Chapter 5 Hybrid Diagnosis

In the last two chapters, a rule-based inference engine and a MLP based modular network have been built up for power transformer fault diagnosis. To obtain a better performance system, this chapter will attempt to combine them together to form a hybrid diagnosis system. First let's analyze the possibility.

5.1 The basis of hybrid diagnosis

Darwin' evolutionary theorem says competition resulted in stronger and more adaptive species. It is generally true if the offspring inherit the superior genes from the parents. In case of power transformer diagnosis, a hybrid system combining the rule based inference engine and the MLP based modular network likely have better performance if the two can compete with each other in the diagnosis.

The effectiveness of the rule based inference engine is basically depending on the precision and completeness of accumulated human knowledge. IEC standards and industrial experiences form the major part of the rule base. They are quite robust in some cases but may not be so in other cases. They are also subject to change in the future and hard to be incorporated into the system.

The neural network approach can acquire experiences directly from the training data through a learning process, and acquire new experiences easily through incremental training on newly obtained data. The experiences include those known to human experts as well as those unknown. As a result, the approach is more adaptive and robust than the rule based inference engine if the training data set is large enough to be representative and the data samples are consistent with each other. The condition is normally not available in most cases.

The neural network can interpolate and extrapolate from its experiences, providing at least a best guess of the fault type under given circumstance. This is another natural advantage of the neural network approach because it will avoid the "no decision" problem that often occurs with the ratio methods. This advantage may be less attractive after we solved the "no decision" problem partly in Chapter 3, but is still a potential winning factor in the competition with the rule based inference engine. We will see in Section 5.5.

5.2 The topology of hybrid diagnosis

The hybrid diagnosis has been developed into a power transformer fault diagnosis system and named as ANNEPS. The flow chart of the ANNEPS is shown in Figure 5-1. It consists of the following function modules:

- *Neural Network Based Abnormal Detector*, used to screen out abnormal cases for further diagnosis;
- *Rule Based Abnormal Detector*, also used to screen out abnormal cases;
- *Neural Network Based Fault Detector*, used to detect all possible faults;
- *Rule Based Fault Detector*, also used to detect all possible faults;
- *Combined Fault Diagnosis*, the heart of hybrid diagnosis, integrates the outputs of neural network and rule based fault detectors;
- *Maintenance Action Recommendation*, estimates oil re-sampling intervals and maintenance actions.

The input data include all information related to an oil sample, such as gas-in-oil concentrations, gassing rates, oil sample and transformer nameplate, etc. The consideration is that many factors affect the gas-in-oil development behaviors, and it is important to preserve as many factors as possible for future use even if some of them are not used at this moment.

Diagnosis outputs include fault type, diagnosis confidence, oil re-sampling interval and maintenance action recommendations. The fault types include those can be diagnosed using previous DGA methods, as well as "overheating of oil" and "cellulose degradation" that cannot be diagnosed by some earlier methods.

- Normal condition (NR)
- Overheating regardless of oil or cellulose (OH)
- Overheating of oil (OHO)
- Low energy discharge (LED)
- High energy discharge or arcing (HEDA)
- Cellulose degradation (CD)

