Supporting the life cycle of complex technical object on the basis of predictive analytics

V.N. Blinov[1], S.S. Valeev[2], N.V. Kondratyeva[2], R.R. Karimov[2], A.S. Kovtunenko[2], E.A. Kuzmina[2]

[1]Omsk State Technical University, Mira str. 11, Omsk, Russia, 644050
[2]Ufa State Aviation Technical University, K. Marx str. 12, Ufa, Russia, 450008

Abstract. Application of predictive analytics in design, production and exploitation to achieve efficiency of life cycle of complex technical systems is discussed. Predictive model for life cycle information support of microsatellite propulsion system on the basis of system of neural networks is suggested. The predictive model can solve tasks of estimation of fuel consumption, diagnostics and possible failures detection for the small propulsion system.

1. Introduction

Application of modern life cycle information support systems for large scale technical objects as aircrafts, gas-turbine engine are implemented widely. But for small dynamic objects as drones or microsatellite application of life cycle information support systems is not so obvious for many reasons. One of the main reasons why researchers and manufacturers are not ready for applying this technology is lack of experience and rather expensive life cycle information support systems equipment and software.

The microsatellite can be considered as subclass of cyber physical system functioning in autonomous mode during its mission for rather long period of time. It is possible to control its position and payload periodically remotely from ground flight center in telecommunication sessions. Operator can send control commands through, for example, GlobalStar and change operation mode for microsatellite effective use with help of special software-hardware interface [1-6].

The mission tasks of microsatellite in information sense is the data collecting, processing, and transmitting to the ground flight center the compressed information about its environment and flying conditions. Microsatellite, as a subset of cyber physical system, contains a lot of mechatronics subsystems: micro electromechanical elements and mechanisms. So, it can be considered as complex technological product, which is designed within enterprises cooperation on the base of information flows interchanging [7, 8].

On designing stage of life cycle for autonomous technical objects, designers have to keep in mind the possible uncertainty factors which can influence on the object operation and can cause failures of onboard equipment, energy overconsumption, noise influence and the other different factors. So, to provide the efficiency of microsatellite mission the information support based on predictive analytics technologies can be applied [9, 10].

2. Life cycle of complex technical object and predictive analytics

In sense of life cycle paradigm of microsatellite, the amount of data generated on prototyping and testing stages are more times bigger then data had generated on the implementation stage (figure 1).

So it is obvious, if we are trying to optimize total expenditures for life cycle of the microsatellite:

- It is necessary to decrease durations of the stages from prototyping to implementation.
- It is needed to increase the usefulness of information that had been generated on before the implementation stage.

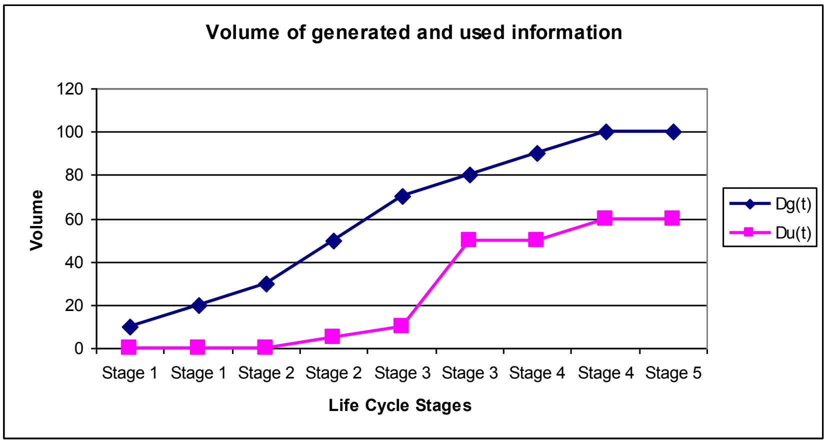


Figure 1. Volume of information generated on all stages of life cycle.

In general, the effectiveness of generated information D_E on stages of life cycle of complex technical object can be presented as the solution of optimization task:

$$D_E(t) = \int_0^t (D_G(t) - D_U(t))dt \to \min, \quad (1)$$

where D_G is generated information, and D_U is used information.

