Sensors and Materials, Vol. 33, No. 9 (2021) 3345–3359
MYU Tokyo

S & M 2694

Effective Maintenance of Components in T700 Engine Using Backpropagation Neural Network

Dong-Kai Qiao,[1] Yan-Zuo Chang,[1*] Tian-Syung Lan,[2**] Yung-Jen Lin,[3] and Tung-Keng Yang[3]

[1]College of Mechanical and Electrical Engineering, Guangdong University of Petrochemical Technology, Maoming Guangdong 525000, China
[2]Department of Information Management, Yu Da University of Science and Technology, Miaoli County 36143, Taiwan
[3]College of Engineering, Tatung University, Taipei City 104, Taiwan

(Received March 31, 2021; accepted June 17, 2021)

Keywords: aircraft component, component failure, prediction of component failure, Delphi method, MAPE, backpropagation neural network

Predicting the exact time of failure for aircraft components is critical as a failure may cause a fatal accident, have a high cost, and waste a large amount of time. Accurate prediction will help reduce the occurrence of unexpected failures and ensure safe flights. Thus, we propose a model for predicting the lifetime and failure of components, which uses the modified Delphi method and a backpropagation neural network (BPNN). To select the significant factors that affect the lifetime, a questionnaire survey on experts was first carried out. As a result, 17 factors were defined, and through a second survey, the following seven factors were selected from the criteria of average scores and standard deviations: operation hours after installation, the resistance of the thermocouple assembly, and the ohm values obtained from a hydraulic machinery control unit linear displacement sensor, a power turbine speed sensor, a torque and overspeed sensor, an overspeed leakage solenoid valve, and the torque motor of the hydraulic control unit. The training data were obtained from maintenance data using various sensors of the electronic control unit (ECU) of an engine (T700) of a helicopter in Taiwan collected during 2011–2013. By using Alyuda NeuroIntelligence software, the relationship between the input and output data (predicted time to component failure) was found and used in the prediction model. The coefficients of relevance and model fitting were 0.999 and 0.997, respectively, and the average prediction accuracy of 15 data sets calculated from the mean absolute percentage error (MAPE) was 92.45%. This result confirmed that the new BPNN model predicted the time of component failure effectively. The validated prediction ability of the BPNN model provides a reference for the maintenance management of various aircraft components and an effective maintenance strategy.

*Corresponding author: e-mail: changyanzuo@gmail.com
**Corresponding author: e-mail: tslan888@yahoo.com.tw
https://doi.org/10.18494/SAM.2021.3405

ISSN 0914-4935 © MYU K.K.
https://myukk.org/

1. Introduction

Aircraft play an important role in transportation as well as national defense. Unexpected failures in parts and components during flight significantly affect flight safety and require immediate maintenance. The authority overseeing Taiwan's aviation maintenance has analyzed the causes of failure in the control units and modules of aircraft and found that the electronic control units (ECUs) of aircraft most frequently have problems. The main function of the ECU is to process signals from the sensors of the altimeter, power turbine tachometer, torque and overspeed controller, hydraulic mechanical control unit, and various temperature control units.(1) The ECU also receives data on rotor speed, collective rod angle, and changes in rotor load from other sensors. The data are processed for precise control by outputting signals to control the power turbine speed, torque, exhaust temperature, fuel flow control, engine load distribution, torque limitation, and so forth.

The results of the analysis of the causes of component failures show that the main causes are collisions with foreign objects and the misalignment of electrical connectors during reassembly. The causes of failure and prevention measures are shown in Table 1. The damaged components must be replaced without effective technical instruction from the manufacturer. However, this requires time and money along with appropriate stock management. Therefore, an effective plan and strategy for the maintenance are necessary to save time and cost as well as to enhance operational efficiency.

To establish a model for predicting the failure and service life of components, we adopted the Delphi model and a backpropagation neural network (BPNN). Since RAND Corporation developed the Delphi method, it has been widely used in research on the environment, industry, health, transportation, education, and social sciences, and in policy evaluation by government and academic institutions.(2) The Delphi method is a decision-making model that provides quality information for exploratory and controversial research, and the results obtained are valuable.(3) The method uses a series of questionnaires with controlled feedback that is obtained from experts' opinions and a consensus when there is insufficient information. Experts are asked to provide professional knowledge, experience, and opinions to achieve a consensus on a specific issue. As a modification of the Delphi method, in 1995, Murry and Hommons proposed a two-step survey: an open questionnaire survey (modified Delphi method) followed by a structured questionnaire. The modified Delphi method saves time by avoiding speculation and

Table 1
Causes and measures for preventing failures of the ECU.

Damage	Fault location	Causes	Defensive action
Internal damage	Circuit cards, transistors, resistors of each module	Poor engine operation function or abnormal display of related instruments during flight	Quantitative analysis and research to improve equipment reliability
External damage	Electrical connectors, screws, shells	Collision or misalignment of electrical connectors during disassembly and assembly	Training of maintenance personnel, implementation of inspection and maintenance mechanisms

allows participating experts to focus on issues and increase the response rate.[4] The data from the Delphi method has been processed by using a BPNN.

As neural networks have sufficient capability for data classification, prediction, noise filtering, signal analysis, control, and so forth, they have a wide range of applications. Neural networks are used for solving various problems such as turbo engine diagnosis,[5] storm prediction, stock price forecasting,[6] power demand, wafer probing, microchip production,[7] component demand,[8] and heat-mechanical effect processing.[9]

The BPNN was proposed and modified by many researchers,[10,11] and is now widely used. The basic principle is to use the gradient descent method to minimize the error function and then to derive the delta rule. The process of BPNN is divided into forward and reverse transfer, which reduces errors in obtaining desired learning results. The functions are regarded as powerful and extensive for deriving results from a complex and two-layered survey system in the Delphi method. In this study, factors affecting the time of failure of an ECU are defined by the Delphi method by using expert questionnaire surveys.

The aim of our research is to establish a model for predicting the failure and service life of the components of helicopters to enable their repair and replacement at a suitable time. An appropriate maintenance plan and strategy will prevent the occurrence of an unexpected failure during flight and reduce the frequency of unexpected maintenance, thereby increasing the operation time of aircraft. The newly proposed accurate prediction model for the failure time of components will enhance flight safety as well as operational efficiency.

2. Methods

2.1 T700 engine

To establish an appropriate prediction model, the ECU of the engine of a T700 helicopter developed and manufactured by BAE Systems Controls Inc. was used. The ECU is shown in Fig. 1.

According to the statistics of maintenance records from 2006 to 2013, a total of 87 units had failures, among which 45 units suffered from internal module damage and 24 units suffered from damage to external components. The other units were sent to the manufacturer. Detailed information on the damage is shown in Table 2.

