Power Transformer Fault Diagnosis Based On Hybrid Intelligent Algorithm

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Received: June. 28, 2022; Accepted: Mar. 04, 2023

The gas content in the oil is used as the fault input characteristic for the power transformer. Still, the accuracy of the diagnosis results is not ideal, and such a model is unstable. This research proposes a hybrid intelligent fault diagnosis method based on the improved grey wolf algorithm and an optimized probabilistic neural network. Firstly, a strategy of three nonlinear control factors is introduced to fit the grey wolves' search process. The weighted distance was modified to update the position information of grey wolf elements to avoid the algorithm falling into the local optimum. Secondly, the performance of the improved grey wolf algorithm was tested through six commonly used functions. The results show that the improved grey wolf algorithm has high convergence accuracy and stability in both multimodal and unimodal functions. Finally, the improved grey wolf algorithm and the probabilistic neural network were combined to diagnose the oil-immersed power transformer through hybrid intelligent algorithms. As a result, the fault diagnosis model proved valid for transformer fault diagnosis.

Keywords: transformer; fault diagnosis; control factor; weighted distance; grey wolf algorithm; probabilistic neural network

http://dx.doi.org/10.6180/jase.202401_27(1).0002

1. Introduction

The oil-immersed transformer is one of the critical pieces of equipment in the power system. Its operating status is related to the reliable power supply of the grid. Therefore, effectively improving the accuracy of transformer fault diagnosis has an essential impact on the stable operation of the power system. During the process of the transformer, hydrocarbon gases such as hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), and acetylene (C_2H_2) will be produced. Early failure before the damage. Such malfunctions can be diagnosed by dissolved gas analysis (DGA) methods. Its main advantages are that it can reduce downtime and bring expensive repair costs, convenient measurement, etc. [1].

Methods based on dissolved gas analysis (DGA) detection include the following: extraction of oil samples from transformer oil according to IEC-60567; measurement of dissolved gases using hydrogen monitors and photoacoustic spectroscopy (PAS); faults are analyzed according to the concentration of gas dissolved in the oil [2]. Preliminary explanatory theories for using hydrocarbon-dissolved gases to detect early faults are given in the reference [3]. Subsequently, many DGA-based diagnostic methods have emerged, such as the Rogers ratio, the Doernerburg ratio [4], and the GIGRE [5]. Traditional DGA gas data as an input quantity often requires the collection of gas diagnostic data. The reference [6] recommended using the IEC triple ratio method and collecting gas data from different transformers as the input characteristic quantity. However, DGA-based fault diagnosis techniques are based on experience, and these fault diagnosis techniques have certain uncertainties, and significant diagnostic errors often occur in practical applications.

Using simulation software to analyze transformer winding is also one of the effective methods for transformer early fault diagnosis. The primary method is frequency response analysis (FRA), which is highly sensitive. In reference [7], the R diagram, X histogram, and S diagram with eight tests are used for the first time to explain the FRA results. The experimental results show that the classification accuracy is effectively improved. The reference [8] calculates the frequency response in the current state by simulating the mechanical and electrical faults in the transformer windings to obtain the corresponding transfer function and uses the cross-correlation method and cluster analysis to explain the FRA results, which overcomes the problem of the transformer in the FRA method. An expert performs the detection task of the state. In [9], the combination of time series analysis and frequency response analysis (FRA) was used to distinguish and classify transformer windings' mechanical and electrical faults, and good results were achieved. However, the interpretation of FRA results in most of the previous literature still needs further improvement.