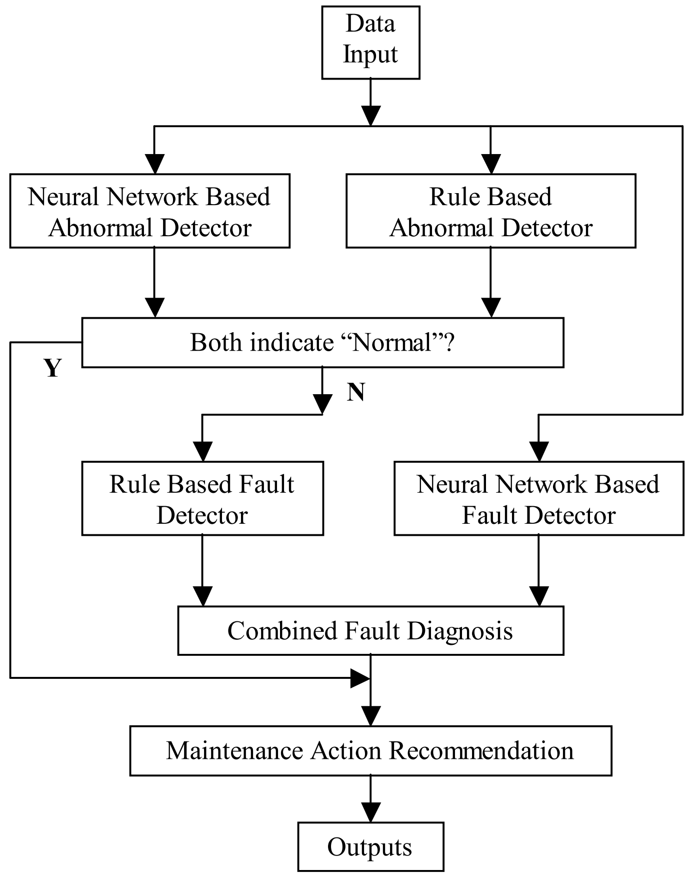

Figure 5-1 Flow chart of the ANNEPS

Temperature range t of OH and OHO are further divided into four ranges: t<T1, T1<t<T2, T2<t<T3, t>T3. Diagnosis confidence is represented by a real value in the range of [0,1].

Since neural network and rule based fault detectors have been addressed in the last two chapters and maintenance action recommendations will be discussed in the next chapter, this chapter will concentrate on abnormal detectors and the combined fault diagnosis.

5.3 The abnormal detectors

These include the neural network based and the rule based detectors.

5.3.1 Neural network based abnormal detector

In Chapter 4 it was found that a five-input neural network is the best choice for "normal condition" diagnosis. This network can be used as an abnormal detector, too. The only requirement is to use the complementary value of the "normal condition" output as the output of the abnormal detector.

5.3.2 Rule based abnormal detectors

These include four detector modules, as shown in Figure 5-2.

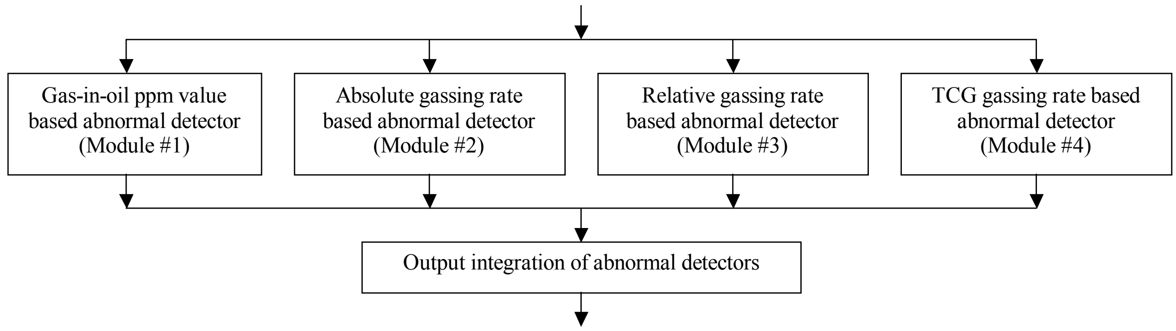

Figure 5-2 Rule based abnormal detector

Module #1 compares the gas-in-oil concentrations (ppm) of H_2, CH_4, C_2H_2, C_2H_4, C_2H_6, CO, CO_2, TDCG (Total Dissolved Combustible Gas) and TDHG (Total Dissolved Hydrocarbon Gas) with the preset L1 norms. If any one of them is greater than its norms, the detector flags an "abnormal" sign. The norms being used are listed in Table 5-1, together with those from different sources. These values were intentionally selected to be conservative in order that no suspect can escape the screening. For example, a 1 ppm was chosen as the C_2H_2 norm, which is significant lower than others, the reason is than any C_2H_2 existence should gain some attentions.

Table 5-1 The L1 norms of gases-in-oil from different sources

Sources	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2	TDCG	TDHG
Values actually being used	100	120	1	50	65	200	2500	536	236
IEEE [C57.104]	100	120	35	50	65	350	2500	720	-
Doble	100	100	5	100	60	250		610	-
General Electric [Lyke77]	200	100	25	100	200	200	2000	-	-
*IEEE Generator *IEEE Transmission	240 100	160 120	11 35	190 30	115 65	580 350	- -	1296 700	- -
Manufacturer	200 (250)	100 (200)	15 (35)	150 (300)	100 (200)	500 (1000)	- -	1076 (1985)	- -
**Electra (CIGRE)	28.6	42.2	-	74.6	85.6	289	3771	520	-
Dornenburg [Dorn70]	200	50	15	60	15	1000	-	-	-

