

Fault Diagnosis of Hydraulic System based on SOM Neural Network

Ji Chen¹, Ao Xiao¹, Zhihui Li¹, Jiaqing Liu¹, Mengyuan Feng¹, Hao Xue¹, Siwen Gu^{1,2,*}

¹ School of Optoelectronic Engineering, Changzhou Institute of Technology, Jiangsu, 213302, China

² School of Chemical Engineering, Dalian University of Technology, Liaoning, 116024, China

Abstract: The working principle of hydraulic system is to use the flow and pressure of liquid in the system for energy transfer and conversion. Hydraulic system realizes various work tasks such as pushing, grasping, lifting, rotating, etc. by controlling the action of hydraulic actuators. Its advantages are high power density, good stability, fast response time, smooth power output, etc. The disadvantage is that the hydraulic system is easy to lose control of more points. In this paper, taking the horizontal outrigger hydraulic circuit as an example, the hydraulic pump leakage, etc. is used as a fault sample, and the SOM neural network is used for fault diagnosis to make timely and accurate diagnosis of the abnormal or fault state of the hydraulic system, give guidance on the operation of the hydraulic system, improve the reliability and safety of operation, and reduce the fault loss to a minimum.

Keywords: Fault Diagnosis; Neural Network; Hydraulic System.

1. Problem Description

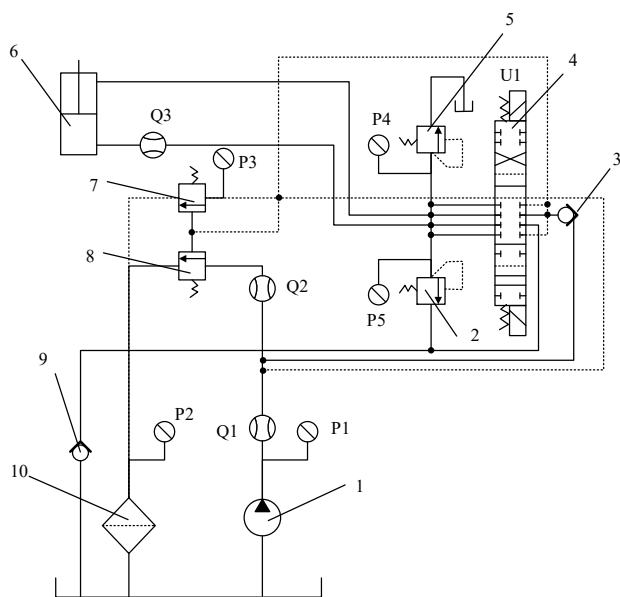


Figure 1. Schematic diagram of horizontal outrigger hydraulic circuit

A horizontal outrigger hydraulic circuit of a construction machine was applied as a test device to verify the application

of SOM neural network in fault diagnosis. The schematic structure of the horizontal outrigger hydraulic circuit is shown in Figure 1. Sensors are used to monitor the output values of the various test points when the equipment failure occurs. Their measurement results are listed in Table 1.

The main role of the horizontal outrigger hydraulic circuit is used to support and stabilize the balance of large machinery and equipment or vehicles. The working process is that the hydraulic pump pushes the liquid to the hydraulic cylinder through high pressure, and the piston moves accordingly to achieve the expansion and contraction of the horizontal leg to maintain the balance. By controlling the opening and closing of the valve and relief valve, the flow and pressure of the fluid can be adjusted to precisely control and stabilize the horizontal legs. In Figure 1, 1 is the hydraulic pump, 2, 3 is the relief valve, 3 is the check valve, 4 is the solenoid reversing valve, 6 is the outrigger hydraulic cylinder.

There are eight common causes of failure in this hydraulic system, which are leakage of hydraulic pump, blockage of screen, burned solenoid valve, damage of outlet relief valve of reversing valve, blockage of damping hole or spring of system safety valve, blockage of damping hole of pressure compensation valve, leakage in hydraulic cylinder and overload of hydraulic pump. As shown in Table 1, this paper collects eight fault samples, each containing ten features, in addition to two fault states to be identified as shown in Table 2.