Artificial intelligence (AI) technology has also recently been used in fault diagnosis. This method has established a complex nonlinear relationship between dissolved gas analysis (DGA) gas content and transformer faults in many studies. Support vector machines (SVM) [10], fuzzy logic inference systems (FLIS) [11], Artificial neural networks (ANN) [12], etc., have improved the accuracy of transformer fault diagnosis, but there are also certain limitations. The Support vector machines (SVM) training algorithm has problems such as high complexity and long calculation time. The inference rules of the fuzzy logic inference systems (FLIS) rely heavily on experience. The Artificial neural networks (ANN) network structure and weight are difficult to determine, and it is easy to fall into local optimum. Other intelligent algorithms, such as Gray Cluster Analysis (GCA), are also used to classify early failures of power transformers. GCA does not need to design membership functions, develop rules, and assign linguistic variables, which is an advantage over fuzzy systems. Compared with popular neural networks, only fewer training samples are required [13]. However, this method is still in its infancy and requires further research. Furthermore, In [14], a systematic review of Fault Detection and Diagnosis (FDD) techniques and algorithms for power transformers from 1990 to 2020 from different aspects provides a comprehensive background for future research.

The grey wolf algorithm is an algorithm that uses iterative methods to continuously find its optimal value by simulating the wolf group hierarchy and predation process in the natural environment [15]. Probabilistic neural networks are suitable for classification and have strong generalization ability. Therefore, this paper improves the grey wolf algorithm and combines the improved grey wolf algorithm with the probability neural network (Improved Grey Wolf Optimize PNN, IGWO-PNN). And the improved hybrid intelligent algorithm is used in transformer fault diagnosis, and the four ratios are used as the input feature quantity of the model. The results show that transformer fault diagnosis accuracy has significantly improved.

2. Grey wolf algorithm

Mirjalili Mirjalili et al. [15] In 2014 a swarm intelligence optimization algorithm was proposed based on the hierarchy of grey wolf populations in nature and their collective siege and hunting process. α is the wolf with the highest level in the wolf group, representing the optimal solution in the people; β is the second-level wolf in the wolf pack, meaning the suboptimal solution of the people; δ is the wolf with the third level, representing the third optimal solution in the people; ω It is the ordinary gray wolf, meaning the candidate solution. Assuming the number of common grey wolves in the grey wolf population is K. The search space has N dimensions. The position of the i-th grey wolf in the N dimension can be represented as $\boldsymbol{G}_i = \left(g_i^1, g_i^2, \cdots, g_i^N\right), i = 1, 2 \cdots, K$. The grey wolf pack gradually approaches and surrounds the prey through the formula Eq. (1).

$$\mathbf{G}_{in}(t+1) = \mathbf{G}_{pn}(t) - \mathbf{A} \times \left|\mathbf{C} \times \mathbf{G}_{pn}(t) - \mathbf{G}_{in}(t)\right| \quad (1)$$

where t represent the current number of iterations. $\boldsymbol{G}_{pn}(t) = \left(g_p^1, g_p^2, \cdots, g_p^N\right)$ Position for prey. $\boldsymbol{A} \times \left|\boldsymbol{C} \times \boldsymbol{G}_{pn}(t) - \boldsymbol{G}_{in}(t)\right|$ Enveloping step.

A and C are the coefficients, which can be defined as:

$$\boldsymbol{A} = 2a \times r_1 - a \quad (2)$$

$$\boldsymbol{C} = 2 \times r_2 \quad (3)$$

Where: r_1 And r_2 are random numbers between $[0, 1]$. a is called the distance control factor, which decreases linearly from 2 to 0 with the increase of the number of iterations, ie

$$a = 2 - \frac{2t}{t_{\max}} \quad (4)$$

Where: $t_{\max}$ represent the maximum number of iterations. Other grey wolf individuals $\boldsymbol{G}_i$ in the pack update their positions according to the places $\boldsymbol{G}_\alpha$, $\boldsymbol{G}_\beta$ and $\boldsymbol{G}_\delta$ of α, β and δ.