Note: *Before [C57.104] **Corrected values 1978
Values in brackets are of transformers 6-7 years old
Unmarked sources are all cited from [Griffin86, Griffin88]

Module #2 compares the absolute gassing rate of H_2, CH_4, C_2H_2, C_2H_4, CO, TDCG and TDHG, represented in ppm/day, with a universal limit of 10ppm/day. Module #3 compares the relative gassing rate of H_2, CH_4, C_2H_2, C_2H_4, CO, TDCG, and TDHG, represented in percentage per month, with a universal limit of 10% per month. If any one of these gassing rates exceeds the limit, the modules flag an "abnormal" sign. These limits originate from IEEE standard C57.104-1991 [C57.104] but are different.

Module #4 compares TCG (Total Combustible Gases) gassing rate, represented in ft^3/day, with a limit of 0.1 ft^3/day. This limit comes from IEEE standard C57.104-1991.

In the output integration process, any "abnormal" output of the four detectors will flags an overall "abnormal" sign.

The abnormal detectors screen out the abnormal cases for further investigation. They can also help determining if a minor fault should be treated as a normal condition, as will be discussed in Section 5.5.

5.4 Artificial neural network (ANN) and rule based fault detectors

5.4.1 ANN based fault detectors

The optimal ANN topology for power transformer fault diagnosis has been found in Chapter 4. They are the basis of the ANN based fault detectors here. Figure 5-3 shows the arrangement of these detectors. As we can see, they are in parallel in the arrangement and each of then is responsible for detecting one individual fault. This is actually the structure of a modular network.

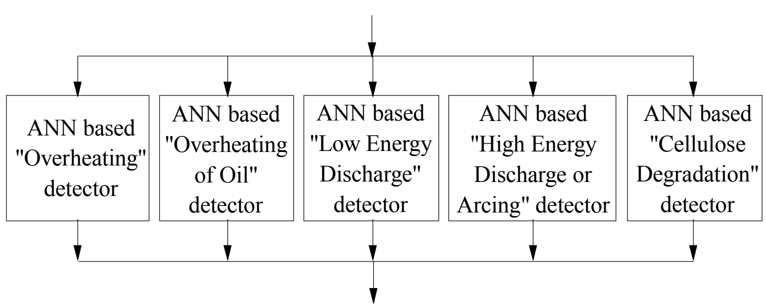

Figure 5-3 ANN based fault detector

5.4.2 Rule based fault detector

The rule based fault detector has been introduced in Chapter 3. It is summarized in Figure 5-4 again for simplicity. This detector has three parts: the major part is the "Normal", "Overheating"

(OH), “Low-energy Discharge” (LED) and “High-energy Discharge or Arcing” (HEDA) detector whose rules are derived from IEC Standard 599 with new code combinations added and ratio interval boundaries slightly revised. The rules for “Overheating of Oil” (OHO) and “Cellulose Degradation” (CD) are revision of industrial experiences.

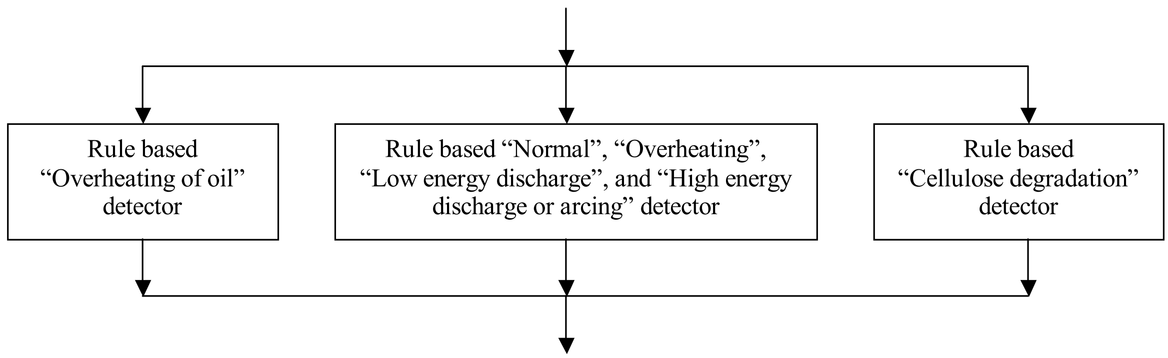

Figure 5-4 Rule based fault detector

5.5 Combined fault diagnosis

This includes three series steps, as shown in Figure 5-5.

