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Diagnostics of complex system with the help of neural nets

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ABSTRACT

The paper deals with the problem of a complex system state diagnostics. As a complex system state is affected by a lot of various parameters, the problem of the system condition diagnostics can be treated as the problem of classification of multidimensional objects and solved with the use of neural networks. The method offered was exemplified by determining status of propulsion system with the help of Neural Network Toolbox in MATLAB system.
Keywords: complex system, spacecraft, diagnostics, classification

1. INTRODUCTION

Due to continuous improvement of target and support systems of spacecraft in context of their reliability, variety of their functions, and their complexity, the problem of systems state diagnostics is critical.

Now, the problem of spacecraft systems diagnostics and state management is mostly solved by ground control. For this reason there can be some time-lag between the moment of a decision-making and the moment of the system reaction during which the off-normal situation may transform into accident. Additionally, the ground control command can be garbled during its transmission. So, it is preferable to solve the above problems with the help of on-board control software, that is why appropriate models and algorithms must be developed.

As a rule, a complex system state is affected by a lot of various parameters. So, the problem of the systems condition diagnostics can be treated as the problem of classification of multidimensional objects, all of each present certain state of the system and are characterized by respective values of the parameters [1], [2].

This paper aims to analyze the possibility of a system state diagnostics with the help of neural networks [3]-[7].

2. THE SYSTEM UNDER CONSIDERATION

Propulsion system of one of land remote sensing satellites was taken as an example of diagnosed system. Basic parameters affecting the propulsion system state, their values and corresponding system status are given in table 1.

The following abbreviations are used:

- ERLV - electrically driven liquid valve;
- FPMI – fuel pressure of the manifold indicator;
- FPNC – fuel pressure in the nozzle chamber;
- FTP – fuel tank pressure;
- MPL – main pressurization line;
- MT – microthruster;
- OPMI – oxidizer pressure of the manifold indicator;
- OPNC – oxidizer pressure in the nozzle chamber;
- OTP – oxidizer tank pressure;
- PI – pressure indicator;
- ROPI - regulator outlet pressure indicator;
- SPI – standby pressure indicator;
- SPL – standby pressurization line;
- VRE - vernier reverse engine.

The table analysis shows that all the system failures, depending of the basic parameters, can be allocated to one of five groups, as it is shown in table 2.

One more group includes normal states of the system when all the parameters values are within acceptable limits.

Table 1: The propulsion system basic parameters

Parameter	Parameter value, Mpa	The system status
OTP	from 1.5 to 2.4	Normal state
	< 1.5	PI nonoperation. MT thrust decreases in proportion to tanks pressure
FTP	from 1.5 to 2.4	Normal state
	< 1.5	PI nonoperation. MT thrust decreases in proportion to tanks pressure
OPNC	From 1.0 to 1.4	Normal state
	≤ 0.7	VRE ignition failure. VRE thrust is less than 0.1 of its nominal value
FPNC	1.0 … 1.4	Normal state
	≤ 0.7	VRE ignition failure. VRE thrust is less than 0.1 of its nominal value
ROPI	≥ 2.4	Possible failure of regulator in MPL or SPL
	< 2.4	Normal state
PI	≤ 1.5	Possible failure of MPL or PI
	> 1.5	Normal state
SPI	≤ 1.7	MPL or SPI failure
	> 1.7	Normal state
FPMI 1, OPMI1	> 0.7	Normal state
	≤ 0.7	ERLV1(2) unopening (within the MT operating period) MT1 leakage (out of the MT operating period)
FPMI 2, OPMI2	> 0.7	Normal state
	≤ 0.7	ERLV1(2) unopening (within the MT operating period) MT1 leakage (out of the MT operating period)

Table 2: Summary table of failures

No.	The system status	Affecting parameters
1	Normal state	
2	PI nonoperation. MT thrust decreases in proportion to tanks pressure	FTP, OTP
3	VRE ignition failure. VRE thrust is less than 0.1 of its nominal value	FPNC, OPNC
4	Possible failure of MPL or SPL	ROPI, PI
5	Pressurization system or SPI failure	SPI
6	ERLV1(2) unopening (within the MT operating period) MT1 leakage (out of the MT operating period)	FPMI1, FPMI2, OPMI1, OPMI2

So, it may be seen that we need to classify objects characterized by 11 parameters into one of 6 groups. The problem may be solved by Neural Network Toolbox, which is the part of MATLAB system [8].

3. THE PROBLEM SOLUTION

3.1 Preparing the Data

First of all, initial data must be formed. Those data are organized into array X and the target array T. The array X consists of 12 samples, each including 25 elements. Every element includes 11 values of parameters affecting the system. Elements with numbers from 1 to 25 include parameters values corresponding to normal system state, parameters values of elements with numbers from 26 to 50 correspond to the case when the first system parameter (for instance, FTP) is outside its nominal range and so on. Due to lack of information about the real system failures, the parameters are generated as uniform random numbers. So, each column of the input matrix has eleven values of the system parameters, and total number of columns equals to 300.

Each corresponding column of the target matrix T has six elements, consisting of five zeros and a 1 in the location of the associated fault mode according to table 2 (one more status corresponds to normal system work):

T(1:6,1:300)=0;
T(1:1,1:25)=1; % normal work
T(2:2,26:75)=1; % fault mode No.1
T(3:3,76:125)=1; % fault mode No.2
T(4:4,126:175)=1; % fault mode No.3
T(5:5,176:200)=1; % fault mode No.4
T(6:6,201:300)=1; % fault mode No.5

3.2 Creating a neural network

The next step is to create a neural network that will learn to classify the system statuses. Networks with one, two and tree hidden layers and various number of neurons in each layer were tried (table 3). The validation and test data sets, by default, were set to 15% of the original data.

Table 3: Results of the neural networks testing

No.	Number of layers	Number of neurons in each layer	Percentage of correct classifications
1	1	6	36 %
2	1	12	71 %
3	1	18	90 %
4	1	24	97 %
5	1	36	56 %
6	2	6	53 %
7	2	12	48 %
8	3	6	73 %

It may be seen, that the best results were obtained by the net with a single hidden layer of 24 neurons. Validation performance of the net is shown in figure 1, and confusion matrix is shown in figure 2.

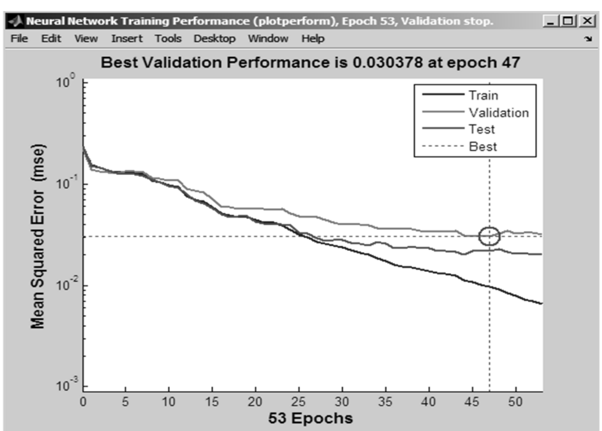

Figure 1 Neural net validation performance

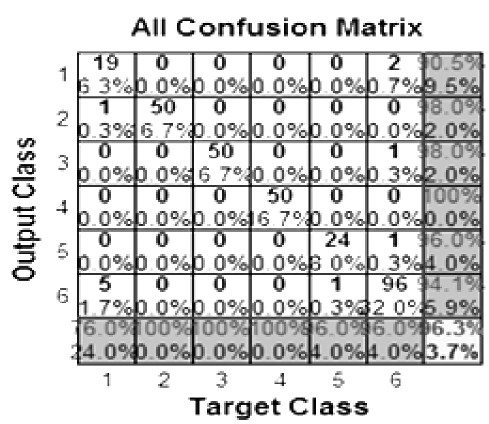

Figure 2 Neural net confusion matrix

Here the confusion matrix is plotted across all samples. The confusion matrix shows the percentages of correct and incorrect classifications. Correct classifications are the light colored squares on the matrices diagonal. Incorrect classifications form the dark colored squares. It may be seen that the percentages in the dark colored squares are very small, indicating few misclassifications.

3.3 System status determination with a neural network

Now we will test the network on input array N containing 13 new elements that were not used for its training.

The parameter values were set in such a way that they correspond to various statuses of the system under consideration according to table 4.

As the network outputs range within 0 to 1, it is suitable to use ***vec2ind*** function to get the class indices as the position of the highest element in each output vector:

```
>> V=vec2ind(net(N'))
```

Table 4: Correlation between array N rows and the system status

Rows of array N		The system status
1		1 - normal work
2		1- normal work
3		2 –fault mode No.1
4		2 – fault mode No.1
5		3 – fault mode No.2
6		3 – fault mode No.2
7		4 – fault mode No.3
8		4 – fault mode No.3
9		5 – fault mode No.4
10		6 – fault mode No. 5
11		6 – fault mode No. 5
12		6 – fault mode No. 5
13		6 – fault mode No. 5

The system response is as follows:

```
V =
   1   1   2   2   3   3   4   4   5   6   6   6   6
```

Comparing elements of vector V with the system status in table 4, we find that the network classifies states of the system correctly.

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