$$\begin{cases} G_{in}^{\alpha}(t+1) = G_{n}^{\alpha}(t) - A \times \left| C \times G_{n}^{\alpha}(t) - G_{in}(t) \right| \\ G_{in}^{\beta}(t+1) = X_{n}^{\beta}(t) - A \times \left| C \times G_{n}^{\beta}(t) - G_{in}(t) \right| \\ G_{in}^{\delta}(t+1) = G_{n}^{\delta}(t) - A \times \left| C \times G_{n}^{\delta}(t) - G_{in}(t) \right| \end{cases} \tag{5}$$

$$G_{in}(t+1) = \frac{G_{in}^{\alpha}(t) + G_{in}^{\beta}(t) + G_{in}^{\delta}(t)}{3} \tag{6}$$

Eq. (5) defines the step size and direction of individuals α heading towards β and δ, respectively, while Eq. (6) defines the final position ω.

Due to the linear attenuation of the control factor in the late iteration, the GWO algorithm is prone to fall into local optimization. The control factor was changed into exponential form in literature [16, 17]. Local optimization ability has improved. The exponential control factors are shown in Eqs. (7) and (8).

$$a = 2 - 2 \times \frac{\left(e^{\frac{t}{t_{\max}}} - 1\right)}{e-1} \tag{7}$$

$$a = 2 - 2 \times \left(\frac{t}{t_{\max}}\right)^{u} \tag{8}$$

The above formula t is the current number of iterations, $t_{\max}$ is the maximum number of iterations, and u is the nonlinear coefficient. This paper proposes three nonlinear control factors, adjusts the proportional weight accordingly, and discusses the advantages and disadvantages of its performance to reduce the probability of falling into the local optimum.

The logarithmic control factor is

$$a = \left[\frac{2}{(\log t_{\max})}\right] \log\left(t_{\max} - t\right) \tag{9}$$

The index control factor 1 is

$$a = 2e^{-5t/t_{\max}} \tag{10}$$

The index control factor 2 is

$$a = 2e^{-\left(\frac{20}{19}t\right)t_{\max}} \tag{11}$$

The process of the control factor with the number of iterations is shown in Fig. 1.

Inspired by the other statues of α, β, δ wolves in the wolf pack, assigning the weights of $\alpha, \beta, \delta 4, 3,$ and 2 , respectively, and the sum of the weights being equal to 9 , according to the weighted average method, the expression is as follows:

$$G_{in}(t+1) = \frac{4G_{in}^{\alpha}(t) + 3G_{in}^{\beta}(t) + 2G_{in}^{\delta}(t)}{9} \tag{12}$$

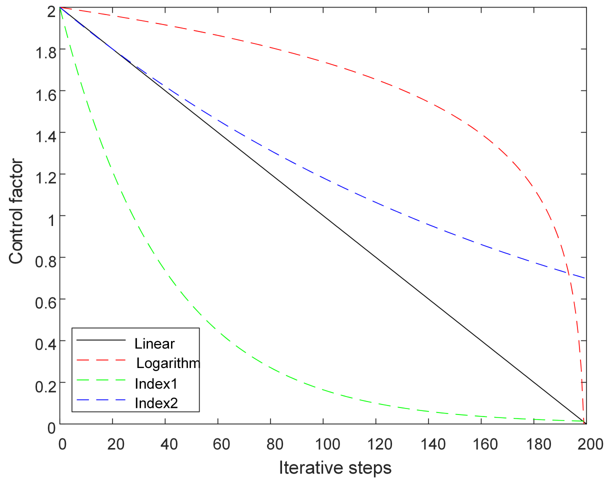

Fig. 1. Comparison of different control factors changes.

3. Algorithm testing and analysis

Six commonly used benchmark functions were selected to test the improved algorithm. The improved grey wolf algorithm is defined as GWOx$(x = 1, 2, 3)$. There are 2 unimodal functions (F_1, F_2) ,3 multimodal functions (F_3, F_4, F_5), and 1 fixed-dimensional multimodal function (F_6). The details are shown in Table 1. Among them, unimodal functions can be used to test the local optimization ability of the algorithm; Multimodal functions can be used to test the algorithm's convergence and global optimization abilities. The four algorithms were tested and run 20 times, respectively, and the mean, standard deviation, optimal value, and worst value of the objective function were taken in the test experiment.