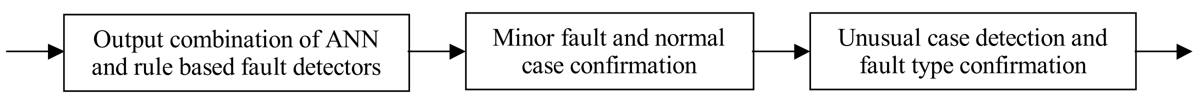

Figure 5-5 Combined fault diagnosis

The output combination of ANN and rule based fault detectors is based on competition and compromise. Assuming an output confidence RB_i is from the rule based fault detector and ANN_i from the ANN based fault detector for a particular fault type “i”, the combined output confidence COC_i is given according to the following rule for OH, OHO, LED and CD:

If ($ANN_i > 0.6$ OR $ANN_i < 0.4$) let $COC_i = ANN_i$

Else let $COC_i = \sqrt{RB_i \times ANN_i}$

Here the ANN output was selected to dominate the combined output because it is more reliable in most cases of the 210 data samples in the study. When the ANN output is ambiguous, a compromise is made between the two outputs to get help from DGA standards and experiences.

For HEDA, COC_i is given as:

If ($RB_i > 0.9$) let $COC_i = RB_i$

Else let $COC_i = \sqrt{RB_i \times ANN_i}$

Because rule based diagnosis was found to be more reliable for high-energy discharge diagnosis in the study.

In "minor fault and normal case confirmation", if the output of the rule based detector turns out to be a minor fault such as "low energy discharge" or "low temperature overheating", the actual condition could be normal and the result of ANN based abnormal detector is used to confirm the situation.

"Unusual case detection and fault type confirmation" was employed when a fault is detected from the combination of ANN and rule based diagnosis but gas generation rates are not high. This situation was named as an unusual case.

5.6 Performance improvement via hybrid diagnosis

5.6.1 Overall fault diagnosis performance of the ANNEPS system

The fault diagnosis capability of the ANNEPS is tested by 210 data samples, among which 22 are normal cases. Majority of these data samples are from Doble (Appendix 6), some of them are collected from literatures (Appendix 7, named as data set SUP_TST). In some cases the true incipient fault condition was revealed from visual inspection or other types of tests such as Resistance Test, Turn Ratio Test or Furanic Test. In others the fault types were classified based on industrial experiences. 150 samples are selected to train the ANNs of the ANNEPS (see Appendix 6 for detail). The other 60 samples serve as testing data.

Table 5-2 shows the test accuracy of the ANNEPS. Test accuracy is the percentage of correct diagnosis out of the total tested data samples. The total tested data samples for training and testing are 150 and 60, respectively. Both training and testing accuracies are shown in the table.

As can be seen from Table 5-2, the test accuracy of the combined diagnosis is better than or at least equal to that of either the ANN or rule based detector alone for all the five types of fault, especially for OH, HEDA and CD type fault. This happens to all the three data categories: "training", "testing" and "overall". In general we can say that the hybrid diagnosis is much better than either ANN or rule based detectors.

For most fault types, the test accuracy of rule based detector for the training data is much higher than that for the testing data. This is due to the elaborate selection of training data (see discussions in Chapter 4).

The 98% and 98.7% ANN test accuracies (for HEDA and CD diagnosis, respectively) of the training data set reflect the inconsistency of the training data samples. This number should be close to 100% for a perfect training data selection. The ANN test accuracy of the testing data set reflects its diagnosis capability. This capability is quite impressive at a glance but can be and was improved in the ANNEPS.

Table 5-2 Test accuracy (%) of the training and testing data sets

Tool	ANN based detector			Rule based detector			ANNEPS		
Data set	Training	Testing	Overall	Training	Testing	Overall	Training	Testing	Overall
OH	100	95	98.6	97.3	90	95.2	100	96.7	99
OHO	100	95	98.6	99.3	90	96.6	100	95	98.6
LED	100	95	98.6	95.3	90	93.8	100	95	98.6
HEDA	98	88.3	95.2	96.7	85	93.4	99.3	96.7	98.6
CD	98.7	91.7	96.7	90.7	91.7	91	99.3	93.3	97.6

Table 5-2 shows the improved diagnosis accuracy of ANNEPS in general. Following are some examples to illustrate how the combination of ANN and rule based detector outputs can increase the diagnosis accuracy.