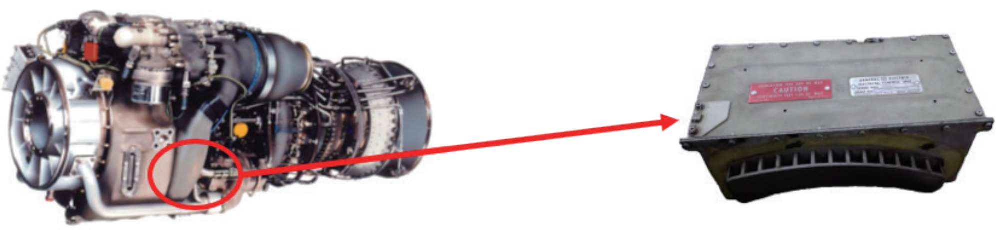


Fig. 1. (Color online) T700 engine (left) and ECU (right).

Table 2
Damage to ECUs and their frequencies of occurrence.

Damage	Damaged component	Occurrence	Total	Proportion (%)
Internal damage	Power shaft speed signal module	13	45	52
	Tail temperature signal control and compensation module	12		
	Torque signal module	4		
	Linear displacement sensor square wave generator module	1		
	Power shaft overspeed module	8		
	Sudden deceleration compensation module	7		
External damage	Electrical connector	10	24	27
	Others (substrate, heat shield, cover)	14		
Others	Test without damage	18	18	21

2.2 Modified Delphi method

RAND Corporation developed the Delphi method, which uses a series of questionnaires with controlled feedback information. The main purpose of the Delphi method is to use experts' opinions and develop a strategic plan. The Delphi method is mainly used when information is insufficient or unknown. Experts are asked to contribute their professional knowledge, experience, and opinions to achieve a consensus on a specific issue. The method has the following properties.

(1) The depth and continuity of a group's consideration of future trends are expressed better than those of individuals.
(2) An objective consensus is found by employing anonymous and written opinions and discussions among experts.
(3) The interviewed experts are generally well recognized in their fields for delivering representative opinions.
(4) At least two rounds of opinion surveys are carried out to quantify and analyze the collected opinions.

The modified Delphi method was used for this study with 12 senior experts with more than 10 years of experience on the T700, as certified by the manufacturer, and various positions and educational backgrounds (Table 3). The purpose of the first questionnaire was to select the important factors that affect the maintenance of the ECU of the T700. As a result, 17 key factors were selected, as shown in Table 4.

Then, the experts were asked to rate the importance of the items with the following Likert scale: "very important" (5), "important" (4), "normal" (3), "not important" (2), and "very unimportant" (1).(12) To select representative factors, a consistency index was calculated. For the index, the average and standard deviation of the scores were calculated for each item. The standard deviation was used to check whether the scores were consistent. Items with an average of 4.5 points or more were classified as "most important", while those with an average of 4.0 to 4.5 were classified as "important", and those with an average of 3.5 to 4.0 were classified as "reference" items.(13) Standard deviation is a measure of the degree to which a set of values

Table 3
Invited experts for the questionnaire survey.

Number	Working department	Position	Experience (years)	Education
1	Technology R&D Department	Engineer	25	Ph.D.
2		Engineer	16	Ph.D.
3		Engineer	10	Master's degree
4	Engineering Department	Engineer	16	Ph.D.
5		Inspector	18	Master's degree
6		Foreman	15	Bachelor's degree
7	Professional Maintenance Department	Inspector	17	Master's degree
8		Foreman	13	Master's degree
9		Technician	11	Bachelor's degree
10	Station Maintenance Department	Inspector	16	Master's degree
11		Foreman	14	Bachelor's degree
12		Technician	10	Diploma

Table 4
Counts of the factors chosen by experts in the questionnaire survey.

No.	Factor	Count
1	Times of disassembly	3
2	Maintenance period	2
3	Thermocouple assembly	10
4	Operating environment humidity	2
5	Operating environment temperature	3
6	Storage environment humidity	4
7	Storage temperature	5
8	Operation hours after installation	12
9	Improper operations	4
10	Hours of use after renovation	6
11	Sudden deceleration compensation module	7
12	Torque and overspeed sensor	10
13	Overspeed leakage solenoid valve	10
14	Power turbine speed sensor	11
15	Tail temperature signal control and compensation module	7
16	Hydraulic-mechanical control unit torque motor	12
17	Hydro-mechanical control unit linear variable displacement sensor	12

diverge from the average.(14) A standard deviation of less than 1 was considered to mean that the opinions of experts converged and were representative.(15)

2.3 BPNN

NeuroIntelligence software by Alyuda Research LLC was used as it is one of the best prediction software packages. Its main application functions are prediction, classification, function calculation, and data anomaly detection. The data of the ECU of the Taiwan Aviation Maintenance Department obtained from 2011 to 2013 was used to test the BPNN model. The data included 80 sets of parameters of 50 ECUs with different serial numbers.

3. Results

3.1 Important factors for maintenance of ECU of T700

The results of the second expert questionnaire are shown in Table 5. The average score and standard deviation of each factor were calculated. The factors with average > 4 and standard deviation < 1 were regarded as important and consistent factors.(16)

The selected factors are as follows: operation hours after installation, thermocouple assembly, hydraulic machinery control unit linear displacement sensor, power turbine speed sensor, torque and overspeed sensor, overspeed leakage solenoid valve, and hydraulic mechanical control unit torque motor. These were used as the main parameters and input values for the BPNN modeling. The data for the selected factors are shown in Appendix I.

3.2 Prediction model and training

Selected parameters of the seven factors were used to establish a prediction model using Alyuda NeuroIntelligence software. The sensitivity of the prediction data was obtained to understand how the model changed with changes in each parameter.

The results of the learning model obtained through training were as follows:

(1) The software automatically connects the input, hidden, and output layer for the best matching. One hidden layer has 12 neurons. The learning rate of 0.2 and 2000 epochs yielded the best training result. Figure 2 shows that stable convergence is reached under these conditions.

Table 5
Results of questionnaires showing expert scores.