Table 1. Hydraulic system standard failure samples

Cause of failure	Q1	Q2	Q3	P1	P2	P3	P4	P5	U	I
hydraulic pump leakage	10	9	1	5	0.05	5	0	5	24	2
filter blockage	28	26	2	15	0.5	15	0	15	24	2
solenoid valve burned out	28	0	2	18	0.05	17.5	0	0	24	2
damage to the outlet relief valve of the reversing valve	28	26	2	15	0.05	17.5	0	17.5	24	2
system safety valve damping hole blockage or spring damage	28	0	0	18	0	18	0	16	24	2
pressure compensation valve damping hole blockage	28	26	2	15	0.5	15	0	15	24	2
leakage in the hydraulic cylinder	28	28	0	15	0.05	15	0	15	24	2
hydraulic pump overload	28	26	2	15	0.05	15	0	10	24	2

Table 2. Fault samples to be tested

Number	Q1	Q2	Q3	P1	P2	P3	P4	P5	U	I
D1	26	26	0	12	0.04	14	0.08	14	21	19
D2	25	24	1.6	18	0.05	16	0.002	16	25	19

2. Fault Diagnosis Steps based on SOM Neural Network

The application of SOM neural networks in fault diagnosis is generally divided into the following steps [1-5]:

1. Common fault types are selected to extract fault features. Each type contains feature values that are used to characterize the faults.

2. Build SOM neural network and train on common fault types. During training, input feature values and get the similarity between neurons and feature values. After the training is completed, label the standard output neurons. Repeat the above process so that the neural network can learn and adapt to various fault types.

3. Input the data to be tested into the SOM neural network after the training is completed for testing.

4. Compare the position of the standard output neuron with the position of the output neuron of the sample to be tested.

5. Determine the fault type based on neuron positions.

The flow chart of the algorithm is shown in Figure 2.

Relying on the MATLAB software platform, click Import Data on the menu bar, select the data file (e.g., .txt format) to be imported, and then convert it to .mat format. Click on the converted file in the workspace to obtain the corresponding data [6-8]. Be sure to save the converted file to the correct folder. The steps are as follows [9, 10]:

1. Web sample design

From the above table, 8 fault samples are obtained, each with 10 characteristics.

2. Web creation

Create a SOM network using the function newSOM.

The code is `net=newSOM(minmax(P), [10 10])`.

Where P is the input vector, derived from the table above. The `minmax(P)` specifies the maximum and minimum values of the input vector elements, and `[10 10]` indicates that the competitive layer of the created network is a 10×10 structure. the network structure is able to be adjusted, and if the number of neuron nodes is too small, it will be insufficient to distinguish all patterns, and the training results will inevitably combine similar pattern classes into one class. The sample size here is large, so the choice of such a competitive layer is appropriate.

3. Web training and testing

In order to train and simulate the network, this paper sets different training steps: 10, 30, 50, 100, 200, 500 and 1000, and observes and compares the changes of its weight distribution. The code for training 10 times is:

```
plotSOM(net.layers{1}.positions)
a= [10 30 50 100 200 500 1000].
```

Showing the different number of times of 7 neural network trainings with placement values of 10, 30, 100, 200, 500 and 1000 times.

```
yc=rands(10,8);
```

Setting up a random initialization of a 1×10 vector;

```
net.trainparam.epochs=a(1);
```

Starting training with a training count of 10;

```
net=train(net,P); y=sim(net,P);
```

```
yc(1,:)=vec2ind(y);
```

```
plotSOM(net.IW{1,1},net.layers{1}.distances)
```

Training the web as well as viewing the classification, the classification results are in the first row of the output result yc.

