediately on a problem based on the results of the decision support system. This will reduce the risk of shutdown and support the reliability of plant operations.

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