3.1. Analysis of test experiment results

Under the same test conditions, through 20 repeated experiments, the experimental results are shown in Table 2. From the perspective of the average value, taking the function F_1 as an example, the average value of the GWO1 algorithm has increased by 10 orders of magnitude compared with the traditional GWO algorithm. The average of the results is better. According to the standard deviation, taking the function F_2 as an example, the standard deviation of the GWO1 algorithm has increased by 5 orders of magnitude compared with the traditional GWO algorithm. The standard deviation of the results is better. From the perspective of the optimal value, taking the function F_3 as an example, the optimal value of the GWO1 algorithm is 0 . The GWO algorithm is 3.6947 . The optimal value of the results is better. Besides, the four indicators were combined to rank. According to the comprehensive ranking, the (GWO1) algorithm has a more robust convergence performance and

Table 1. Standard test function table

Function	Dimensionality	Searching space	Optimal value
$F_1(g)=\sum_{i=1}^{n} g_i^n$	30	$[-100,100]$	0
$F_2(g)=\sum_{i=1}^{n}\lvert g_i\rvert+\Pi_{i=1}^{n}\lvert g_i\rvert$	30	$[-10,10]$	0
$F_3(g)=\sum_{i=1}^{n}\left[g_1^2-10\cos(2\pi g_i)+10\right]$	30	$[-5.12,5.12]$	0
$F_4=-20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} g_i^2}\right) -\exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi g_i)\right)+e+20$	30	$[-32,32]$	0
$F_5(g)=\frac{1}{400}\sum_{i=1}^{n} g_i^2-\prod_{i=1}^{n}\cos\left(\frac{g_i}{\sqrt{i}}\right)+1$	30	$[-600,600]$	
$F_6(g)=\left[1+(g_1+g_2+1)^2(19-14g_1+3g_1^2 -14g_2+6g_1g_2+3g_2^2)\right]\times\left[30+(2g_1-3g_2)^2 \times(18-32g_1+12g_1^2+48g_2-36g_1g_2+27g_2^2)\right]$	2	$[-2,2]$	3

higher optimization accuracy.

3.2. Convergence curve analysis

Based on the unimodal test function convergence curves, as shown in Fig. 2(F_1) and (F_2), and compared with the other three algorithms, the (GWO1) algorithm has an ideal optimization effect in the later stage of optimization. As shown in the curve in the search process, the (GWO1) algorithm can effectively avoid local convergence, mainly due to improved control factors and weight ratios. Fig. 2(F_3) – (F_6) show the convergence curves of the multimodal test functions. At an early stage, the optimization ability of the four algorithms is the same. However, the (GWO1) algorithm can quickly jump out of the local optimal compared to other algorithms. It is shown in the curve. The (GWO2) algorithm stops searching when the optimal solution is first found. In contrast, The (GWO1) algorithm continues to improve and locks faster with better results. Based on the above analysis, it can be seen that the GWO1 algorithm has a good optimization ability.

4. Transformer fault diagnosis

Power transformer fault types can be divided into five categories, including Partial discharge(PD), Low-energy discharge(D1), High-energy discharge(D2), Thermal fault of low and medium temperature(T1), and Thermal fault of high temperature(T2). The data in this paper come from 117 sets of data from the International Electrotechnical Commission [6], 78 sets of data from Gansu Electric Power Research Institute [18], and 456 sets of data from the doctoral dissertation of North China Electric Power University [19]. After removing the unavailable data, the three sets of transformer fault data are shown in Table 3.

