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Research Article

Improving the Efficiency of Angular Velocity Sensors on Aircraft

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Abstract

With the development of science and technology, intelligent systems on aircraft help users know the device's operating status in real time. Using smart devices shortens the time for maintenance, repair, and operation of ground equipment and aircraft equipment. Therefore, building devices capable of self-diagnosis and warning failure are essential in aeronautical engineering. In many published studies, the authors often use the foundation of classic algorithms such as genetics, neural networks, and AI to solve the problem of identification and troubleshoot some simple devices. In Vietnam, there are currently not many published studies on failure diagnosis in aviation engineering, so the author's research has built the foundation for developing studies on fault diagnosis crash in the future. The primary purpose of the research is to create a complete automatic fault diagnosis and repair system for a specific class of inductance (angular speed sensor). The algorithms proposed in the paper are simulated on Matlab Simulink software, which will prove the feasibility of the proposed algorithm. In future studies, the author will apply new algorithms to build more complex fault diagnosis systems for other objects on the flying device.

Keywords

Angular velocity sensor
Fault detection
Fault diagnosis
Aircraft

Time Scale of Article

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1. Introduction

Given the expected growth in passenger levels and the continued expansion of the world's aviation network with more aviation connectivity, sustainable air transportation will be a critical global concern. To manufacture gradually more efficient and ecologically friendly airplanes, new technical alternatives are becoming increasingly necessary (Arockiam, Jawaid and Saba, 2018), (Iemma, Pisi Vitagliano and Centracchio, 2018), (Vieira and Bravo, 2016). Early and reliable

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automated and self-diagnosis of faults (Wang, Zarader, and Argentieri, 2012) (Chen et al., 2009) that may affect structural loads contribute to overall aircraft design optimization(CHU et al., 2022) and, as a result, weight reduction for improved overall performance (Cardei and Du, 2005) in terms of sustainable aviation systems, optimal fuel, noise, range, and environmental footprint.

Sensors play a very important role in aerial vehicles (AV); the quality of sensor operations determines the stability and safety of the AV operation (Khamis, 2021; Yang, 2021). As a result of the reduced flying duration, the least overall maintenance cost is offered. The standard operating procedure in this industry is to maintain an aircraft at optimal maintenance time and cost (Orhan, Kapanoğlu, and Karakoç, 2011). Many authors have researched the sensors on AVs and have come up with methods to fix the sensor damaged during the AV operation. For example, Hajiyev and Caliskan (2005), proposed a method for detecting and isolating aircraft sensor and control surface/actuator faults that impact the Kalman filter innovation sequence mean (Hajiyev and Caliskan, 2005). This approach was created to estimate the nonlinear flight dynamics of an F-16 fighter and the impacts of sensors and controlling surface/actuator failures, and it's particularly beneficial for isolating sensors and controlling surface/actuator failures. However, further research (Hajiyev and Caliskan, 2000) highlighted the failures impacting the covariance of the innovation sequence, which are not explored in this study.

On the other hand, the sensors on AVs operate in individual systems (Brooks and Roy, 2021), so their role also varies depending on the importance of the system to which it provides the signal. Therefore, in some studies, researchers also focused on studying a number of different sensors such as air data parameter sensors (P Lu et al., 2015), engine parameter sensors (Xue, Guo and Zhang, 2007) or other sensors on helicopter UAV (Hajiyev and Soken, 2013). In addition, several methods, including Kalman filters (Xue, Guo and Zhang, 2007; P Lu et al., 2015; He et al., 2020), self-diagnostic (Sullivan, 1988; Tuan, Firsov and Pishchukhina, 2012), adaptive models (Peng Lu et al., 2015), fuzzy tuning (Kim, Choi and Kim, 2008), and machine learning (Baskaya, Bronz and Delahaye, 2017) have been applied to identify faults of sensor operations on AVs.

In Vietnam, there have not yet been many studies on sensors on AVs, while several studies have been focused on mining using existing equipment and fixing errors using good block substitution methods available. Therefore, this study presents an approach focusing on building a self-diagnostic, fault-resolving sensor system using the output parameters of the sensors, which can be applied to research and development of intelligent sensor systems on AVs. In a previous study (Tran et al., 2021), an algorithm to diagnose the fault location of the sensor was give in the following Fig. 1.