Factors	1	2	3	4	5	6	7	8	9	10	Total	Average	S.D.
Operation hours after installation*	5	4	4	5	5	5	4	5	4	5	46	4.6	0.52
Thermocouple assembly*	4	5	5	4	4	4	4	5	5	4	44	4.4	0.52
Torque and overspeed sensor*	4	4	5	4	4	5	5	4	5	4	44	4.4	0.52
Overspeed leakage solenoid valve*	5	4	4	5	5	4	5	4	4	4	44	4.4	0.52
Power turbine speed sensor*	5	4	4	5	5	4	4	5	4	4	44	4.4	0.52
Torque motor of hydraulic mechanical control unit*	5	5	4	4	5	4	4	5	4	5	45	4.5	0.53
Linear displacement sensor of hydro-mechanical control unit*	5	5	4	4	5	4	4	5	4	5	45	4.5	0.53
Tail temperature signal control and compensation module	3	3	2	3	3	2	3	3	2	3	27	2.7	0.48
Improper operations	2	3	2	2	3	3	2	3	2	3	25	2.5	0.53
Times of disassembly	3	3	2	3	2	3	2	3	1	2	24	2.4	0.70
Sudden deceleration compensation module	3	4	2	3	2	2	2	3	2	3	26	2.6	0.70
Maintenance period	3	4	2	2	2	2	2	3	2	3	25	2.5	0.71
Operating environment humidity	3	4	2	2	2	2	2	3	2	3	25	2.5	0.71
Operating environment temperature	2	3	1	2	2	2	2	3	1	2	20	2	0.67
Hours of use after renovation	2	2	1	1	1	1	1	2	1	2	14	1.4	0.52
Storage temperature	3	3	2	2	2	2	2	3	2	3	24	2.4	0.52
Storage environment humidity	3	3	2	2	2	3	4	4	3	4	30	3	0.82

S.D.: standard deviation, *: factors selected for further investigation
10 questionnaires were returned from 12 distributed ones.

(2) The software calculates the relevance and matching of the model. A value of relevance close to 1 represents a high degree of positive correlation and high prediction accuracy. A value of matching close to 1 signifies the appropriateness of the model. This is because the high explanatory ability of an independent variable corresponds to a good fit of the model. The training results of the relevance and matching of the model are shown in Table 6.
(3) The training reduced the error between the target value (red line) and the output value (blue line) (Fig. 3) and obtained a better prediction. The learning result of the comparison between the target value and the output value is shown in Fig. 3.
(4) After inputting the parameters of the seven factors, the software calculated the predicted hours to failure after fault detection as shown in Fig. 4. According to the example, the failure was predicted to occur 193 h after fault detection. This means that the failure would have occurred 2193 h after the installation of the ECU.

3.3 Forecast accuracy

The mean absolute percentage error (MAPE) is an indicator of the quality of a prediction model. MAPE is a relative value and is not affected by the unit and size of the measured and estimated values. MAPE of less than 10% implies highly accurate prediction, while those of 10–20%, 20–50%, and larger than 50% imply good, reasonable, and inaccurate prediction, respectively.[17]

We used 15 sets of real failure data of the ECU in 2014 to obtain MAPEs. By importing the data into the input layer of the software, the time (in h) to component failure after fault detection

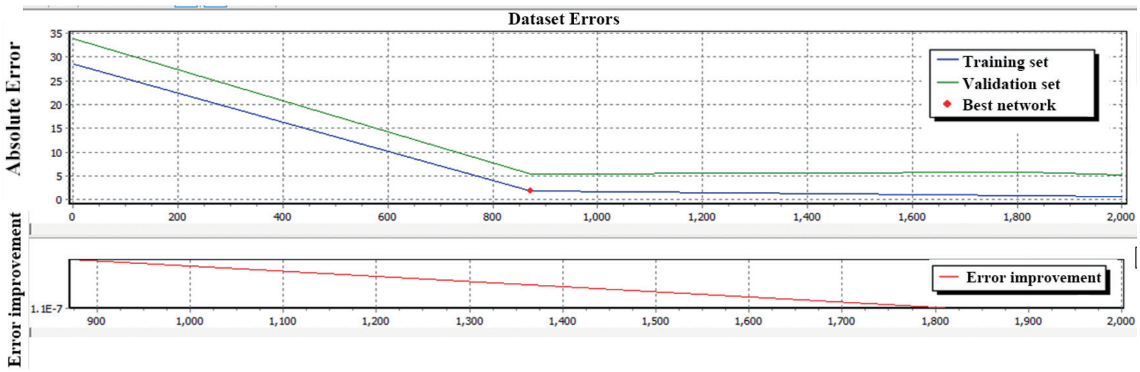


Fig. 2. (Color online) Diagram showing best training mode.

Table 6
Relevance and matching values of the prediction model.

Statistic	Target value	Output value	Absolute error	Relative error
Average	150.828571	150.82453	0.763588	0.005516
Standard deviation	32.392667	31.872821	1.224086	0.009735
Maximum value	85	87.609564	0.000307	0.000002
Minimum value	198	193.814397	6.530368	0.056260
Relevance: 0.999				
Mode fit: 0.997				

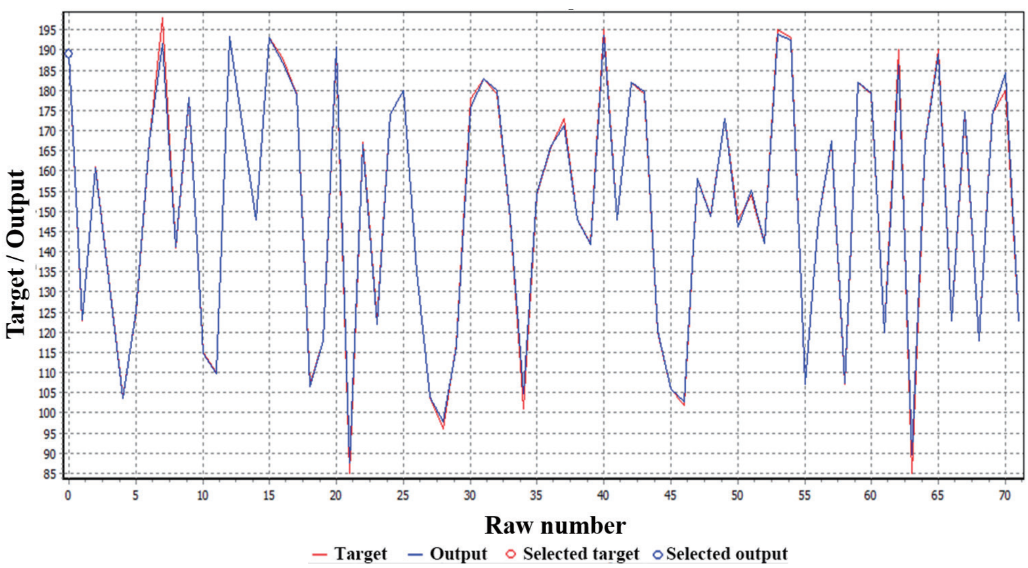
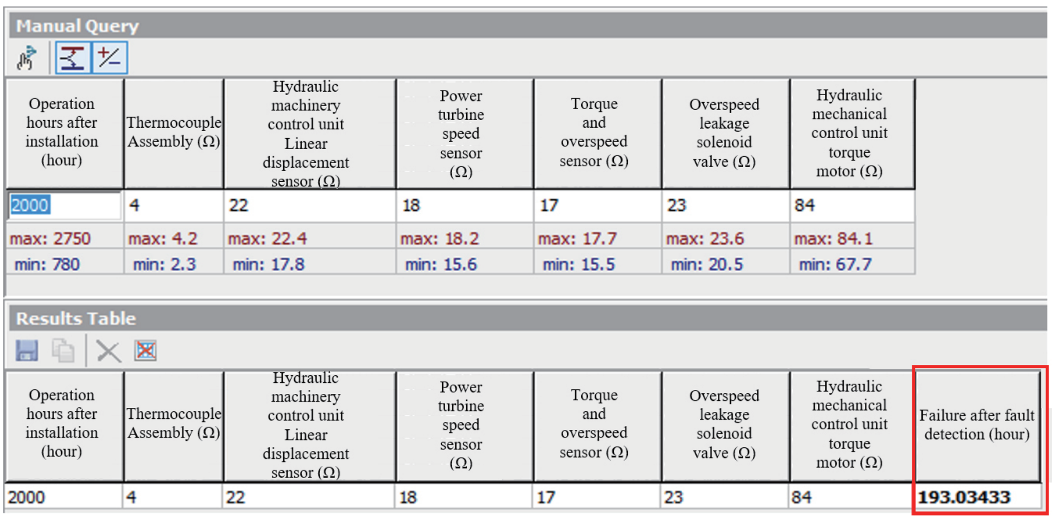


Fig. 3. (Color online) Comparison of target value and output value.



Manual Query

Operation hours after installation (hour)	Thermocouple Assembly (Ω)	Hydraulic machinery control unit Linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Hydraulic mechanical control unit torque motor (Ω)
2000	4	22	18	17	23	84
max: 2750	max: 4.2	max: 22.4	max: 18.2	max: 17.7	max: 23.6	max: 84.1
min: 780	min: 2.3	min: 17.8	min: 15.6	min: 15.5	min: 20.5	min: 67.7

Results Table

Operation hours after installation (hour)	Thermocouple Assembly (Ω)	Hydraulic machinery control unit Linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Hydraulic mechanical control unit torque motor (Ω)	Failure after fault detection (hour)
2000	4	22	18	17	23	84	**193.03433**

Fig. 4. (Color online) Schematic diagram of the learning model prediction.

was obtained by the output layer and compared with the 15 sets of data. MAPE was 7.55% with the highest error rate of 9.47%. The result shows that the prediction of the number of hours to component failure after fault detection by the BPNN model was highly accurate (Table 7).

3.4 Important key factors for prediction of failure time

The prediction model verified which factors directly affected the failure time. The verification process was as follows.

(1) Operation hours after installation of 2700, 2500, 2000, 1500, and 1000 h were input to the model with the other six factors constant. The predicted times to failure after fault detection

Table 7
Percentage errors and MAPEs of input and output layers and real data.

Set	Input layer							Output layer (Prediction)	Verification (real data)	Absolute percentage error (%)
	Hours of operation after installation	Thermocouple assembly (Ω)	Hydraulic machinery control unit linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Hydraulic mechanical control unit torque motor (Ω)	Failure after fault detection (h)		
1	1570	3.1	20.7	17.1	17.0	22.6	75.2	175	187	6.42
2	1680	3.1	19.9	17.1	16.7	22.4	77.3	105	114	7.89
3	2130	4.1	22.4	17.9	17.5	23.1	75.3	140	149	6.04
4	2050	3.1	19.1	17.0	16.8	22.6	78.3	179	191	6.28
5	1950	2.7	1.4	16.6	16.2	22.2	71.7	166	179	7.26
6	1850	2.7	18.7	16.2	16.3	22.2	73.7	132	144	8.33
7	1730	2.8	21.6	17.1	17.2	22.2	80.3	112	120	6.67
8	1750	3.0	19.0	17.2	16.5	22.0	77.0	129	142	9.15
9	1450	2.6	21.9	16.0	16.3	21.6	69.8	172	190	9.47
10	1550	2.5	21.5	16.3	16.3	21.3	71.0	173	186	6.99
11	1780	3.2	19.9	16.8	16.5	22.0	73.4	164	174	5.75
12	1800	3.2	19.5	16.6	16.5	22.0	73.9	191	208	8.17
13	1250	3.4	20.6	17.5	17.0	22.8	75.4	128	141	9.22
14	1650	3.7	20.5	17.5	17.3	23.1	76.3	106	97	9.28
15	2250	3.1	19.4	16.8	16.9	22.5	75.6	134	143	6.29
								MAPE		7.55

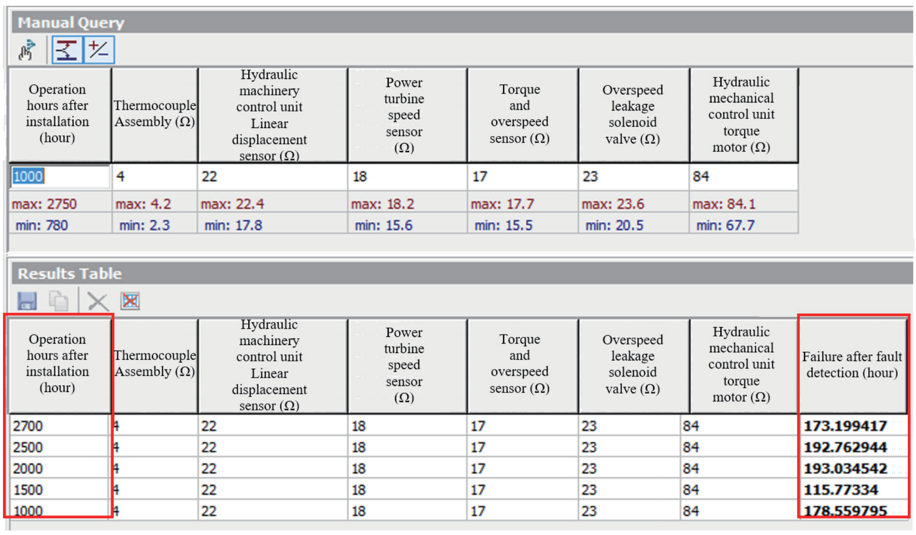


Fig. 5. (Color online) Result of model showing the relation between hours of operation after installation and the predicted time of component failure.

were 173, 192, 193, 115, and 178 h, respectively. This showed that the operation time after the installation was not directly related to the prediction (Fig. 5).

(2) The times of thermocouple assembly of 4.2, 4.1, 4, 3, and 2.5 were input with the other six factors constant. The predicted times were 191, 192, 193, 185, and 164 h, respectively, which implied that the time of thermocouple assembly was related to the prediction (Fig. 6).

(3) The ohm values of the linear displacement sensor of the hydraulic machinery control unit were input as 22.4, 22.2, 22, 20, and 18 Ω with the other factors constant. The predicted times were 195, 194, 193, 148, and 147 h, respectively, which shows that the ohm value of the linear displacement sensor affected the prediction significantly (Fig. 7).

(4) The ohm values of the power turbine speed sensor of 18.2, 18.1, 18, 17, and 16 Ω with the other factors constant were used in the calculation, and the predicted times were 195, 194,

Manual Query

Operation hours after installation (hour)	Thermocouple Assembly (Ω)	Hydraulic machinery control unit Linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Hydraulic mechanical control unit torque motor (Ω)
2000	2.5	22	18	17	23	84
max: 2750	max: 4.2	max: 22.4	max: 18.2	max: 17.7	max: 23.6	max: 84.1
min: 780	min: 2.3	min: 17.8	min: 15.6	min: 15.5	min: 20.5	min: 67.7

Results Table

Operation hours after installation (hour)	Thermocouple Assembly (Ω)	Hydraulic machinery control unit Linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Hydraulic mechanical control unit torque motor (Ω)	Failure after fault detection (hour)
2000	4.2	22	18	17	23	84	**191.608836**
2000	4.1	22	18	17	23	84	**192.182267**
2000	4	22	18	17	23	84	**193.034542**
2000	3	22	18	17	23	84	**185.87039**
2000	2.5	22	18	17	23	84	**164.489277**

Fig. 6. (Color online) Result of model showing the relation between time of thermocouple assembly and predicted time of component failure.

Manual Query

Operation hours after installation (hour)	Thermocouple Assembly (Ω)	Hydraulic machinery control unit Linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Hydraulic mechanical control unit torque motor (Ω)
2000	4	18	18	17	23	84
max: 2750	max: 4.2	max: 22.4	max: 18.2	max: 17.7	max: 23.6	max: 84.1
min: 780	min: 2.3	min: 17.8	min: 15.6	min: 15.5	min: 20.5	min: 67.7

Results Table

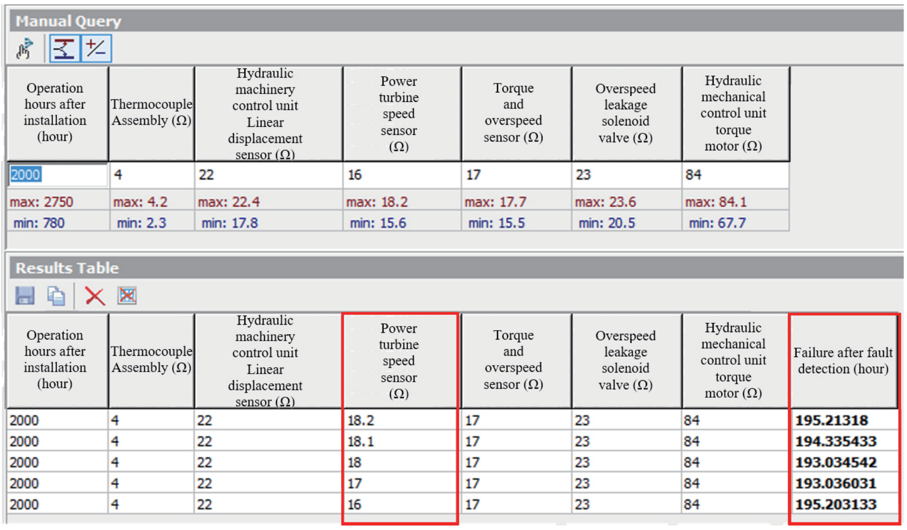
Operation hours after installation (hour)	Thermocouple Assembly (Ω)	Hydraulic machinery control unit Linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Hydraulic mechanical control unit torque motor (Ω)	Failure after fault detection (hour)
2000	4	22.4	18	17	23	84	**195.603037**
2000	4	22.2	18	17	23	84	**194.595594**
2000	4	22	18	17	23	84	**193.034542**
2000	4	20	18	17	23	84	**148.381949**
2000	4	18	18	17	23	84	**147.347174**

Fig. 7. (Color online) Result of model showing the relation between the ohm value of the linear displacement sensor of the hydraulic machinery control unit and the predicted time of component failure.

193, 193, and 195 h, respectively. There was no direct correlation found between the ohm value of the power turbine speed sensor and the prediction (Fig. 8).

(5) The ohm values of the torque and overspeed sensor were input as 17.6, 17.3, 17, 16, and 15.5 Ω with the other factors constant. The predicted times to failure were 193, 191, 193, 173, and 167 h, respectively, which showed that the ohm value of the torque and overspeed sensor was not directly related to the prediction (Fig. 9).

(6) The ohm values of the overspeed leakage solenoid valve of 23.6, 23.3, 23, 22, and 21 Ω were input with the other factors constant. The predicted times to failure were 159, 182, 193, 195, and 177 h, respectively, showing that the ohm value of the valve did not affect the predicted time (Fig. 10).



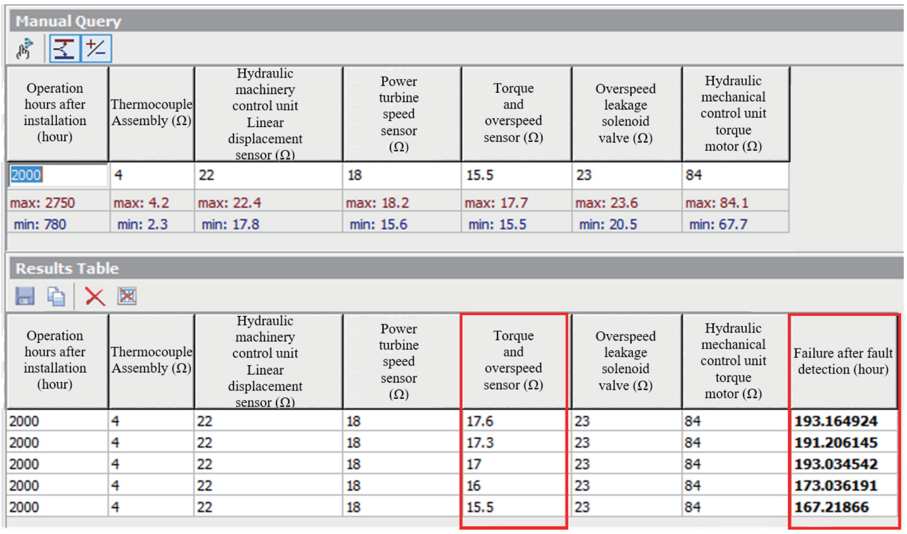
Manual Query

Operation hours after installation (hour)	Thermocouple Assembly (Ω)	Hydraulic machinery control unit Linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Hydraulic mechanical control unit torque motor (Ω)
2000	4	22	16	17	23	84
max: 2750	max: 4.2	max: 22.4	max: 18.2	max: 17.7	max: 23.6	max: 84.1
min: 780	min: 2.3	min: 17.8	min: 15.6	min: 15.5	min: 20.5	min: 67.7

Results Table

Operation hours after installation (hour)	Thermocouple Assembly (Ω)	Hydraulic machinery control unit Linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Hydraulic mechanical control unit torque motor (Ω)	Failure after fault detection (hour)
2000	4	22	18.2	17	23	84	**195.21318**
2000	4	22	18.1	17	23	84	**194.335433**
2000	4	22	18	17	23	84	**193.034542**
2000	4	22	17	17	23	84	**193.036031**
2000	4	22	16	17	23	84	**195.203133**

Fig. 8. (Color online) Result of model showing the relation between the ohm value of the power turbine speed sensor of the ECU and the predicted time of component failure.



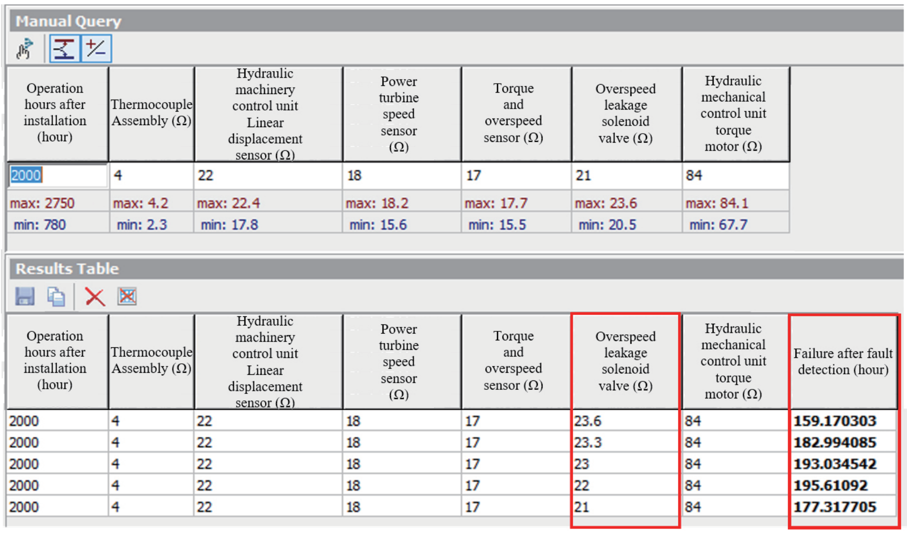
Manual Query

Operation hours after installation (hour)	Thermocouple Assembly (Ω)	Hydraulic machinery control unit Linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Hydraulic mechanical control unit torque motor (Ω)
2000	4	22	18	15.5	23	84
max: 2750	max: 4.2	max: 22.4	max: 18.2	max: 17.7	max: 23.6	max: 84.1
min: 780	min: 2.3	min: 17.8	min: 15.6	min: 15.5	min: 20.5	min: 67.7

Results Table

Operation hours after installation (hour)	Thermocouple Assembly (Ω)	Hydraulic machinery control unit Linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Hydraulic mechanical control unit torque motor (Ω)	Failure after fault detection (hour)
2000	4	22	18	17.6	23	84	**193.164924**
2000	4	22	18	17.3	23	84	**191.206145**
2000	4	22	18	17	23	84	**193.034542**
2000	4	22	18	16	23	84	**173.036191**
2000	4	22	18	15.5	23	84	**167.21866**

Fig. 9. (Color online) Result of model showing the relation between the ohm value of the torque and overspeed sensor of the ECU and the predicted time of component failure.



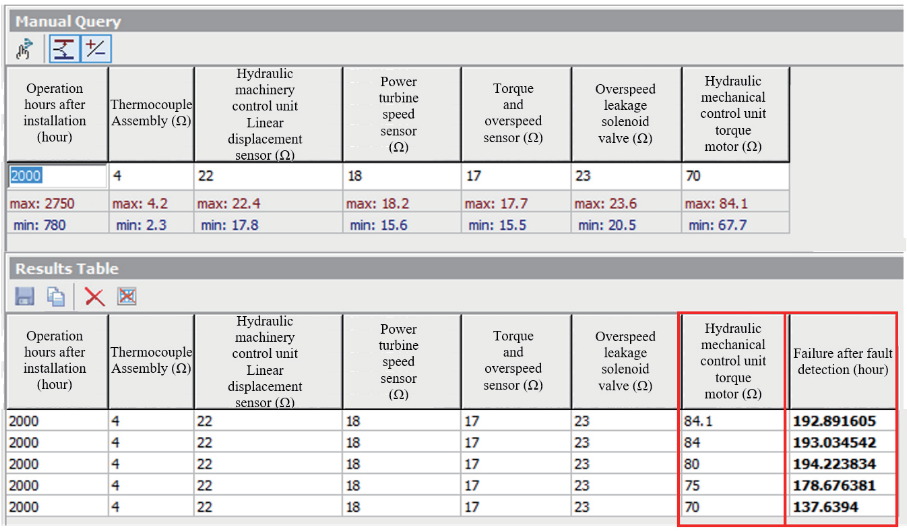
Manual Query

Operation hours after installation (hour)	Thermocouple Assembly (Ω)	Hydraulic machinery control unit Linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Hydraulic mechanical control unit torque motor (Ω)
2000	4	22	18	17	21	84
max: 2750	max: 4.2	max: 22.4	max: 18.2	max: 17.7	max: 23.6	max: 84.1
min: 780	min: 2.3	min: 17.8	min: 15.6	min: 15.5	min: 20.5	min: 67.7

Results Table

Operation hours after installation (hour)	Thermocouple Assembly (Ω)	Hydraulic machinery control unit Linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Hydraulic mechanical control unit torque motor (Ω)	Failure after fault detection (hour)
2000	4	22	18	17	23.6	84	**159.170303**
2000	4	22	18	17	23.3	84	**182.994085**
2000	4	22	18	17	23	84	**193.034542**
2000	4	22	18	17	22	84	**195.61092**
2000	4	22	18	17	21	84	**177.317705**

Fig. 10. (Color online) Result of model showing the relation between the ohm value of the overspeed leakage solenoid valve and the predicted time of component failure.



