COMPARISON OF FDI METHODS APPLIED ON NANOSATELLITES WITH ACTUATORS FAILURES

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This paper presents two Fault Detection and Isolation (FDI) methods for a brushless DC motor (BLDC) nanosatellite actuator. The main objective is to compare a classical multi-model FDI strategy with a method based on Neural Network approach. The FDI algorithms must detect any error occurring in the Attitude Determination and Control System (ADCS) of the satellite and then to assign it to a possible fault scenario. The performances of the two fault detection algorithms are analysed and compared considering external disturbances acting on the satellite motion. Moreover, this paper highlights the fact that a FDI based on neural networks can be successfully used as a redundant method for the satellite FDI subsystem.

Keywords: Fault Detection and Isolation System, Neural Network method, BLDC motor, FDI, Comparative analysis, Failure scenarios, Deterministic fault detection.

1. Introduction

The advantages of a FDI system are obvious in terms of costs and technical solutions. For example, diagnostic and recovery algorithms can detect, identify and fix vehicle damage (minor and major) in real time, which most likely would save the mission during the procedure. Moreover, the ability to plan activities on board the vehicle allows a rapid response in case of a major event and the system can generate new sequential commands. These commands allow a continuation of the mission in order to achieve the objectives that are still possible after the failure. One of the main problems in implementing FDI algorithms structures is finding a vigorous way to distinguish the effects given by disturbance couples and the real failures. Thus, the development of a robust FDI method is essential: in case of a major event, the vehicle needs to be able to respond quickly and generate new commands to continue the mission objectives that remain possible after the failure.

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The purpose of developing and implementing these algorithms is to maintain as much as possible the performances of a vehicle even in presence of sensors, actuators or other components failures.

There were in the last years multiple approaches to the method including: analytical redundancy [13], adaptive observers and residual generation [14], estimating states and other system parameters simultaneously – this method was approached by Qinghua Zhang in [11], Fault Tolerant Control considered and treated in [12].

There are also other methods which do not require the system model. Among them one mentions: fuzzy logic based approach (see for instance, [10], [3]), methods based on artificial neural network (for example [9], [15], [10], [3]), analysis of stochastic signals method (idea developed in [7]).

The FDI domain for nonlinear systems is not entirely covered. For some nonlinear systems, it was shown that linearization around the operating points is sufficient in order to apply a FDI method. However in general it would not be possible for strong nonlinearities (for instance generated by position saturation). Therefore, several FDI methods were improved in order to cope with such systems [4].

For instance in [1], the FDI system was configured using the neural network method and fuzzy logic for a small AC motor. The paper [1] shows that a FDI system is feasible for both sensors and actuators if you combine the use of fuzzy logic and artificial neural networks. The simulations were performed in MATLAB and SIMULINK and the detection was implemented using the neural network method. The signals were analysed using fuzzy logic. In order to test the method there were used three types of faults: current and speed faults for the actuator and sensor error. The conclusion was that all faults have been detected and isolated successfully [1].

The aim of the current paper is performing a comparison between a classical deterministic method and a method that it is not implemented yet, but has captured attention in the past few years and it is currently a widely researched topic using neural networks based configurations. It will be shown that a Fault Detection and Isolation System with neural networks can be used in space applications as a secondary solution that corrects and verifies continuously the FDI deterministic method. The novelty of the proposed approach consists in creating and comparing two important FDI methods. Although neural networks are not very reliable and a deterministic method is much safer, a FDI system with neural networks can be implemented as a parallel system in order to increase accuracy, robustness and reliability of the total system.

The theoretical method described in the paper is illustrated via a FDI system of a nanosatellite actuated by a DC motor. This brushless DC motor is frequently used for the attitude control of unmanned vehicle systems. It is noted that the well-functioning of these elements is crucial in accomplishing the mission objectives The Brushless DC motor Faulhaber 2610T006B SC was chosen due to its important specifications, such as a large moment of inertia that does not require a flywheel.

The paper is organized as follows: the second section describes the multi-model method approach and the neural network method together with the common failures, risks, constraints and advantages/disadvantages. The third section presents the case studies and lastly, section four consists in the final conclusions and the comparison between the two presented methods.

2. FDI methods for faults of nanosatellites actuators

In the present section a brief presentation of the two FDI methods under investigation are provided. The main failures scenarios and constraints will be also discussed.