The following tasks of predictive analytics application have to be solved in order to obtain the positive effect in sense of (1):

• big data technologies can be applied on all stages of the life cycle. Supporting actual, operational and authentic information about the state of complex technical object operation with help of estimating and forecasting the complex technical object state on the basis of predictive models;

• decision making support using different predictive models to estimate the meaning of goal function on the different stages;

• simulation of different "suboptimum" and "worse" cases on the base of multi-agent real time simulation system;

• diagnostics on the base of on-line predictive models of complex technical object state with application of onboard computer.

These tasks can increase the economic efficiency of life cycle of complex technical system due to effective interactions of all information subsystems with application of predictive analytics on all stages of life cycle.

3. Microsatellite engine predictive model

One of the unresolved problems at present remains the creation of end-to-end information systems for supporting the life cycle of satellite, which is of particular relevance to the microsatellite, since the periods of their active existence are relatively small and there are significant uncertainties in the design, production and operation processes.

On all stages of life cycle the huge amount of different data flows are generated. All these information may be useful in different life cycle support applications. One of the modern techniques of predictive model design is the application of different neural networks.

A neural network predictive model of the microsatellite propulsion system was developed, which allows solving a number of tasks associated with the assessment of fuel reserves and technical condition under conditions of uncertainty. This neural network predictive model is an integral part of the information support system of the life cycle of the microsatellite (figure 2).

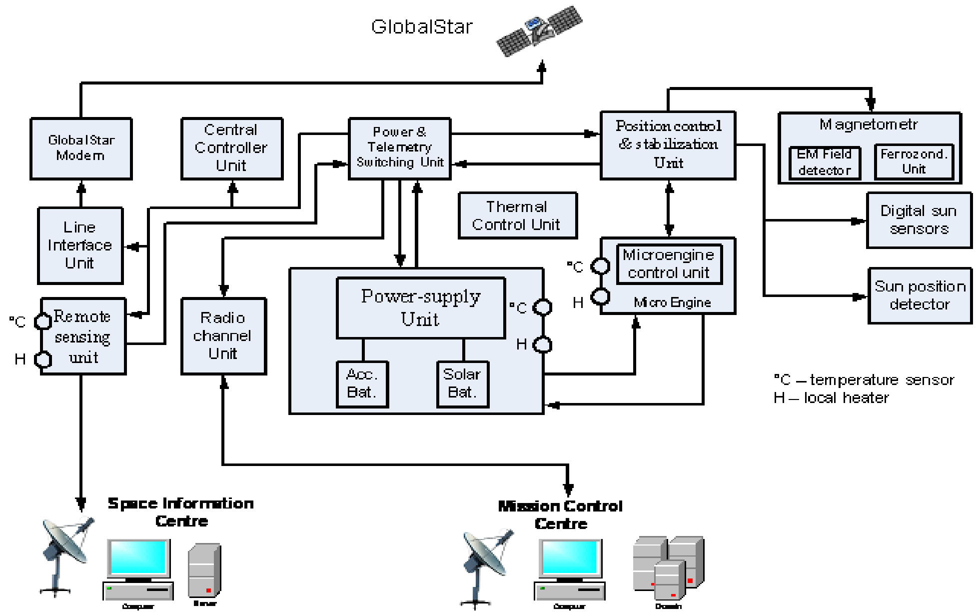


Figure 2. Predictive estimation of remaining fuel on the base of telemetry data.

The modern stage of space exploration, both abroad and in Russia, is characterized by creation and use of maneuvering small spacecrafts weighting 30–500 kg. Practical and actual tasks of small spacecraft orbital maneuvering are: minimizing orbit errors, maintaining orbital parameters during active life, interorbital maneuvering for scientific and applied purposes, building small spacecraft orbital groupings, moving the spacecraft into recycling orbit, etc.

The research and practical implementation work that was carried out and the results of flight and ground tests of ammonia propulsion engine with a thrust price of up to 4 W/mN for electrothermal microengine of up to 30 mN showed their high efficiency in the small satellites “Demonstrator”, “Orbkomm” and “UgatuSat” [2].

Let us consider the resource and state assessment subsystem on the example of a propulsion system, which is designed to correct the orbital position of the micro satellite. The propulsion system consists of a cylindrical fuel tank, a filter, an electropneumatic valve, an evaporator for converting liquid ammonia into a gaseous state, a pressure regulator to maintain a predetermined pressure value, as well as an electrothermal engine. The considered PS is developed in the PE "Polet" (Omsk) and is used on Russian and foreign microsatellites.

The main non-renewable resource on board the microsatellite is the fuel supply. The task of determining the amount of fuel on board the spacecraft is very relevant due to the lack of a fuel sensor, extreme external conditions, the inability to refuel and other services. The factors of uncertainty include the occurrence of failures of the components of the control, loss of fuel due to leaks, chemical decomposition of fuel, etc.

The principal pneumohydraulic scheme of propulsion system is presented in figure 3, which includes electrothermal engine, pressure sensor, pressure regulator (controller), evaporator, electropneumatic valve, filter, ammonia tank (fuel tank).

The key feature of the considered propulsion system is the formation of small impulses of thrust and operation in the “cold start” mode, as a result of which the thrust and fuel consumption are functions of time.

The principle of operation of a micro jet engine with an ammonia electro thermal engine is based on the dissociation of ammonia with its decomposition into hydrogen and nitrogen. Due to the decomposition and, accordingly, a twofold decrease in the molecular weight of the out flowing gas compared to ammonia gas, it is possible to significantly increase (up to 2600 N · s / kg) the specific thrust impulse of the electro thermal engine [3].

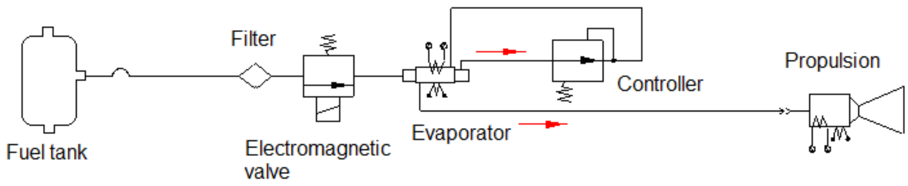


Figure 3. Schematic view of propulsion system.

For the micro-propulsion systems under consideration there are no analytical models that allow determining the technical condition of the object, fuel consumption and its reserves with the necessary accuracy. At the same time, in the process of designing and testing, a large amount of computational and experimental information is accumulated, which can be used to create a predictive model of a micro-propulsion system based on neural networks technologies.

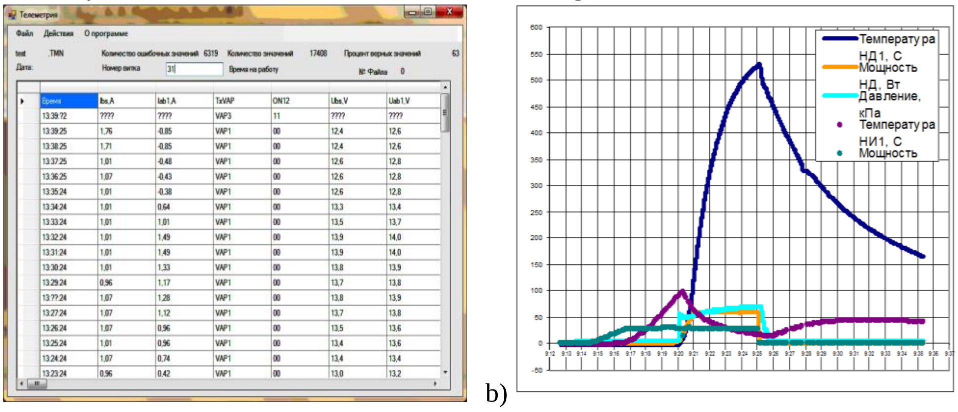


Figure 4. Data set of microsatellite parameters state (a) and telemetric information (b).

In the process of control the fuel consumption data received telemetric information, parameters of the control program, including the settings of the operating modes of the micro-propulsion system, data on previous inclusions of the micro-propulsion system are used (figure 4).

All data that we have received on the different stages of life cycle are stored in information life cycle support system. This system includes the high performance computers, data warehouse subsystems, predictive analytics software and etc.

During operation, such a predictive model will allow to solve the following tasks:

- evaluate the fuel reserves on board the microsatellite;
- diagnose the technical condition of the micro-propulsion system and detect its failures;
- determine the fuel consumption required to complete the orbital maneuver.

In the process of modeling fuel consumption, telemetric information, parameters of the control program, including the settings of the operating modes of the micro-propulsion system, data on previous inclusions of the micro-propulsion system are used.

4. Predictive neural network of fuel consumption model

In the process of modeling, telemetric information, parameters of the control program, including the settings of the operating modes of the propulsion system, data on previous inclusions of the micro jet propulsion are used. A fragment of the list of used parameters and their description are presented in table 1.

To build a model of the propulsion system, we will divide all available information into two groups:

$$X = \{T_{\max\,\mathrm{EH}}, T_{\max\,\mathrm{EvH}}, P_{\max\,\mathrm{EH}}, P_{\max\,\mathrm{EvH}}, S, U_{\mathrm{EH}}, I_{\mathrm{EH}}, U_{\mathrm{EvH}}, I_{\mathrm{EvH}}, t_{\mathrm{EP}}, t_{\Sigma}, t_{\mathrm{N}}\}, X \in R^{1\times 12}.$$

The second group is the output data group $Y = \{T_{\mathrm{EH}}, T_{\mathrm{EvH}}, p\}, Y \in R^{1\times 3}$. The input data are fed to the propulsion system to form a thrust impulse, while the output data allow the trust impulse to be estimated.

Table 1. Description of the parameters.

Parameters	Description
T_{EH}	engine heater temperature
U_{EH}	voltage on the engine heater
I_{EH}	engine heater current
T_{EvH}	evaporator heater temperature
U_{EvH}	voltage on the evaporator heater
I_{EH}	evaporator heater current
N	number of the received block with initial data (settings)
t_N	instrument time value
p	pressure in the engine chamber
T_{maxEH}	maximum engine heater temperature
T_{maxEvH}	evaporator heater maximum temperature
P_{maxEH}	maximum power of the electric current supplied to the engine heater
P_{maxEvH}	maximum power of the electric current supplied to the evaporator heater
t_{EP}	engine preparation time
t_{Σ}	engine running time

All developed neural networks are multilayer perceptrons trained in the backpropagation method. As a training sample, the calculated and experimental data obtained during the design and testing stages of the propulsion system were used. The structure of neural networks is given in table 2.

Table 2. Neural Network Architecture.

NN	Neural Network Architecture
NN1	12-5-3-3
NN2	3-3-5-12
NN3	15-6-4-2

The predictive neural network of fuel consumption of electrothermal micropropulsion engine includes three separate neural networks NN1-NN3, which are having multilayer perceptron structure trained with back propagation learning algorithm.

System of neural networks NN1-NN3 and their architectures, logics block selecting simulation and monitoring modes are presented on figure 5.

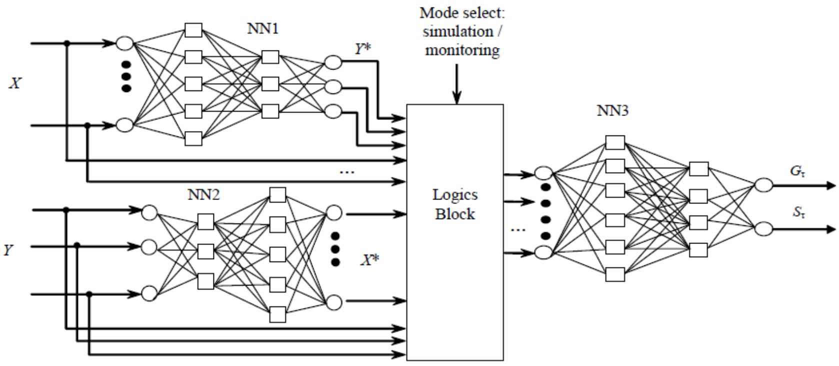


Figure 5. Predictive estimation of remaining fuel for microsatellite.

The NN1 neural network is designed to determine the dependence of the output information *Y* on the input *X* and is used in the simulation mode of the propulsion system.

The NN2 neural network solves the inverse problem and determines the dependence of the input information X on the output Y. The results of the NN2 neural network are used in the monitoring mode to solve the problem of diagnosing the technical condition of the engine.

The NN3 neural network is used to determine the fuel consumption G_τ and assess the technical state of Sτ. In the NN3, data streams X and Y are used as input.
Data on fuel consumption obtained in the process of testing the engine, can improve the accuracy and reliability of the training set. The complex of neural networks based on NN1, NN2 and NN3 is shown in figure 5. In the simulation mode of the propulsion system, the logic unit provides interaction between the NN1 and the NN3, and in the monitoring mode, the NN2 and the NN3, which improves the accuracy of the fuel consumption estimate using additional information about the technical condition of the engine.
Data sets from databases of simulations results, telemetry information and control data, settings and additional information are applied for training process for this system of neural networks.

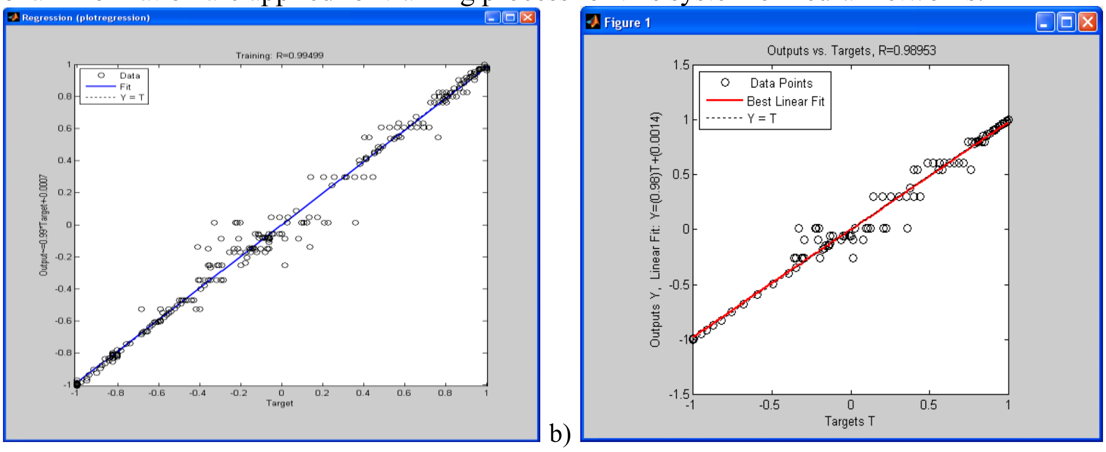
a)  b)

Figure 6. The predictive neural network model NN1 (a) and NN2 (b) learning results.

The telemetric information of a microsatellite with an electrothermal engine, which performs a single-pulse maneuver for orbit correction, is used as a training sample. Data sets include telemetry information on temperature of fuel thermal condition, fuel pressure, and control unit state.
The learning results of the NN1 neural network are presented in figure 6. As we can see, the quality of training of the neural network is good. The architecture of NN1 neural network includes input layer, hidden layer and output layer and has the following structure 12-5-3-3 neurons.
To assess the reliability of the results of the neural network, a regression analysis was performed, obtained by comparing the reference values with the results of processing a test sample. For this, the postreg function is used in the MATLAB environment. The correlation coefficient between output prediction and sample data is R≈0.995 (figure 6, a).
The result of the regression analysis for neural network NN2 is presented in figure 6, b). The correlation coefficient is R ≈ 0.989.
The architecture of NN2 neural network includes input layer, hidden layer and output layer and has the following structure 3-3-5-12 neurons.
The experiment on teaching the intellectual model and determining the fuel supply showed that the accuracy of solving the problem under consideration increased by 10% compared with the analytical method.

5. Conclusion

One of the modern ways to achieve efficiency of life cycle of complex technical systems is application of predictive analytics information support in design, production and exploitation stages of life cycle.
As it known the life cycle of complex technical objects usually contains following stages: prototyping, designing, manufacturing, implementation, operation, utilization. The duration of stages from prototyping to implementation for microsatellite is more times longer the duration of exploitation stage. One of the modern ways to achieve efficiency of life cycle of such systems is application of predictive analytics information support in design, production and exploitation.
Predictive models and methods for life cycle information support on the basis of system of neural networks are proposed. System of neural networks that can be estimated on onboard computer is

presented. This predictive model can solve the task of estimation of fuel consumption, diagnostics and possible failures detection.
Predictive models and methods for life cycle information support on the basis of system of neural networks can be applied.
System of neural networks that can be applied on onboard computer is presented. This predictive model can solve the tasks of estimation of fuel consumption, diagnostics and possible failures detection for the small propulsion system.

6. References

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