Manual Query

Operation hours after installation (hour)	Thermocouple Assembly (Ω)	Hydraulic machinery control unit Linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Hydraulic mechanical control unit torque motor (Ω)
2000	4	22	18	17	23	70
max: 2750	max: 4.2	max: 22.4	max: 18.2	max: 17.7	max: 23.6	max: 84.1
min: 780	min: 2.3	min: 17.8	min: 15.6	min: 15.5	min: 20.5	min: 67.7

Results Table

Operation hours after installation (hour)	Thermocouple Assembly (Ω)	Hydraulic machinery control unit Linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Hydraulic mechanical control unit torque motor (Ω)	Failure after fault detection (hour)
2000	4	22	18	17	23	84.1	**192.891605**
2000	4	22	18	17	23	84	**193.034542**
2000	4	22	18	17	23	80	**194.223834**
2000	4	22	18	17	23	75	**178.676381**
2000	4	22	18	17	23	70	**137.6394**

Fig. 11. (Color online) Result of model showing the relation between the ohm value of the torque motor of the hydraulic machinery control unit and the predicted time of component failure.

(7) The ohm values of the torque motor of the hydraulic machinery control unit were input as 84.1, 84, 80, 75, and 70 Ω with the other factors constant. The predicted times were 192, 193, 194, 178, and 137 h, respectively, which shows that ohm value of the torque motor of the hydraulic machinery control unit did not affect the prediction (Fig. 11).

4. Conclusions

A new model that uses the modified Delphi method and BPNN to predict the time of component failure in the ECU of a T700 engine was proposed. The predicted values were verified using the results of statistical analysis such as the expert consistency index and MAPE. Seventeen factors were chosen after the questionnaire survey, then through a second survey with 12 experts of various experience, the following seven important factors were chosen for the model: operation hours after installation, times of thermocouple assembly, and the ohm values of the linear displacement sensor of the hydraulic pressure control unit, power turbine speed sensor, torque and overspeed sensor, overspeed leakage solenoid valve, and the torque motor of the hydraulic control unit. Fifteen sets of the real maintenance data obtained during 2011–2013 were used to train the model using Alyuda NeuroIntelligence software through the comparison of the predicted and real times. In the case of 12 neurons in the hidden layer, a learning rate of 0.2, and 2000 epochs, the prediction result showed correlation and matching rates of 0.999 and 0.997, respectively. The prediction accuracy calculated from MAPE analysis was 92.45%. The lowest accuracy was 90.53% for one data set. Assuming that the ECU of a T700 has been operating for 2000 h after installation, the longest interval before failure was predicted to be around 193 h. On average, the predicted operating time until failure was between 174 and 178 h, corresponding to total operating times of 2174 to 2178 h until failure. Therefore, the results indicate that the ECU of a T700 should be maintained after 2100 h of operation. Inspection of the components also needs to be performed after every 100 h of flight, while the engine should be inspected after every 50 h of flight. Appropriate maintenance of the ECU will prevent unexpected failures and accidents.

The results of this research provide the manufacturer with basic information for improving the quality of the ECU, which will increase its reliability and flight safety. This research is expected to lead to related future studies on a preventive maintenance and management strategy for aircraft components. The balance between cost and time saving and efficiency also needs to be investigated. The BPNN model in this study will be improved in the future by employing sufficient training data to obtain higher accuracy.

References

1 M. Foust, D. Thomsen, R. Stickles, C. Cooper, and W. Dodds: Proc. 2012 50th AIAA Aerospace Sciences Meeting including the New Horizons Forum and Aerospace Exposition (AIAA, 2012) 1–12. https://doi.org/10.2514/6.2012-936
2 S. Kelly and T. Stanley: Mind Soc. **2** (2012) 335. https://doi.org/10.4236/sm.2012.24044
3 H. Zou, X. Gong, S. Wang, and W. Chen: Int. J. Clin. Med. **11** (2020) 242. https://doi.org/10.4236/ijcm.2020.115025
4 J.-W. Murry and J.-O. Hammons: Rev. Higher Educ. **18** (1995) 423. https://doi.org/10.1353/rhe.1995.0008
5 B. Mashood and G. Millbank: J. Behav. Brian Sci. **6** (2016) 219. https://doi.org/10.4236/jbbs.2016.65022.
6 S. O. T. Ogaji and R. Singh: Appl. Soft. Comput. **3** (2003) 259. https://doi.org/10.1016/S1568-4946(03)00038-3
7 P.-C. Chang, C.-H. Liu, J.-L. Lin, C.-Y. Fan, and C. S. P. Ng: Exp. Syst. Appl. **36** (2009) 6889. https://doi.org/10.1016/j.eswa.2008.08.077
8 T. Chen: Appl. Soft. Comput. **2** (2003) 211. https://doi.org/10.1016/S1568-4946(02)00066-2
9 F.-L. Chen, Y.-C. Chen, and J.-Y. Kuo: Exp. Syst. Appl. **37** (2010) 4358. https://doi.org/10.1016/j.eswa.2009.11.092
10 K. Dehghani and A. Nekahi: Mater. Des. **31** (2010). https://doi.org/10.1016/j.matdes.2009.10.020
11 W. Yuan and Y. Zeng: Creat. Educ. **8** (2017) 305. https://doi.org/10.4236/ce.2017.83024
12 G. Li, S. Kumar. S. Hari, M. Sullivan, T. Tsai, K. Pattabiraman, J. Emer, and S. W. Keckler: Proc. 2017 Int. Conf. High Performance Computing, Networking, Storage and Analysis (ACM, 2017) 1–12. https://doi.org/10.1145/3126908.3126964
13 S. Jawahar and P. Ramamoorthy: Circuits Syst. **7** (2016) 3371. https://doi.org/10.4236/cs.2016.710287

14 S. Zhang: JSSM **12** (2019) 126. https://doi.org/10.4236/jssm.2019.122008
15 S. H. Ling: JILSA **2** (2010) 1. https://doi.org/10.4236/jilsa.2010.21001
16 M. Maqableh, H. Karajeh, and R. Masa'deh: Comm. Netw. **6** (2014) 191. https://doi.org/10.4236/cn.2014.63021
17 A. Yayík and Y. Kutlu: Neural Netw. World **2** (2014) 177. https://doi.org/10.14311/nnw.2014.24.011

Appendix I

Data sets of parameters for selected factors of 50 ECUs.

Group	Input layer							Output layer
	Operation hours after installation	Resistance of thermocouple assembly (Ω)	Hydraulic machinery control unit linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Torque motor of hydraulic machinery control unit (Ω)	Time of failure after detection (h)
1	1420	2.8	22.4	16.2	16.5	22.1	71.6	189
2	2750	2.6	21.3	16.6	16.8	21.7	70.5	123
3	1400	2.3	21.5	16.2	17.1	20.5	71.5	161
4	165	3.7	20.5	18.1	18.0	22.5	76.4	95
5	1480	2.9	19.0	17.0	16.7	22.4	76.8	104
6	1630	2.8	18.8	16.3	16.8	22.7	77.1	125
7	2450	3.6	19.0	17.3	17.2	22.7	73.4	167
8	2380	4.0	20.3	17.6	17.2	22.6	76.3	198
9	1740	2.7	21.6	16.4	16.0	21.3	71.2	141
10	1720	2.8	21.7	16.8	16.3	22.4	72.2	178
11	1750	2.7	19.0	16.4	16.5	22.4	74.3	115
12	1700	2.7	20.4	17.0	17.2	22.3	84.1	110
13	2140	3.0	19.6	17.4	16.7	22.4	79.0	193
14	2430	4.6	22.0	18.1	17.6	23.6	76.9	176
15	2260	3.3	20.1	17.0	16.8	22.8	76.7	148
16	2260	3.8	19.5	16.6	16.7	21.9	76.6	193
17	2120	2.5	19.1	15.7	15.6	20.9	70.2	188
18	1960	2.6	20.9	15.7	15.5	21.3	68.1	179
19	2280	2.8	17.8	15.6	16.1	21.6	73.6	107
20	2060	2.8	20.3	17.3	16.8	22.6	73.4	118
21	780	2.8	21.7	16.9	17.2	22.1	74.0	190
22	1670	2.8	18.6	15.9	15.8	21.5	73.1	85
23	1780	2.9	17.9	16.0	15.9	21.4	71.2	167
24	1470	2.9	20.6	16.5	16.1	21.0	71.5	123
25	2150	3.2	18.6	16.2	16.3	21.5	74.4	174
26	1720	2.7	18.4	16.1	15.8	21.1	71.5	180
27	1800	2.9	20.7	15.9	16.6	21.4	68.1	135
28	1950	3.8	19.6	16.4	16.7	22.3	69.8	104
29	2160	3.5	21.5	16.2	15.8	21.5	68.8	96
30	2050	3.2	19.9	16.5	16.6	22.5	71.9	117
31	950	2.8	22.2	16.4	15.9	22.3	76.1	178
32	1250	2.7	17.8	17.5	17.5	22.4	74.0	183
33	1370	3.1	18.7	17.5	16.5	22.6	73.3	179
34	1280	2.8	21.4	16.1	15.6	21.0	67.7	148
35	2200	3.0	18.4	15.9	15.8	21.2	69.7	101
36	2140	3.0	22.2	16.5	16.9	22.8	73.7	154
37	1860	3.0	18.7	17.0	16.7	22.3	76.8	166

Group	Input layer							Output layer
	Operation hours after installation	Resistance of thermocouple assembly (Ω)	Hydraulic machinery control unit linear displacement sensor (Ω)	Power turbine speed sensor (Ω)	Torque and overspeed sensor (Ω)	Overspeed leakage solenoid valve (Ω)	Torque motor of hydraulic machinery control unit (Ω)	Time of failure after detection (h)
38	1940	3.1	19.0	17.0	17.1	22.9	78.0	173
39	1580	3.1	20.2	17.4	17.0	22.7	75.7	148
40	1730	2.7	19.0	16.7	16.6	21.9	73.9	142
41	890	2.5	22.2	16.9	16.4	22.7	70.8	195
42	1960	3.1	19.7	16.5	17.5	22.5	75.1	148
43	1570	2.9	19.7	17.3	16.8	23.2	75.8	182
44	1780	2.8	19.2	16.5	16.5	22.1	74.4	179
45	1670	2.8	21.8	17.3	17.7	22.1	73.2	120
46	2020	3.0	19.6	18.2	16.9	23.1	78.8	106
47	2060	3.2	20.0	16.9	16.8	22.7	75.8	102
48	1870	2.7	21.3	16.0	16.2	22.4	74.2	158
49	1730	2.8	21.5	16.5	17.4	21.9	73.1	149
50	1960	3.8	19.0	16.0	17.2	21.3	69.8	173
51	2280	3.5	20.2	16.5	16.0	21.6	68.8	148
52	2260	2.7	22.2	18.2	16.8	21.9	71.5	154
53	2060	3.2	19.0	17.7	16.3	22.6	71.9	142
54	780	2.8	22.2	16.9	16.5	22.1	76.1	195
55	1630	2.8	19.0	16.9	15.9	22.7	77.1	193
56	1740	3.7	22.0	16.5	15.6	22.1	71.2	107
57	1670	2.7	19.7	15.9	17.2	21.5	74.0	148
58	2140	4.0	20.9	16.4	17.1	22.4	79.0	167
59	2260	4.2	20.0	17.7	17.4	23.6	74.6	107
60	1780	3.1	19.7	16.0	16.7	21.4	73.3	182
61	1470	2.8	19.2	16.5	17.6	21.0	67.7	179
62	2150	3.0	21.8	16.2	16.8	21.5	69.7	120
63	2140	2.7	22.2	18.2	16.9	22.1	74.3	190
64	1860	2.9	18.7	16.9	16.7	21.7	84.1	85
65	1940	3.8	19.0	16.0	17.1	20.5	79.0	167
66	1750	2.8	19.5	16.1	16.9	23.1	74.3	190
67	1580	3.5	20.2	16.5	17.0	22.5	76.9	123
68	2260	2.8	20.3	16.5	16.6	23.6	76.7	174
69	1720	2.9	20.1	16.2	15.8	22.1	72.2	118
70	1730	3.2	19.0	17.7	16.6	22.4	76.7	174
71	890	2.8	22.2	16.9	16.8	22.7	76.6	180
72	2430	2.7	17.8	16.2	17.0	21.9	76.9	123
73	1960	2.7	19.7	15.9	17.2	22.7	70.2	135
74	2450	2.6	20.4	15.9	17.5	22.5	73.4	188
75	1700	3.6	19.1	15.9	16.7	22.7	84.1	85
76	2120	2.9	18.7	16.9	17.2	20.9	68.1	166
77	1570	3.1	19.7	16.0	17.2	22.6	68.1	104
78	1780	2.8	19.2	16.5	16.0	21.3	73.6	96
79	2380	2.3	19.6	16.0	16.5	23.2	76.3	179
80	1670	3.0	21.8	16.2	16.3	22.4	73.4	117