2.1 Multi-model FDI System Approach

The multi-model method is a simple approach when it comes to designing a Fault Detection and Isolation system. The architecture consists of several possible scenarios, including

order the nominal scenario. These scenarios represent the state of the actuator in different situations.

The multi-model method consists in developing a system using several models and scenarios in to detect and identify faults. More details concerning this approach may be found for instance in [5]. The main idea of the method is to consider the following configuration:

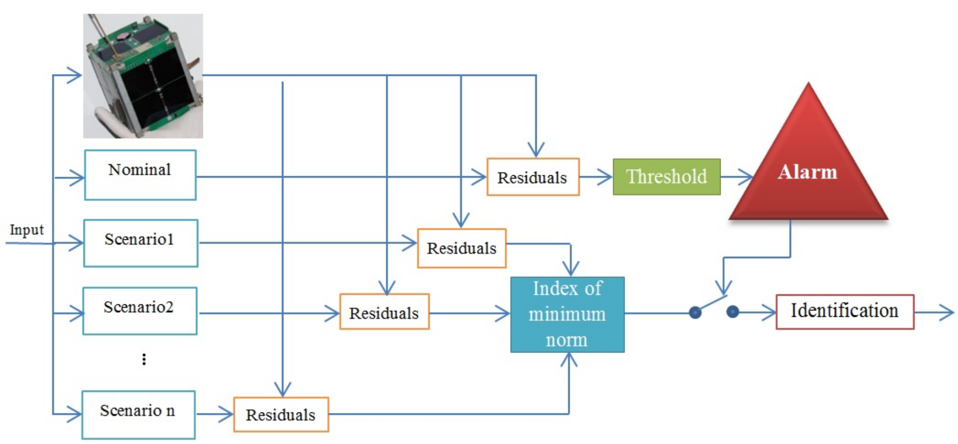

Fig1. Multi-model diagram block

In Figure 1, the block "Nominal" includes the satellite model when no failure occurs. The block "Scenario 1" contains the satellite model corresponding to the failure number 1. Similarly for i=1…n, the block "Scenario i" give the model of the satellite when the failure "i" occurs.

One can say that in the case of no failure, the residual corresponding to the nominal model is below a chosen threshold. Similarly, one of the residuals from 1 to n will be close to zero when the real plant corresponds to a specific model of the failures.

The obvious advantage in general use of an FDI system is clear in terms of total cost reduction. Moreover, the use of a deterministic method which is based on a model increases the reliability of the entire system, thus making the multi-model method a very used approach in designing Fault Detection and Isolation systems.

Regarding the disadvantages, this method is not very fast when the system is as complex as a satellite. Our proposed FDI system contains a model that represents the plant's real dynamics and compares its output with those generated by the models of each of the proposed scenarios.

In the case study presented in the next section, six models will be considered. These models correspond to various operating conditions of the DC motors.

Remark: Although the theoretical developments are illustrated for actuator failures, they can also be extended to the case of sensor failures.

2.2 Neural Network FDI system approach

The configurations based on artificial neural networks (ANN) can be also used in fault detection and isolation applications (see e.g. [1], [15]). The idea of such configuration is presented in figure 2:

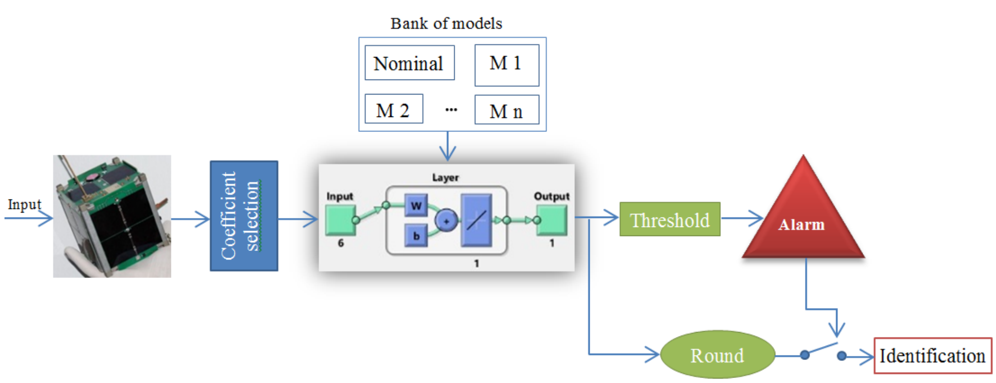

Fig2. Neural Network-based diagram block

In the above figure, the “Coefficient Selector” block provides, based on specific measurements including inputs, outputs and time responses, a model of the real dynamics of the actuator. This model is compared with the models included in the Bank of models. The final block, “Identification”, gives the index of the model from the bank of models which best approximates the real dynamics of the actuator.