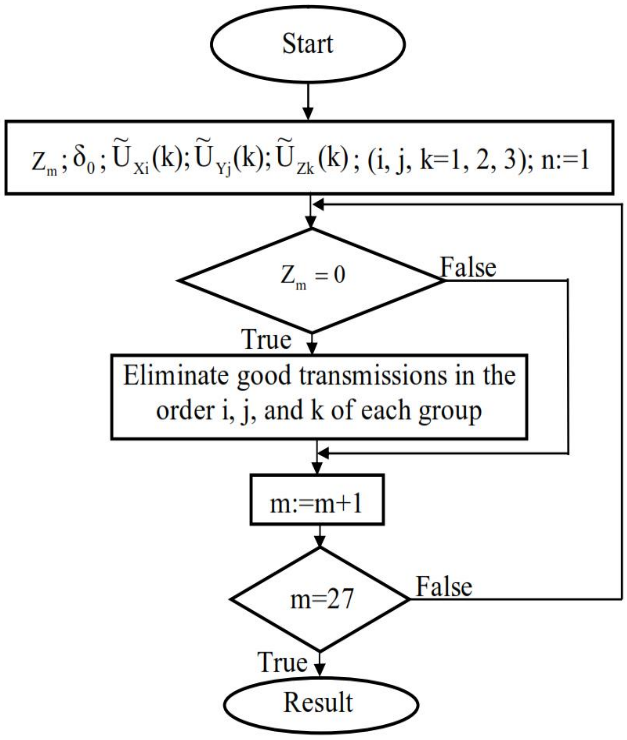

Fig. 1. Algorithm flowchart representing fault diagnostic algorithm

A next problem needs to be solved that is to find the cause of the fault and fix it (if possible). To solve this problem, it is necessary to consider the typical fault modes of angular velocity sensor (Isermann, 2005) such as drifting signal, changing gain, and broken wire. The graph representing the signal form of the failed angular velocity sensor is shown in Fig. 2.

Where:

1- The standard characteristic curve of the sensor.

2- Positive drift signal characteristic curve of sensor.

3- Negative drift signal characteristic curve of the sensor.

4- Up amplification coefficient characteristic curve of the sensor.

5- Down amplification coefficient characteristic curve of the sensor.

6- Broken negative wire characteristic curve of the sensor

7- Broken positive wire characteristic curve of the sensor.

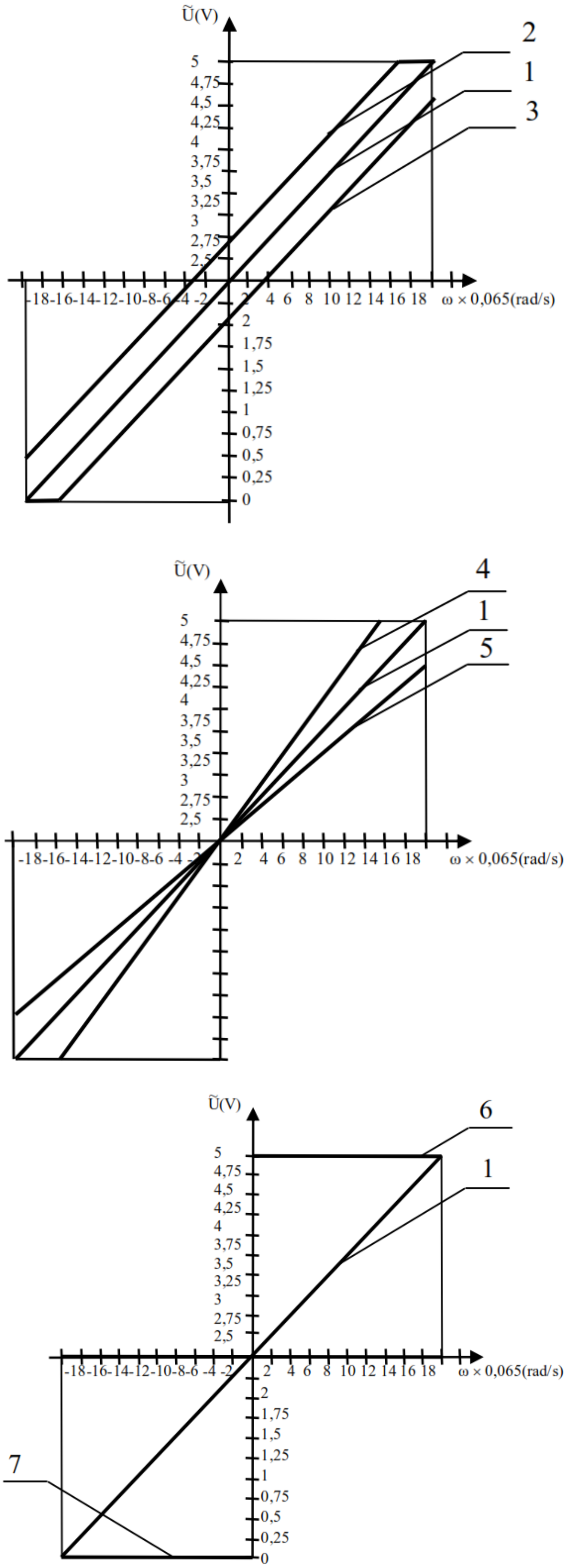

Fig.2. The graph shows the signal form of the fault sensor

When a fault occurs, for each type of fault, the mathematical model of angular velocity sensor has different forms and is specifically shown as follows:

- For the drift signal type

$$\widetilde{U}_{Dx}(k) = k_{Dx}\omega_X(k) + \Delta U_0(k); \Delta U_0(k) \neq const \qquad (1)$$

- For the amplification coefficient changes type

$$\widetilde{U}_{Dx}(k) = \tilde{k}_{Dx}\omega_X(k) + M_1(k);\ M_1(k) = \frac{\tilde{k}_{Dx}}{k_{Dx}} = const \neq 1 \qquad (2)$$

- For the broken wire

$$\widetilde{U}_{Dx}(k) = \underbrace{\widetilde{U}_{Dx}(k)}_{Max} = const\ ;\ \widetilde{U}_{Dx}(k) = \underbrace{\widetilde{U}_{Dx}(k)}_{Min} = const \qquad (3)$$

Thus, for the above three types of fault, we find that the fault due to drift signal or by changing the gain can be overcome if we determine the values $\Delta U_0(k)$ and $M_1(k)$, and for damage caused by broken wire, it cannot be fixed.

2. Methods

Firstly, we build an algorithm to identify fault of the sensors in the improved sensor block. To simplify the calculation, we divide it into two types of faults: wire break and zero drift or gain change. The fault parameter calculation to lead to the fault identification is determined by the following expression:

$$Z_1 = \{|\widetilde{U}_D(k)| > U_{D\_max}\} = \begin{cases} 0 - \text{fault for signal drift or amplification coefficient changes} \\ 1 - \text{fault for broken wire} \end{cases} \qquad (4)$$

Where: $\widetilde{U}_D(k)$: the value output of sensor.

U_{D_max} : the maximum value output of sensor.

From expression (4), we build an algorithm to determine the fault type in the general case as follows:

The value N depend on the accuracy of the algorithm. Thus, using the algorithm in Figure 3, we have diagnosed the general form of the problem. After that, we build an algorithm to diagnose specific types of problems.

For the fault type due to wire break. The expression to calculate the parameter to determine the broken wire is as follows:

$$Z_2 = \{|\widetilde{U}_D(k)| < U_{D\_min}\} = \begin{cases} 0 - \text{fault for broken positive wire} \\ 1 - \text{fault for broken negative wire} \end{cases} \qquad (5)$$

Where: U_{D_min}: the minimum value output of sensor.

From the above expression, it is possible to build a diagnostic algorithm to determine the fault caused by the wire break as follows:

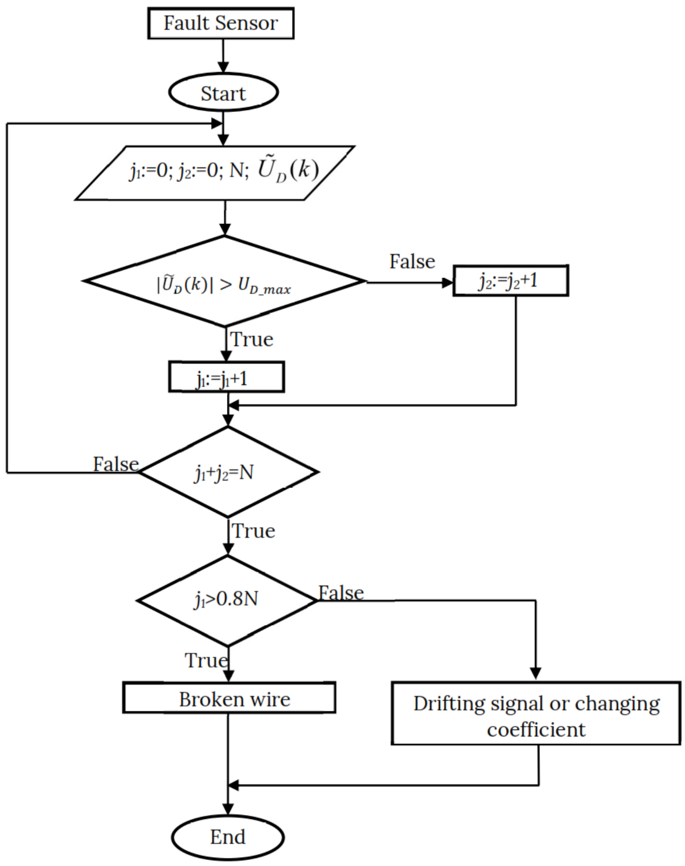

Fig.3. