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Intelligent Fault Diagnosis Method For Spacecraft Fluid Loop Pumps

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China space station has achieved full completion, with spacecraft fault diagnosis technology being a pivotal element to ensure the sustained, secure, and reliable operation of the space station. It directly supports a series of important tasks such as status monitoring, life extension, on-orbit maintenance, and spare parts reserves. The paper takes the spacecraft fluid loop pump as an example and conducts research on the application of four neural network models, namely, back propagation neural network (BP), particle swarm neural network (PSO-BP), genetic algorithm neural network (GA-BP), and fuzzy neural network (FNN), in fault diagnosis.

In the field of spacecraft fault diagnosis, NASA and ESA have conducted early research on in-orbit fault diagnosis technology for manned spacecraft. They have developed the manned spacecraft fault management system—the Advanced Caution and Warning System (ACAWS), which achieves spacecraft fault diagnosis and health status management at the system level. However, due to the earlier design era of the International Space Station, its fault diagnosis lacks intelligence.

Specifically, based on the experience of the Mir space station and the international space station, the thermal control subsystem, especially the fluid loop pump, has a higher failure rate. It is a product that should be a key focus of on-orbit maintenance and fault diagnosis for the space station. The fluid loop pump is the "heart" of the spacecraft fluid loop system, and any failure may directly lead to the failure of the fluid loop system and temperature control, directly affecting the safe and reliable operation of various equipment on the spacecraft and even the lives and health of astronauts. Therefore, researching fault diagnosis technology for spacecraft fluid loop pumps is of great significance for ensuring the safety of spacecraft and personnel. In the future, the fault diagnosis technology for spacecraft fluid loop pumps will continuously improve its applicability to diverse faults and multidimensional data, and intelligent fault diagnosis technology is an important development trend.

The studied spacecraft fluid loop pump is equipped with a pressure sensor, a rotation speed sensor, a temperature sensor, and a flow rate sensor, providing data on pressure, speed, temperature, and flow—four categories of status parameters that form the data foundation for fault diagnosis. The proposed fault diagnosis method in this article is based on four neural network models: BP, PSO-BP, GA-BP, and FNN. Each neural network has an input layer with four neurons corresponding to four status parameters and an output layer with one neuron corresponding to the status indicator. Due to space constraints, detailed parameter settings for each neural network are not discussed here.

The training of neural networks is based on a dataset. The dataset in this article reflects the mapping relationship between status parameters and status indicators and is derived from in-orbit data, ground test data, and expert experience data. As shown in Table 1, the dataset includes six categories of status indicators, with temperature (℃), flow rate (L/h), outlet pressure (kPa), and rotation speed (rpm) as inputs, and each status indicator represents a type of status.

The training and prediction effects are evaluated using a 6-fold cross-validation method, with 85% of the data used for training and 15% for testing. After inputting the diagnostic data into the trained neural network model, the model will output the predicted value P_0 of the status indicator. The status indicator P is obtained by rounding to the nearest integer, completing the fault diagnosis. Status indicators 1, 2, 3, 4, 5, and 6 represent “normal”, “slight rubbing between the impeller and pump casing”, “severe rubbing between the impeller and pump casing”, “fatigue spalling of bearing raceway”, “severe fatigue spalling of bearing raceway”, and “impeller jammed, pump functionality lost”, respectively.

Table 1. Fluid loop pump data set (Partial Data)

Number	Temperature (℃)	Flow rate (L/h)	Outlet pressure (kPa)	Rotation speed (rpm)	Status indicator
1	5.30	337.75	339.18	9399.99	1
2	6.90	310.68	330.83	8286.40	2
3	15.30	239.61	239.30	5325.57	3
4	23.28	342.67	329.18	8388.24	4
5	35.29	237.44	238.14	6313.82	5
6	4.92	342.68	159.49	1.92	6

Following 6-fold cross-validation calculations, the mean value of mean squared errors and correlation coefficients of the test sets for BP, PSO-BP, GA-BP, and FNN are as follows: 0.1299 and 0.988, 0.2625 and 0.9551, 0.0323 and 0.9945, 0.0286 and 0.9973, respectively. Notably, the FNN exhibits the smallest mean squared error and the highest correlation coefficient, underscoring its superior predictive performance.

Building upon the aforementioned algorithms, a spacecraft fluid loop pump fault diagnosis software has been created. This software encompasses functionalities such as data import, model training, and fault diagnosis. By importing in-orbit data from the two sections of the fluid loop pump depicted in Figure 1 into the software and averaging the four categories of status parameters, the software performs fault diagnosis. The results indicate "normal" and "impeller jammed, pump functionality lost," respectively, aligning seamlessly with the actual on-orbit working states. All four neural networks demonstrate accurate identification of these two states.

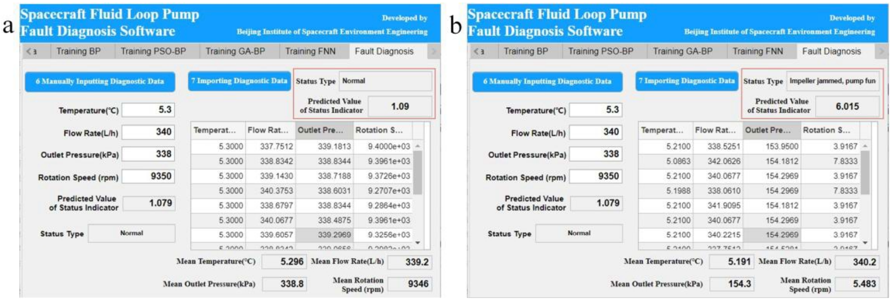

Fig. 1 spacecraft fluid loop pump fault diagnosis software and preliminary application verification. (a) normal state; (b)fault state.

The research results of this article demonstrate that all four neural network models in the paper can accurately identify the on-orbit normal and fault states of the fluid loop pump, with the FNN showing the best performance. Intelligent fault diagnosis models like neural networks will be practically applied in more Chinese spacecraft products.

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References

Cao, J., Gu, Y., Chen, G., et al. 2017. The flight experiments of active thermal control system with micro-mechanical pumped fluid loop. Spacecraft Environment Engineering 34(04), 343-349 (in Chinese).

Colombano, S. P., Spirkovska, L., Baskaran, V. et al. 2013. A system for fault management and fault consequences analysis for NASA’s Deep Space Habitat. In AIAA SPACE 2013 Conference and Exposition, San Diego, USA, September 10-12, 1-17.

McCann, R. S., Spirkovska, L., Smith, I. 2013. Putting integrated system health management to work: development of an advanced caution and warning system for next-generation crewed spacecraft missions. In AIAA Infotech@ Aerospace (I@A) Conference, Boston, USA, August 19-22, 1-15.

Thurman, R.L. 1996. Automation of space station thermal control systems-the important role of software. SAE Technical Paper 961604, 1-11.