The case when the neural network output is close to zero corresponds to the nominal model (no failure). Any other output of the network greater than 0.5 will be rounded such that the obtained integer will indicate the scenario number.

A neural network consists of a large number of interconnected elementary processors operating in parallel called *artificial neurons* or *nodes*, which cooperate to solve specific tasks. In order to limit the amplitude of the output signal of the neuron, an *activation function* is added. For classification problems, in which case the output network recognizes a class from a finite set of possible classes, a single *hidden layer* is sufficient (see for more details [1, 15]). The number of neurons needed in the hidden layer is determined experimentally [3].

The main advantage of the method is that the system model is not needed. This method is not as reliable as a deterministic method, but due to its advantages, could be used as a second and parallel system. Also, the property to adapt of the neural network is very important in case of a complex system because unlike the multi-model method, the neural network method can work with imprecise and unknown data.

Remark: The same scenarios as in the previous subsection will be considered for the neural network-based configuration. This helps us to make a relevant comparison between the two methods.

Description of selected scenarios

Scenario 1 – Speed controller faults - the created scenario aims to describe the situation in which the speed controller is poorly tuned. The system is very slow due to the large coefficients of the PI controller that runs inside of the actuator. The result in such situation is that the response time is too big (3 seconds instead of 1second) and therefore the generated accelerations are too small for an efficient satellite attitude control algorithm.

Scenario 2 – loss of feedback / locked output - in this scenario the output is zero or any other number. This means that amplification is zero and that the final transfer function is 0. This simulates the case in which the sensor inside the motor is faulty and we lose feedback, or the output is blocked.

Scenario 3 – Battery operation below the minimum voltage required by the manufacturer - the created scenario describes the moment when the battery does not work properly (6-7V). Moreover, the voltage selected is below the minimum

requested by the manufacturer (1.7V). The power supply voltage for determining the dynamics of this scenario was 1.5V.
Scenario 4 – the motor is not perfectly centred. To simulate and determine the scenario dynamics we unbalanced the actuator with an 11 grams weight, which represents more than half of its total mass.

The aforementioned scenarios were simulated and recorded with the described perturbations using a microcontroller and a motor. Each obtained system was stimulated with an input step response. The data was logged and analysed in order to collect the models that best approximate these scenarios. The method used for the functions determination was based on the identification system using time domain data [16].

Table 1

System Dynamics

Real system	Nominal model (0)	Scenario 1	Scenario 2	Scenario 3	Scenario 4
$\frac{0.50}{s+1}$	$\frac{0.53}{0.9s+1}$	$\frac{0.55}{0.3s+1}$	0	$\frac{1.53}{s^2+2.28s+8.16}$	$\frac{50}{s^2+1.77s+1.61}$

3. Case Studies and Comparative Results

In this section two case studies are presented and analysed, based on the FDI procedures mentioned in the previous sections.
Actuator overview:

Fig3. Actuator (Faulhaber 2610006B SC) [8]

There are several types of motors attested for space applications such as DC (direct current) motors, AD (alternating current) motors, brush, brushless, stepper motors or servo motors [5, 6].

According to a study conducted by NASA on motor types suitable for fly wheels and momentum wheels, it was concluded that BLDC (brushless DC) motors are the most compatible. Mechanism used in space must ensure continuous operation under extreme conditions of vacuum, microgravity, temperature and radiation [5, 6]. Furthermore, components must withstand vibrations and must not degrade during launch [5, 6, 9].