The fault data of three sets of transformers are converted into four groups of ratios ($CH_4/H_2, C_2H_6/CH_4, C_2H_4/C_2H_6$, and C_2H_2/C_2H_4), Because there are a lot of data in sample 2, to reduce the differences between the data, the data of sample 2 is normalized. The normalization function is as follows:

$$Z_i=\frac{z_i-z_{\min}}{z_{\max}-z_{\min}} \tag{13}$$

The above equation z_i represents the value before normalization. $z_{\min}, z_{\max}$ represent the minimum and maximum values before normalization.

4.1. Simulation test analysis

IEC TC 10 samples are brought into the GWO1-PNN model to train the model. The sum of squared errors is shown in Fig. 3.

As can be seen from Fig. 3, when the evolution reaches 8 generations, the sum of squared errors reaches the minimum. Therefore, the optimized value of the 8th generation is brought into the polar PNN model to predict the test samples. The diagnosis results are shown in Table 4. Table 4 shows that the correct rate for the test set is 92.59%.

Sample 1 was put into the GWO1-PNN model to train the model. The diagnosis results of various transformer faults by the GWO1-PNN model are shown in Fig. 4. Fig. 4 shows that the correct rate of the test set is 94.44%.

Similarly, we will bring sample 2 into the GWO1-PNN model to train the model. Among them, 196 sets are used as the training set, and 84 sets are used as the test set. There are five types of faults in both the test and training sets. The diagnostic results showed that the accuracy of the test set was 85.1%.

4.2. Comparative analysis with other algorithms

To further verify the superiority of the proposed method in power transformer fault diagnosis, three standard fault diagnosis methods are compared as follows: Optimization of fault diagnosis model of extreme learning machine based

Table 2. comparison results of GWOx algorithms

Result	Function	GWO	GWO1	GWO2	GWO_3
Average value		$0.0442e-9$	$0.0929e-19$	0.0285	$0.0301e-14$
Standard deviation		$0.0417e-9$	$0.1247e-19$	0.0162	$0.0301e-14$
Optimal value	F_1	$0.0053e-9$	$0.0008e-19$	0.0045	$0.0004e-14$
Worst value		$0.1880e-9$	$0.4820e-19$	0.0657	$0.1401e-14$
Ranking		3	1	4	2
Average value		$0.0562e-4$	$0.0282e-9$	0.7250	$0.0490e-7$
Standard deviation		$0.0276e-4$	$0.0334e-9$	0.2911	$0.0316e-7$
Optimal value	F_2	$0.0139e-4$	$0.0053e-9$	0.3263	$0.0160e-7$
Worst value		$0.127le-4$	$0.1842e-9$	1.4421	$0.1468e-7$
Ranking		3	1	4	2
Average value		17.6980	2.3308	71.3417	20.3857
Standard deviation		6.8414	4.4814	20.7534	13.0065
Optimal value	F_3	3.6947	0.0000	41.7085	0.0000
Worst value		34.6044	14.9898	151.2595	47.9688
Ranking		2	1	4	3
Average value		20.9249	20.8338	20.9810	20.9043
Standard deviation		0.0652	0.0970	0.0677	0.0508
Optimal value	F_4	20.7688	20.5880	20.8218	20.8173
Worst value		21.0367	20.9747	21.1022	21.0508
Ranking		3	1	4	2
Average value		0.0074	0.0045	0.0300	0.0075
Standard deviation		0.0099	0.0096	0.0211	0.0149
Optimal value	F_5	0.0000	0.0000	0.0008	0.0000
Worst value		0.0319	0.0324	0.0604	0.0567
Ranking		3	1	4	2
Average value		3.0000	3.0000	6.6004	5.7003
Standard deviation		0.0002	0.0001	15.4263	14.7901
Optimal value	F_6	3.0000	3.0000	3.0000	3.0000
Worst value		3.0011	3.0003	84.0000	84.0087
Ranking		2	1	4	3

Table 3. Fault samples of transformers

Fault type	PD	D_1	D_2	T_1	T_2
IEC TC 10 fault samples	6	24	45	15	17
fault samples 1	7	7	12	23	13
fault samples 2	19	64	66	44	87

on grey wolf algorithm. Fault diagnosis model of a probabilistic neural network optimized by grey wolf algorithm. Fault diagnosis model of probabilistic neural network. The IEC TC, 10 fault samples, were inputted into the four models, and the experiments were repeated 10 times each. The results with the highest accuracy were selected, as shown in Fig. 5. As can be seen from Fig. 5, the fault diagnosis and recognition rate based on GWO1-PNN is higher, which is better than the other three algorithms. The test set fault accuracy of GWO-PNN is 81.48%, the test set fault accuracy of GWO1-PNN is 92.59%, and the accuracy of the improved hybrid intelligent algorithm is improved by 11.11%.

Based on the above analysis, GWO1-PNN has high accuracy and stability for transformer fault diagnosis.

5. Conclusion

The swarm intelligent optimization algorithms have shortcomings, such as incompatibility of global and local search capabilities. The control factor and position update formula limit global and regional search performance in the GWO algorithm. This paper analyzes and compares four control factors and finally uses a logarithmic control factor instead of a linear control factor to improve the position update formula further. The improved GWO1 is combined with PNN for transformer fault diagnosis, proving it has good fault diagnosis performance. The conclusions are as follows:

1. Given the problem that the traditional GWO algorithm quickly falls into local optimal, the GWO1 algorithm in this paper, by improving the control factor and adjusting the corresponding weight, uses the weighted sum to update the position. It finds that the GWO1 algorithm has better optimization ability; by reducing this possibility, the algorithm can more quickly find the optimal global solution and reduce the probability that it will fall into the optimal local solution.

Table 4. Diagnosis results for GWO1-PNN

Type	GWO1-PNN			
	training/group	test/group	wrong / group	accuracy rate/%
1	5	1	0	100
2	19	5	0	100
3	36	9	0	100
4	10	7	1	80
5	10	7	1	85.71
sum	80	27	2	92.59

2. Through six standard function test experiments, it is concluded that compared with the traditional grey Wolf algorithm. The GWO1 algorithm has better optimization accuracy and a more substantial convergence effect, which verifies the effectiveness of the improved strategy proposed in this paper.

3. The GWO1-PNN algorithm has a better fault identification rate than the GWO-ELM, GWO-PNN, and PNN algorithms. The input of feature parameters into the GWO1-PNN model can achieve an accurate diagnosis of transformer faults.

Acknowledgments

In writing this article, I consulted many documents and books. I referred to the published articles and officially published books of relevant experts and scholars. I also quoted the experimental data of doctoral students and experts. This data is typically transformer fault data that is representative and reliable. I thank master's student Wu Ma er for contributing to English error correction. Lu Xiaojuan, for her valuable comments. Please correct and critique the errors since the author's ability and level still need improvement. I would be very grateful.

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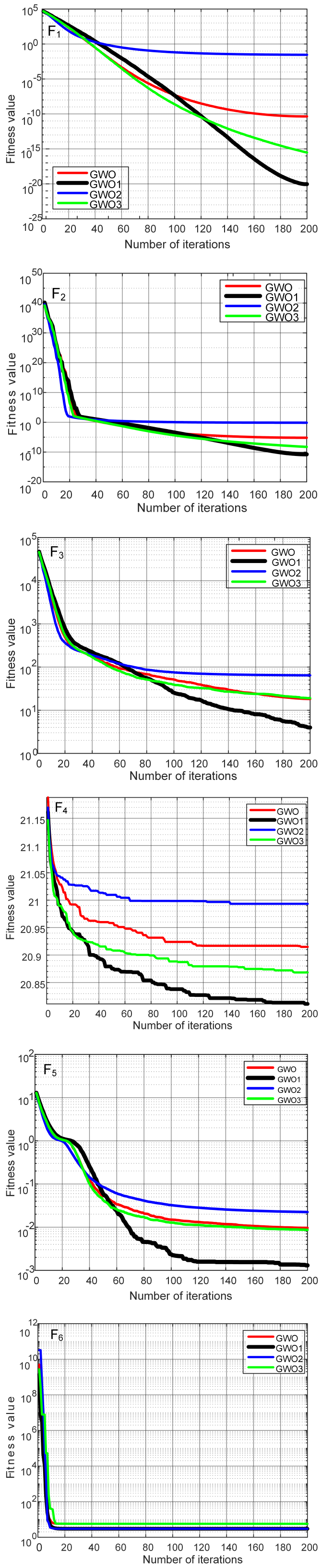

Fig. 2. Convergence Curves Based on Test Functions from F_1 to F_6

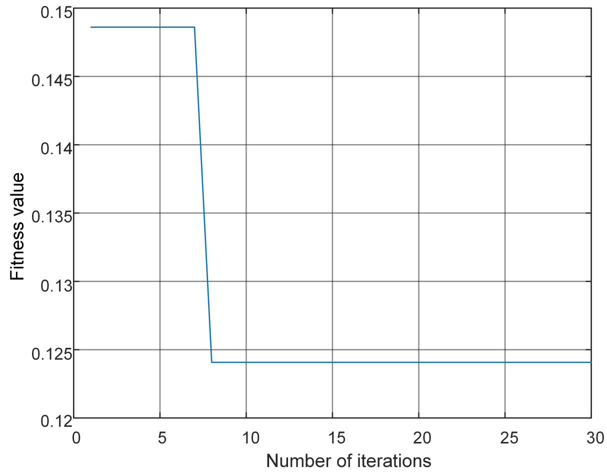

Fig. 3. Grey wolf iteration curve

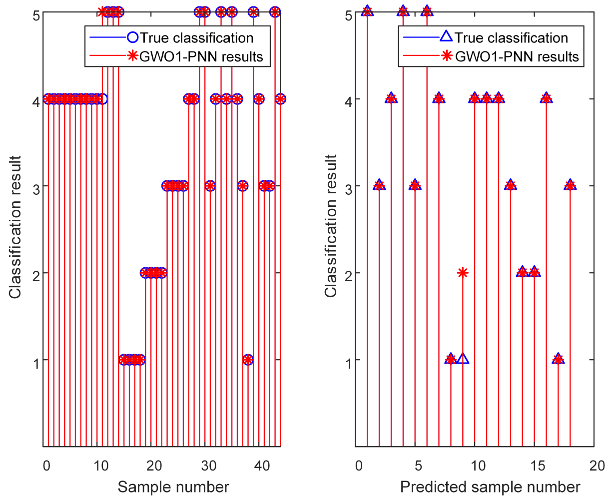

Fig. 4. Diagnosis results for GWO1-PNN

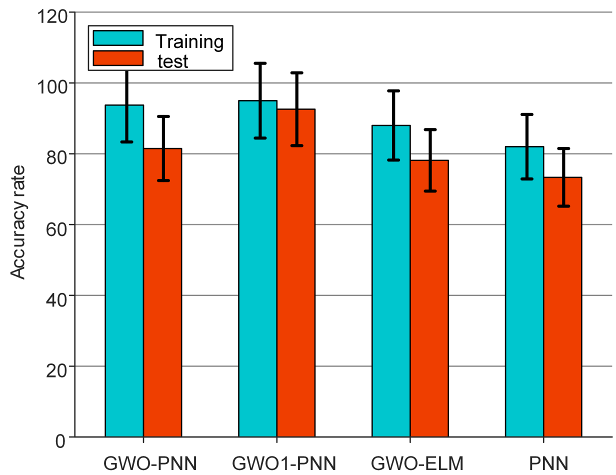

Fig. 5. Comparison diagram

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