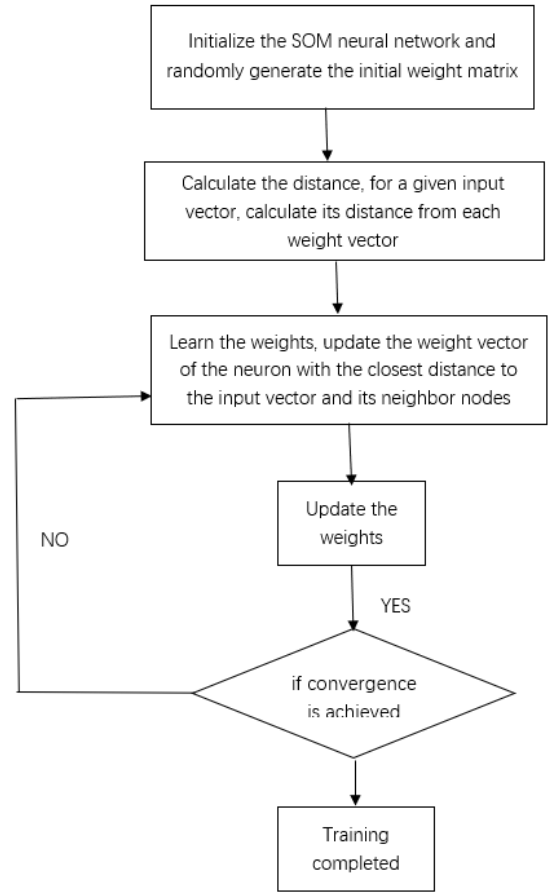


Figure 2. SOM neural network algorithm flow chart

3. Analysis of Results

In the MATLAB simulation experiment, the SOM neural network is created, and the standard fault samples are input to train the SOM neural network. The neural network training process is shown in Figure 3, where input is 10, indicating that there are 10 sample sizes, SOM Topology SOM is the neural network topology, SOM Neighbor Connections is the SOM each neighborhood connection, SOM Neighbor Distances is the distance distribution between adjacent neurons after completing the training SOM Input Planes are the weights of each output, SOM Sample Hits are the positions of SOM neuron weight vectors, and SOM Weight Positions are the distribution of each neuron.

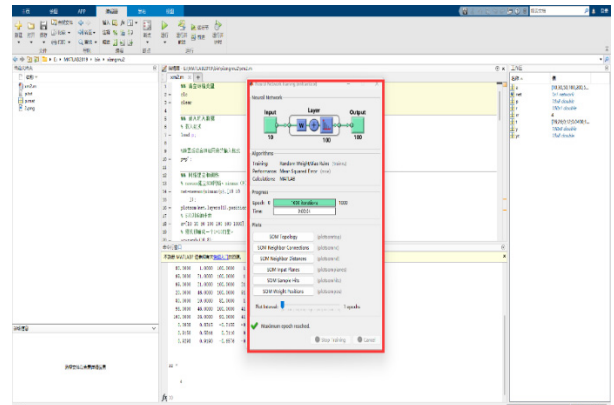


Figure 3. Neural network training process

The results of the operation are shown in Table 3, and the result of rr is 4.

Table 3. Operation results

Training steps	Clustering results							
10	80	1	100	1	100	1	1	1
30	99	21	100	1	90	21	2	3
50	99	21	100	21	80	21	3	12
100	20	46	100	91	96	46	45	1
200	80	10	81	1	95	10	5	46
500	96	46	100	41	92	46	2	40
1000	100	26	93	41	76	26	1	10

Based on the results of the above operation, it can be seen that at a training step of 200, the neural network is already able to classify each sample correctly, and further increasing the number of training steps will not change the classification results. Therefore, when training the network, choosing a training step of 200 can achieve satisfactory clustering performance while avoiding the problem of overfitting. This ensures that the network can accurately classify the input vectors and has a good generalization capability.

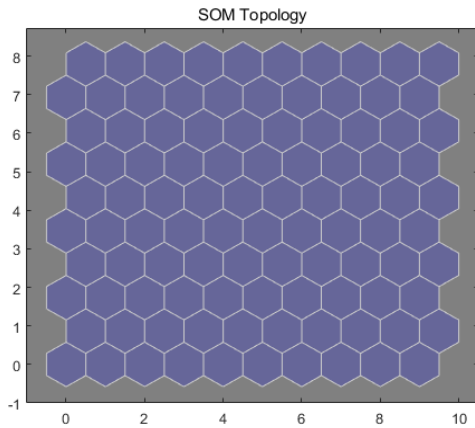


Figure 4. SOM neural network topology diagram

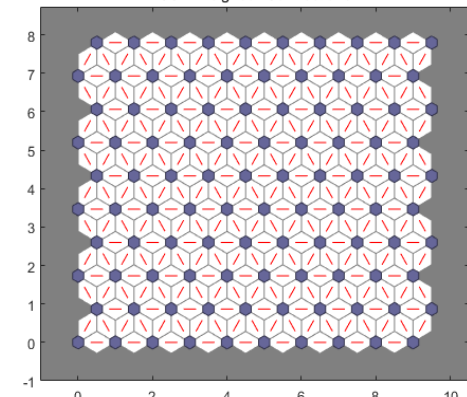


Figure 5. Connection of the SOM neighbors

The topology of the SOM neural network is shown in Figure 4. Each hexagon represents a neuron, starting from 0 to 10 on the bottom and starting from -1 to 8 on the right vertical axis, forming a 10*10 neuron matrix for training the neural network. The connection diagram of each neighborhood of SOM is shown in Figure 5. The plotSOMnc (net) plots a SOM layer showing the neurons as gray patches and their direct neighborhood relationship with the red line. The distribution of distances between neurons is shown in Figure 6, and it is determined that the SOM neural network

achieves clustering by calculating the distances between neurons. However, in some cases, the complex distribution of distances between neurons may lead to unclear boundaries between clustering results. This may also mean that the parameters of the neural network need to be further adjusted or other algorithms introduced to improve the clustering performance.

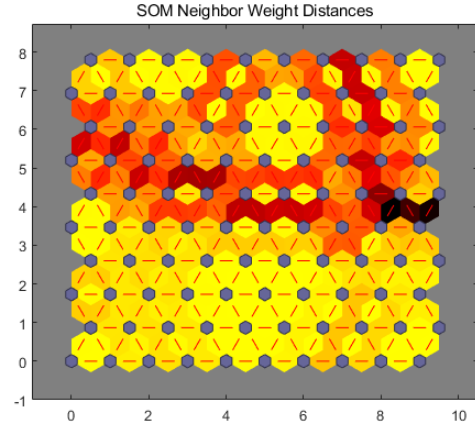


Figure 6. Distribution of distances between adjacent neurons after completing training

The SOM neuron weight vector locations are shown in Figure 7. The plotSOMpos (net) plots the input vectors as green dots and shows how the SOM classifies the input space by displaying the blue-gray dots of each neuron's weight vector and connecting adjacent neurons to the red line.

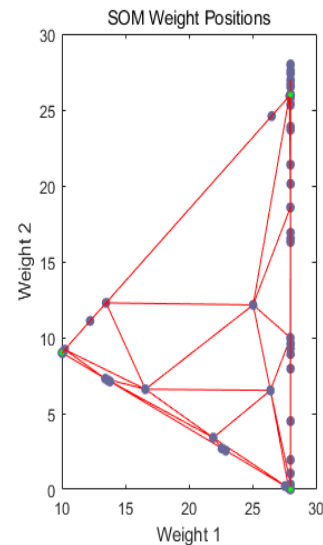


Figure 7. Location of SOM neuron weight vectors

According to the two groups of fault samples to be classified as shown in Table 2, they are entered into the program for classification respectively, and the classification procedure is as follows:

```

t= [ ]; % Enter the sample to be tested;
r=sim(net,t); % Network Simulation;
rr=vec2ind(r) % Transformation function that converts a
single-valued vector into a subscripted vector;

```

The above procedure enables to call the trained SOM neural network to determine which fault type the undetected data belongs to. The distribution of neurons is shown in Figure 8 and Figure 9. It is known that there are eight different states in the mapping from the input layer to the competing layer. Each state is assigned to a corresponding neuron

location, represented by a different token. Using the standard sample state as a benchmark, when the input state is the same or similar to that standard state, the position of the neuron output in the competitive layer will be the same or similar to the position of some standard fault sample. The SOM neural network can be trained to map the input vectors of different states to the corresponding neuron positions on the competing layers to achieve state classification and identification. When the input states are similar to the standard fault samples, the neural network is able to accurately classify them to their corresponding positions. This provides a pattern-matching-based approach to fault diagnosis, making it possible to determine the type of fault based on the similarity of the location of the input vector to the location of the standard sample.

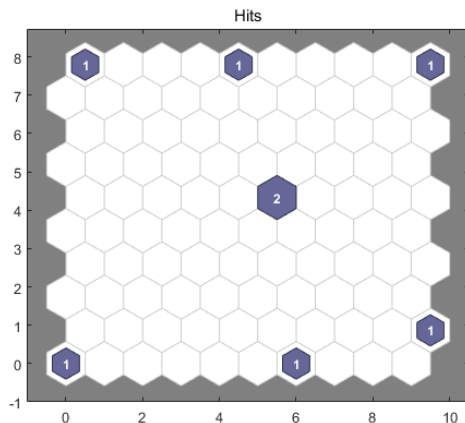


Figure 8. Classification of D1 neurons

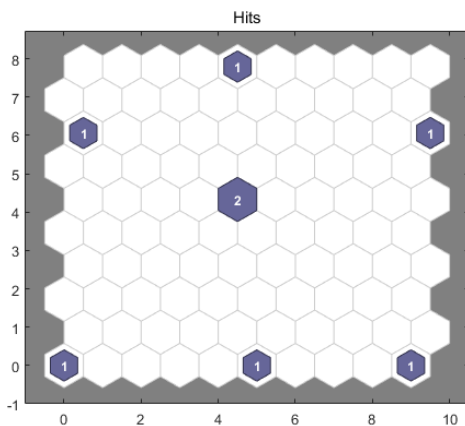


Figure 9. Classification of D2 neurons

4. Conclusion

In this paper, we use SOM neural network to perform fault diagnosis of hydraulic system and confirm that the fault diagnosis method of SOM neural network is a relatively accurate fault diagnosis method. Compared with the traditional rule-based or experience-based diagnosis methods,

SOM neural network can automatically learn the correlation and laws between sample data and identify the fault types by clustering the sample data, thus improving the accuracy and reliability of diagnosis. Through the training of large amount of data, it can accurately identify the given unknown fault data and give hints.

Acknowledgments

This paper is supported by the Project of Innovation and Entrepreneurship Training Program for University Students (Provincial General Project, Project No. 202211055075Y); the Project of Industry-University-Research Cooperation in Jiangsu Province (Project No. BY2022786); and the Basic Science (Natural Science) Program for Higher Education Institutions in Jiangsu Province (Project No. 21KJD530002).

References

- [1] Cui, Y. Q.; Shi, J. Y.; Wang, Z. L. System-level operational diagnosability analysis in quasi real-time fault diagnosis: The probabilistic approach. *Journal of Process Control*. 2014, 24(9): 1444-1453.
- [2] Bastani, K.; Kong, Z.; Huang, W.; Huo, X.; Zhou, Y. Fault Diagnosis Using an Enhanced Relevance Vector Machine (RVM) for Partially Diagnosable Multistation Assembly Processes. *IEEE Transactions on Automation Science and Engineering*. 2013, 10(1): 124-136.
- [3] Simani, S.; Zattoni, E. Advanced Control Design and Fault Diagnosis. *Energies*. 2021, 14(18): 5699.
- [4] Afef F.; Hamed H.; Silvio S. Fault Diagnosis and Fault Tolerant Control of Wind Turbines: An Overview. *Energies*. 2022, 15(7186): 7186.
- [5] Ozansoy, C.; Gomes, D.P.S. Volatility Diagnosis in Phase-to-Phase Fault Detection for Branch Across Wire Faults. *IEEE Transactions on Power Delivery*. 2021, 36(1): 19-29.
- [6] Arunthavanathan, R.; Khan, F.; Ahmed, S.; Imtiaz, S. An analysis of process fault diagnosis methods from safety perspectives. *Computers & Chemical Engineering*. 2021, 145: 107197.
- [7] Chen, M.; Zhang, F.; Zhu, Y.; Zhang, K.; Li, Q. A Review of Fault Diagnosis, Status Prediction, and Evaluation Technology for Wind Turbines. *Energies*. 2023, 16(3): 1125.
- [8] Qi, B.; Liang, J.; Tong, J. Fault Diagnosis Techniques for Nuclear Power Plants: A Review from the Artificial Intelligence Perspective. *Energies*. 2023, 16(4): 1850.
- [9] Fu, Y.; Yang, G.; Ma, H.; Chen, H.; Zhu, B. Statistical Diagnosis for Quality-Related Faults in BIW Assembly Process. *IEEE Transactions on Industrial Electronics*. 2023, 70(1): 898-906.
- [10] Rosato, A.; Piscitelli, M.S.; Capozzoli, A. Data-Driven Fault Detection and Diagnosis: Research and Applications for HVAC Systems in Buildings. *Energies*. 2023, 16(2): 854.