5.6.2 Case discussions for fault diagnosis

Table 5-3 shows the diagnosing details of five ANNEPS diagnosis examples. These examples are taken from the 210 data samples. Their actual fault types were revealed from visual inspection or other types of tests, or classified based on industrial experiences.

In example #1, the rule-based detector indicates no possibility of CD but a possible HEDA phenomenon since CD indicator CO is below its L1 limit while there is a little amount of C_2H_2 (HEDA indicator). On the other hand, ANN diagnosis is not based on limits but on a pattern mapping mechanism that may reveal complex relationships between inputs and outputs and in this case indicates CD and OH confidently.

In example #2, the rule based detector indicates OH, OHO and CD clearly since corresponding indicators CH_4, C_2H_4, C_2H_6 and CO are all excessive, but ANN is not sure if CD exists, perhaps due to the lack of experience caused by insufficient training data. Here the large amount of C_2H_2 concentration (78 ppm) is not from arcing but high temperature overheating of oil which can be differentiated by the large amounts of CH_4, C_2H_4 and C_2H_6 generated at the same time.

Table 5-3 Close up of some test examples

<table>
<tr><td colspan="3">Example Number</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td colspan="3">Actual Fault Types</td><td>OH
CD</td><td>OH
OHO
CD</td><td>HEDA</td><td>HEDA</td><td>LED</td></tr>
<tr><td colspan="3">Size (MVA)</td><td>260</td><td>—</td><td>46.7</td><td>105</td><td>11.3</td></tr>
<tr><td rowspan="7">INPUT</td><td colspan="2">H_2 (ppm)</td><td>22</td><td>1770</td><td>86</td><td>34</td><td>142</td></tr>
<tr><td colspan="2">CH_4 (ppm)</td><td>40</td><td>3630</td><td>30</td><td>39</td><td>3</td></tr>
<tr><td colspan="2">C_2H_2 (ppm)</td><td>1</td><td>78</td><td>29</td><td>9</td><td>1</td></tr>
<tr><td colspan="2">C_2H_4 (ppm)</td><td>6</td><td>8480</td><td>35</td><td>40</td><td>8</td></tr>
<tr><td colspan="2">C_2H_6 (ppm)</td><td>36</td><td>1070</td><td>10</td><td>9</td><td>2</td></tr>
<tr><td colspan="2">CO (ppm)</td><td>194</td><td>832</td><td>134</td><td>48</td><td>146</td></tr>
<tr><td colspan="2">CO_2 (ppm)</td><td>3020</td><td>7940</td><td>5090</td><td>443</td><td>2230</td></tr>
<tr><td rowspan="16">OUTPUT</td><td rowspan="3">OH</td><td>ANN based detector</td><td>1.00</td><td>1.00</td><td>0.13</td><td>0.00</td><td>0.00</td></tr>
<tr><td>Rule based detector</td><td>0.01</td><td>0.99</td><td>0.01</td><td>0.01</td><td>0.01</td></tr>
<tr><td>ANNEPS</td><td>1.00</td><td>1.00</td><td>0.13</td><td>0.00</td><td>0.00</td></tr>
<tr><td rowspan="3">OHO</td><td>ANN based detector</td><td>0.00</td><td>1.00</td><td>0.00</td><td>0.00</td><td>0.00</td></tr>
<tr><td>Rule based detector</td><td>0.01</td><td>0.99</td><td>0.01</td><td>0.01</td><td>0.01</td></tr>
<tr><td>ANNEPS</td><td>0.00</td><td>1.00</td><td>0.00</td><td>0.00</td><td>0.00</td></tr>
<tr><td rowspan="3">LED</td><td>ANN based detector</td><td>0.00</td><td>0.00</td><td>0.00</td><td>0.00</td><td>0.65</td></tr>
<tr><td>Rule based detector</td><td>0.01</td><td>0.01</td><td>0.01</td><td>0.01</td><td>0.01</td></tr>
<tr><td>ANNEPS</td><td>0.00</td><td>0.00</td><td>0.00</td><td>0.00</td><td>0.65</td></tr>
<tr><td rowspan="3">HEDA</td><td>ANN based detector</td><td>0.00</td><td>0.00</td><td>0.99</td><td>0.00</td><td>0.00</td></tr>
<tr><td>Rule based detector</td><td>0.60</td><td>0.01</td><td>0.99</td><td>0.99</td><td>0.60</td></tr>
<tr><td>ANNEPS</td><td>0.05</td><td>0.00</td><td>0.99</td><td>0.99</td><td>0.01</td></tr>
<tr><td rowspan="3">CD</td><td>ANN based detector</td><td>0.92</td><td>0.42</td><td>0.57</td><td>0.00</td><td>0.00</td></tr>
<tr><td>Rule based detector</td><td>0.01</td><td>0.99</td><td>0.01</td><td>0.01</td><td>0.01</td></tr>
<tr><td>ANNEPS</td><td>0.92</td><td>0.65</td><td>0.08</td><td>0.00</td><td>0.00</td></tr>
<tr><td colspan="2">Recommended Actions</td><td>Retest monthly</td><td>Inspection</td><td>Inspectio n</td><td>Inspectio n</td><td>Retest monthly</td></tr>
</table>

