Incipient Fault Determination in Oil-Insulated Power Equipment via Neural Network-Social Group Optimization

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***Abstract*— Oil-insulated power equipment such as power transformers are one of the most imperative facilities in power systems. However, they are constantly subjected to electrical and thermal stresses, which accelerates their ageing process and heightens the risk of malfunction during operation due to incipient faults. Therefore, determination of incipient faults in power equipment is of utmost priority, where faults must be detected and diagnosed accurately in the early stages. In this work, determination of the incipient faults within oil-insulated power equipment based on dissolved gas analysis (DGA) data is proposed using artificial neural network (ANN)-social group optimization (SGO) technique. The method was compared with combination with other algorithms, which include particle swarm optimization (PSO) and artificial bee colony (ABC) algorithms. The results in this work demonstrate an improvement in the classification accuracy for the optimized ANN compared to the non-optimized ANN. Comparison among the optimized methods shows that ANN-SGO yields higher classification accuracy compared to ANN-PSO and ANN-ABC. The results obtained indicate that the proposed technique could benefit the power industries in determination of the fault type within oil-insulated power equipment automatically.**

Keywords*— *Dissolved gas analysis, oil-insulated power equipment, artificial neural network, optimization techniques, Social group optimization

I. Introduction

In an extensively interlinked network of an electrical power system, hydrocarbon mineral oil is a type of liquid insulation that is regularly used in indispensable power equipment, such as circuit breaker, power transformer and reactor. While long service life of power equipment is sought after for its durability, prolonged operation term of the mentioned equipment tends to encourage the development of incipient electrical and thermal faults. Such faults, which are influenced by electrical, thermal, mechanical, and environmental stress, degrade the quality of insulation and safe operation state of the equipment, ultimately driving the generation and transmission network to failure. As a result, imperative improvement of state-based maintenance strategies through continuous power equipment health condition monitoring is important as it allows for prediction of equipment malfunctions. Subsequently, this prompts maintenance strategies to obviate risks induced by the faults such as power outages, fires and substantial propriety loss.

To identify the fault type by analyzing dissolved gases in the oil, conventional DGA diagnostic tools such as Key Gas Method (KGM), Rogers' Ratio Method (RRM), IEC Ratio Method (IRM), Doenernburg's Ratio Method (DRM) and Duval's Triangle Model (DTM) are employed [1-4]. However, these tools pose several limitations in yielding good analysis accuracy. One of them is fault evaluation for the same oil sample from the same oil-insulated power equipment is inconsistent between the analyses done. This is due to different personnel may interpret differently based on the experience the personnel has in DGA. Comparison of fault evaluation between these tools may yield conflicting diagnoses.

Several artificial intelligence (AI) tools have been applied to determine the fault type of oil-insulated power equipment [5-7]. However, these AI methods require suitable selection of their features, which is commonly done manually, so that the accuracy results are the best. Hence, optimization algorithms have been applied to improve the performance of AI [2, 8, 9]. However, some optimization algorithms are trapped in local minima and low convergence rate. Hence, improvement of the existing work can be performed.

II. Input and Output Data for ANN

The "IEC TC 10 Database of Faulty Equipment Inspected in Service" is applied as the input and output data of the study [10]. The ratio of gas concentration is used as the input while the fault type is used as the output data. In the case of classification of fault type in oil-insulated power equipment, the same database is used to train and test the artificial neural network (ANN) classifier. The input and output data are summarized in Table I. The input and output data are used to train and test ANN to determine the fault type. The training and testing data are split into 70:30 ratio. Two hidden layers and different number of neurons are tried out to determine a suitable structure of ANN before it is optimized by optimization algorithms. Fig. 1 shows a general structure of ANN used in this work [11-14].

TABLE I. Input and Output Data

Input data	Output data(label)
CH_4/H_2	Partial Discharge (PD)
C_2H_2/C_2H_4	Discharges of Low Energy (D1)
C_2H_2/CH_4	Discharges of High Energy (D2)
C_2H_6/C_2H_2	Thermal Faults < 700°C (T1 & T2)
C_2H_4/C_2H_6	Thermal Faults > 700°C (T3)
	No Fault

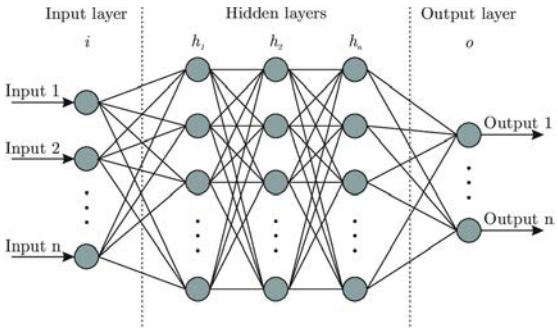

Fig. 1. Structure of ANN [15]

III. Social Group Algorithm

To optimize the performance of ANN, two ANN parameters are varied automatically by social group optimization (SGO). The parameters are learning rate (LR) and momentum constant (MC). These parameters are varied until the fitness function value is the lowest, given by

$$Error = min\ \{(100 - Accuracy)\} \quad (1)$$

SGO is a new meta-heuristic, human behavior based optimization method motivated by humans collaborating with one another to solve complicated problems [16, 17]. Throughout all stages in life, humans have cultivated dormant behavioral traits such as fear, compassion, tolerance and more to navigate through endeavors. While humans naturally are effective problem solvers, the underlying concept is when a much too complex problem is assigned to a single individual, it may become too difficult for that individual to solve. This is due to the individual is limited to his or her individual capability of formulating a solution. However, the bright side of the situation lies in knowing that humans are also great imitators of their surrounding influences. Therefore, when approached with a team effort, the complexity of the problem is reduced and the problem can be solved more effectively. One can say that the aggregation of different individual knowledge and capacity levels leads to a more productive outcome than that of an individual ability. Fig. 2 shows the overall flowchart of ANN-SGO used in this work.

IV. Results and Discussion

Table II shows the results of identification accuracy of each fault type in oil-insulated power equipment using different conventional DGA techniques. Based on the conventional DGA technique results, the best accuracy is achieved by using the IRM diagnostic tool, which has the highest overall accuracy of 73.50%, while the worst accuracy of 26.50% is achieved by using KGM. KGM achieved the highest accuracy in classifying Partial Discharge at 44.44%, Discharges of Low Energy at 76.92%, Discharges of High Energy at 87.50%, Thermal Faults < 700°C at 56.25% and Thermal Faults > 700°C at 61.11%. This observation can be attributed to the fact that KGM only considers four general types of fault and it requires that the concentration of dissolved key gases used to determine the fault must be high, otherwise unresolved diagnoses would result.

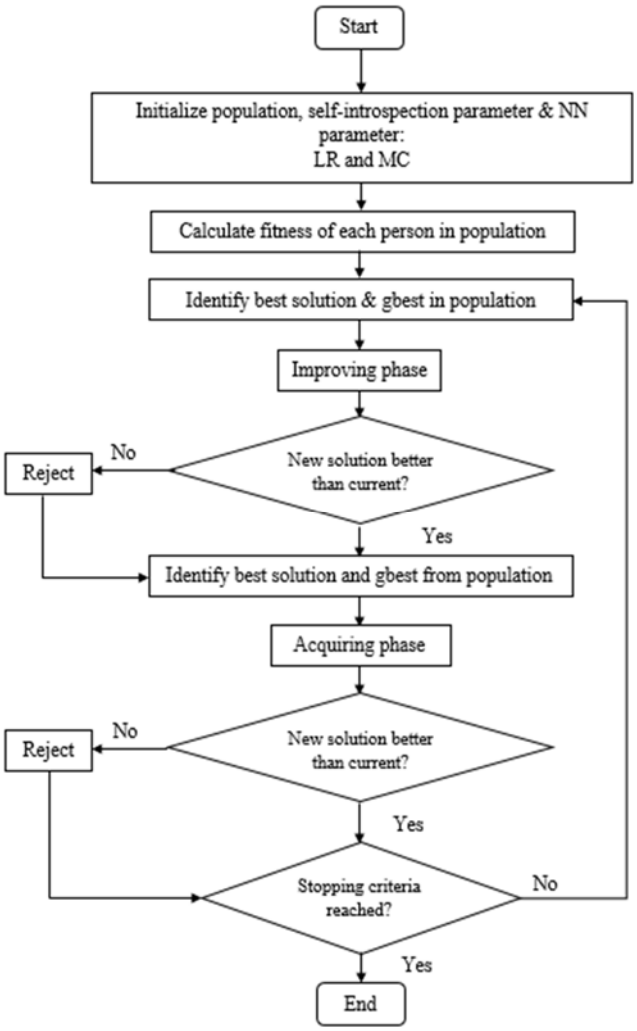

Fig. 2. Overall flowchart of ANN-SGO

TABLE II. Fault Identification Accuracy using Existing Diagnosis Methods

AI Classifier	DGA Diagnostic Tool Fault Identification Accuracy (%)						Overall Accuracy (%)
	PD	D1	D2	T1&T2	T3	No Fault	
KGM	100.00	50.00	0.00	50.00	5.88	8.00	26.50
DRM	44.44	0.00	85.42	62.50	83.33	14.00	59.80
RRM	11.11	0.00	85.42	18.75	61.11	26.00	47.86
IRM	44.44	76.92	87.50	56.25	61.11	68.00	73.50

To determine the number of neurons per layer, different combinations of number of neurons for two hidden layers were obtained. The number of neurons for the second hidden layer is kept constant while the first hidden layer is varied from 1 to 10. It has been found that the combination of neuron numbers that provides the best overall accuracy is when both hidden layers have 10 neurons each. Tables III to VII show the overall accuracy of ANN for different number of neurons tested.

TABLE III. ANN ACCURACY WHEN NUMBER OF NEURON = 2 FOR HIDDEN LAYER 2

L1	L2	ANN Classifier Classification Accuracy (%)						Overall Accuracy (%)
		PD	D1	D2	T1 & T2	T3	No Fault	
1	2	0.00	15.64	56.39	19.58	63.70	0.27	27.52
2	2	0.00	7.18	57.64	22.08	56.67	2.93	26.84
3	2	6.15	40.00	71.53	16.25	69.26	9.20	38.96
4	2	20.00	31.54	83.19	14.17	74.44	16.53	44.28
5	2	9.23	27.18	58.06	25.42	61.48	10.00	33.52
6	2	15.38	40.77	84.17	14.17	82.59	19.20	47.44
7	2	14.62	46.67	79.03	10.83	81.11	10.40	43.72
8	2	20.00	59.49	73.75	21.67	71.85	24.13	48.64
9	2	17.69	52.82	80.14	18.75	75.19	21.33	48.56
10	2	23.85	45.64	62.36	29.17	64.07	11.20	39.40

TABLE IV. ANN ACCURACY WHEN NUMBER OF NEURON = 4 FOR HIDDEN LAYER 2

L1	L2	ANN Classifier Classification Accuracy (%)						Overall Accuracy (%)
		PD	D1	D2	T1 & T2	T3	No Fault	
1	4	0.00	41.03	71.39	9.58	72.96	5.60	37.44
2	4	4.62	44.87	66.25	11.25	67.41	4.27	35.96
3	4	7.69	45.13	70.83	11.67	72.96	11.73	40.36
4	4	20.00	55.13	72.78	12.92	77.78	12.93	44.12
5	4	16.15	46.15	69.72	19.17	67.78	10.27	40.36
6	4	23.85	55.64	77.64	18.75	75.93	19.20	48.04
7	4	15.38	50.77	70.69	20.00	70.00	12.93	42.44
8	4	18.46	48.21	74.58	17.08	78.15	9.87	43.00
9	4	24.62	43.33	73.33	24.17	66.67	17.60	43.96
10	4	17.69	48.72	71.11	24.58	75.93	15.60	44.24

TABLE V. ANN ACCURACY WHEN NUMBER OF NEURON = 6 FOR HIDDEN LAYER 2

L1	L2	ANN Classifier Classification Accuracy (%)						Overall Accuracy (%)
		PD	D1	D2	T1 & T2	T3	No Fault	
1	6	1.54	38.72	65.28	15.42	60.37	9.33	35.72
2	6	15.38	44.10	77.08	17.50	69.63	13.60	43.16
3	6	14.62	46.41	80.28	16.25	73.70	16.93	45.72
4	6	19.23	57.18	73.89	10.00	77.04	12.67	44.28
5	6	25.38	61.28	76.53	20.83	69.63	20.27	48.52
6	6	31.54	62.56	80.69	20.42	84.07	21.47	52.12
7	6	31.54	62.31	79.58	21.67	82.59	24.93	52.76
8	6	27.69	60.26	76.94	19.17	74.81	19.07	48.64
9	6	21.54	57.44	67.36	25.00	74.44	16.67	44.92
10	6	28.46	67.18	77.50	23.33	82.96	22.40	52.20

TABLE VI. ANN ACCURACY WHEN NUMBER OF NEURON = 8 FOR HIDDEN LAYER 2

L1	L2	ANN Classifier Classification Accuracy (%)						Overall Accuracy (%)
		PD	D1	D2	T1 & T2	T3	No Fault	
1	8	3.08	45.13	76.39	9.17	64.44	11.20	40.40
2	8	12.31	52.82	77.08	11.25	71.85	6.67	41.92
3	8	10.77	56.41	76.94	15.42	74.07	9.47	43.84
4	8	19.23	47.18	63.19	21.67	68.52	9.47	38.88
5	8	12.31	42.82	79.03	14.17	74.07	9.33	42.24
6	8	26.92	58.21	79.44	22.50	73.70	20.00	49.48
7	8	26.15	55.13	77.50	17.08	78.15	19.07	48.08
8	8	20.77	54.87	77.92	21.67	77.78	18.27	48.04
9	8	27.69	61.03	78.61	23.33	79.63	20.40	50.56
10	8	28.46	65.13	74.31	22.08	78.15	21.20	49.96

TABLE VII. ANN ACCURACY WHEN NUMBER OF NEURON = 10 FOR HIDDEN LAYER 2

L1	L2	ANN Classifier Classification Accuracy (%)						Overall Accuracy (%)
		PD	D1	D2	T1 & T2	T3	No Fault	
1	10	6.15	38.46	61.39	18.75	64.81	3.87	33.96
2	10	20.77	46.41	81.11	17.50	75.56	12.00	45.12
3	10	19.23	56.41	78.33	15.83	82.22	14.00	46.96
4	10	18.46	55.64	73.47	13.75	76.30	15.07	44.88
5	10	20.00	56.92	75.28	23.75	78.52	19.60	48.24
6	10	32.31	60.00	82.50	25.83	80.37	28.13	54.40
7	10	28.46	62.31	77.92	22.08	81.11	24.80	51.96
8	10	33.85	65.13	76.53	30.42	82.59	27.20	53.96
9	10	36.92	68.21	83.33	30.83	81.85	31.47	57.80
10	10	46.15	80.00	91.81	34.58	87.78	39.33	65.92

Table VIII shows comparison of the results between using ANN alone, ANN-SGO, ANN-PSO and ANN-ABC. The average of classification accuracy and convergence iteration are considered so that the convergence speed and effectiveness of the algorithm can be evaluated among different algorithms. From this table, by varying two main parameters of ANN, the learning rate and momentum constant, the accuracy of ANN combined with optimization algorithm is higher compared to ANN alone or without optimization.

TABLE VIII. ANN ACCURACY USING ANN ALONE, ANN-SGO, ANN-PSO AND ANN-ABC

AI Classifier	Accuracy (%)	Improvement compared to ANN alone (%)	Convergence iteration
ANN	65.92	-	-
ANN-SGO	97.36	31.44	17
ANN-PSO	85.92	20.00	20
ANN-ABC	96.64	30.72	34

From Table VIII, the highest overall classification accuracy is achieved by ANN-SGO with 97.36%, followed by ANN-ABC and ANN-PSO. The highest improvement compared to ANN alone is achieved by ANN-SGO. The fastest convergence is also achieved by ANN-SGO, which is also shown in Fig. 3. This is due to in SGO, there is an improvement phase, where each person gets knowledge from the group's best person to update their knowledge. This improves the convergence rate and fitness value.

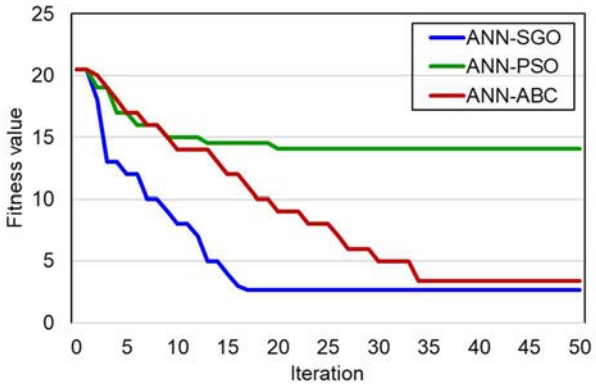

Fig. 3. Convergence curve for ANN-optimization algorithms

CONCLUSIONS

In this work, determination of the incipient faults within oil-insulated power equipment based on dissolved gas analysis (DGA) data has been successfully proposed using artificial neural network (ANN)-social group optimization (SGO) technique. The method was compared with combination with other algorithms, which include particle swarm optimization (PSO) and artificial bee colony (ABC) algorithms. From the results obtained, there is a significant improvement in the classification accuracies for the optimized ANN compared to the non-optimized ANN. Comparison among the optimized methods shows that ANN-SGO yields higher classification accuracy, with 97.36%, followed by ANN-ABC with 96.64% and finally ANN-PSO with 85.92%. ANN-SGO also converges the fastest among ANN-PSO and ANN-ABC. The results obtained indicates that the proposed technique could benefit the power industries in determination of the fault type within oil-insulated equipment automatically.

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