Table 2

Important specifications (Faulhaber 2610006B SC) [8]

Nominal voltage [V]	Output power [W]	Efficiency [%]	Max torque [mNm]	Max current [A]	Max Speed [rpm]	Operating temperature [C]	Rotor inertia [gcm^2]
6	1.92	78	3.77	0.48	7000	-25…+80	8.1

3.1 Multi-model FDI method

The SIMULINK model and the numerical results:

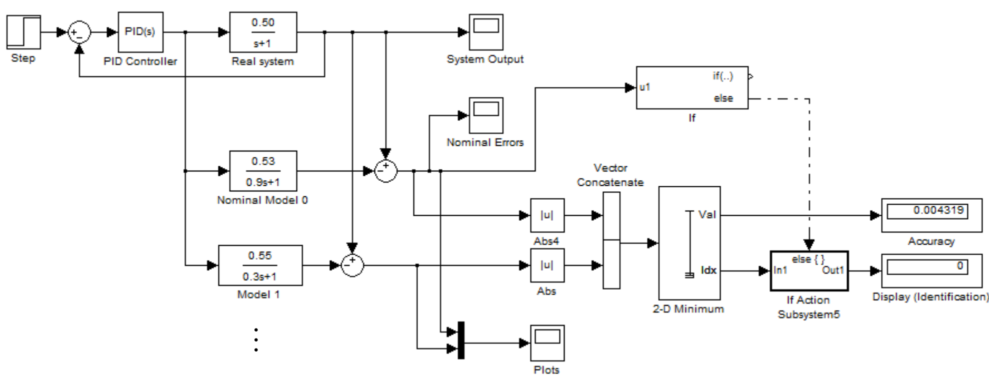

Fig4. – Multi-model FDI method SIMULINK block diagram

This diagram represents all the described scenarios and generates plots that show how the current model differs from the nominal one. Errors are determined for each model and the results are merged in the “Vector Concatenate” block. Afterwards the minimum is computed and shown in the “Accuracy” Block. Its position indicates what scenario was identified. As you can see in the block diagram the real system (current system), was identified as nominal (0).

This simplified method successfully detects a faulty system and identifies the corresponding scenario with a reasonable accuracy. The precision of the identification block can easily be improved with fine tuning. The SIMULINK diagram is identifying faults within an error band of ±15%. This small variation of error is due to the external torques/perturbations. Any value higher than 0.15 is immediately considered a fault.

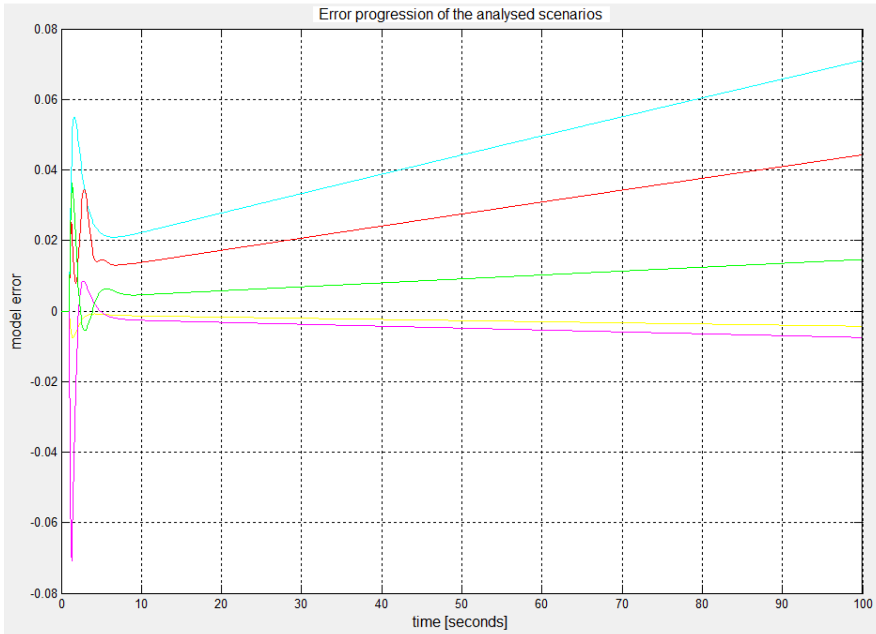

Fig5. Error progression of the analysed scenarios

Table 3

Identification results of multi-model method

	Nominal model 0	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Real dynamics	$\frac{0.53}{0.9s+1}$	$\frac{0.55}{0.3s+1}$	0	$\frac{1.53}{s^2+2.28s+8.16}$	$\frac{50}{s^2+1.77s+1.61}$
Exemplified dynamics	$\frac{0.50}{0.85s+1}$	$\frac{0.54}{0.4s+1}$	0	$\frac{1.60}{s^2+2.2s+8}$	$\frac{51}{s^2+1.75s+1.6}$
Identified model	0	1	2	3	4
Error	0.000002	0.001479	0	0.001844	0.02352

3.2 Neural network FDI method

As it is shown in figure 6, the neural network created for the fault detection and isolation algorithm has one hidden layer (as it was specified in section 2), six input neurons and one output neuron. The coefficients that describe the real system are considered input for the network. The output consists of a number that indicates the scenario which best approximates the real system.

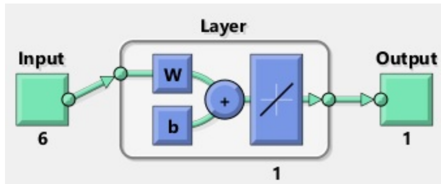

Fig 6. Created neural network

Table 4

Dynamics, vectors for NN method

	Nominal model 0	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Real dynamics	$\frac{0.53}{0.9s+1}$	$\frac{0.55}{0.3s+1}$	0	$\frac{1.53}{s^2+2.28s+8.16}$	$\frac{50}{s^2+1.77s+1.61}$
Exemplified dynamics	$\frac{0.50}{0.85s+1}$	$\frac{0.54}{0.4s+1}$	0	$\frac{1.60}{s^2+2.2s+8}$	$\frac{51}{s^2+1.75s+1.6}$

Same as in the previous method, we used the motor dynamics written in transfer function form. Also, there were created four scenarios that were taken into consideration by the FDI system, thus four possible faults. In the table below you can see the scenarios dynamics used for learning the neural network (same as in the multi-model method) and the dynamics exemplified for the purpose of demonstrating that the neural network identifies the errors and classifies them to the afferent scenario.

Some altered dynamics were introduced as input for testing if the algorithm identifies which scenario it belongs to. Also, the threshold or the error band was taken into consideration, and a deviation of 15% from the expected result was accepted.

Table 5

Results for NN method

Name Expected value	Nominal ~ 0	Model1 ~ 1	Model2 ~ 2	Model3 ~ 3	Model4 ~ 4
Identified model	0.0022	1.0088	1.9229	3.1154	4.0687
Error	0.0022	0.0088	0.0771	0.1154	0.0687

After the neural network was trained to associate the input dynamics to each existing scenario, we determined that 5000 iterations were needed for the neural network to learn the input set correctly. The MATLAB neural network training tool (nntraintool) was used for defining the network and its parameters.

In conclusion, one can say for this method that the trained algorithm through neural networks detects a system fault and assigns that fault to one of the considered scenarios, accomplishing with success the model classification. The main disadvantage of this method is the fact that as the deviation from a created model is higher, the error is larger. Also, if two or more scenarios have a similar dynamics, it becomes difficult for the neural network to identify and classify the fault.

3.3 Comparative Results

Table 6

Error Comparison

Error Multi-model method	0.000002	0.001479	0	0.001844	0.02352
Error NN method	0.0022	0.0088	0.0771	0.1154	0.0687

Table 6 shows the differences between the two studied methods in terms of error. The deterministic method has considerably smaller errors than the neural network errors, as expected.

4. Final Conclusions and Future Developments

In conclusion, one can say for both methods that they fulfilled their task and have accomplished to assign every test model to one of the created scenarios. It is obvious that the multi-model method is more robust and has the highest reliability. Although the advantages are clearly in favour of the multi-model method, we must take into consideration the fact that the ANN has comparable results. For even more accurate classifications, advanced system identification tools could accompany the Neural Network.

Even though the ANN method has not yet been tested in-flight and it is still considered unreliable, it could be used as a second/parallel system that continuously verifies the first method. The neural network method has some evident disadvantages. One inconvenience is the number of iterations required to make a reliable learning, and a second one occurs when two similar scenarios are considered, thus confusing the neural network. However, in the proposed scenarios the error band was not exceeded and for simple systems neural networks could be used.

It is desired to improve and develop the algorithm both in terms of number of fault scenarios and in robustness and error sensitivity. To this end, the following ideas are taken into account.

(i) Combine models – this means creating multiple scenarios (for both scenarios) that incorporate more than one fault;

(ii) For the multi-model method it is best to search for other criteria in order to determine the error minimum (now it is realized with absolute blocks);

(iii) In order to simplify the ANN method the identification part should be based on fuzzy logic;

(iv) Finding for the neural network method, a more efficient training method because the current one tends to specialize in the scenarios models.

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