In examples #3 and #4, the ANN suspects CD for #3 with a confidence of 0.57 while the rule-based detector clearly indicates the existence of HEDA since C_2H_2 is high but C_2H_4 and C_2H_6 are low in both cases. The possibility of CD is eliminated in example #3 since CO is below the L1 limit.

In example #5, the rule-based detector misses LED but suspects HEDA, perhaps due to the fact that the gas ratios do not match the LED pattern and there is a little amount of C_2H_2. Since there is excessive H_2 but very little other combustible gases, ANN detects the LED fault and eliminates the possibility of HEDA. The outputs of ANNEPS are correct.

Cases exist where either ANN or rule based detector indicates fault type correctly, but the combined output is incorrect. This rarely happens and does not affect the overall effectiveness of the ANNEPS.

5.6.3 Fault diagnosis capability comparisons with the Rogers ratio method

Ten data samples with internal inspection results were collected from literatures for the purpose of comparing ANNEPS with the Rogers ratio method. Details of the samples can be found in Appendix 7. Each data sample corresponds to at least but often more one type of fault. For example, when a winding is burnt away, there may exist faults like arcing, and overheating of solid insulation and/or oil.

Testing results of the 10 samples by the Rogers ratio method and ANNEPS are shown in Table 5-4, where "fault numbers" denotes how many samples out of the 10 contain the corresponding fault type, "numbers detected" denotes how many samples are correctly detected for this fault type.

Table 5-4 The testing results of ANNEPS and the Rogers ratio method

Fault type		OH	OHO	LED	HEDA	CD
Fault numbers		9	9	0	7	3
Numbers detected	Rogers	3	-	0	1	-
	ANNEPS	9	9	0	6	3

Table 5-4 shows the general capabilities of the ANNEPS and the Rogers ratio method. The Rogers ratio method can detect a type of fault definitely when the fault is dominate and the data fits the pattern of the fault, but it can not give any diagnosis information in a number of cases because of the "no decision" problem. As a result, it cannot provide at least a "best guess" for almost all of the data samples. It is obvious that the ANNEPS has advantages since we not only hope to know exactly what is happening to a transformer but also to know at least "something" for any data sample. Even if the information we get is not definite, it is better than no information at all.

5.6.4 Overall performance comparison between ratio methods and ANNEPS

The Dornenberg, Rogers and IEC Standard 599 were applied to the 210 data samples and Table 5-5 is formed from the testing results.

Table 5-5 Testing accuracy (%) of some popular ratio methods on the 210 data samples

Diagnosis Methods	Success	Error	Not Identifiable
Dornenberg Ratio	22.9	65.2	11.9
Rogers Ratio	24.8	12.4	62.9
IEC 599	42.9	24.8	32.4

In Table 5-5, "success" counts whenever a fault is correctly diagnosed no matter how many fault types exist; "error" counts when the diagnosis is totally wrong; "not identifiable" counts when "no decision" occurs. From Dornenberg to Rogers and to IEC 599, the "success" rate is increasing but the best is still below 50%. Comparing with Table 5-2, we can see a significant "success" rate improvement when the hybrid diagnosis ANNEPS is used.

5.7 Summary and discussions

In this chapter the principle and implementation of power transformer hybrid fault diagnosis is presented. A hybrid diagnosis system, the ANNEPS, was built up based on rule based fault diagnosis and neural network based fault diagnosis. Testing results proved that the performance of the hybrid diagnosis is better than that of the rule or neural network based diagnosis works alone.

An abnormal condition screening process before the rule-based detector ensures that very minor fault conditions be identified for detailed investigation. The competition and compromise of the combination mechanism ensures that the hybrid diagnosis has better performance than the building components.

Testing results also shows that the ANNEPS is much better than conventional ratio methods.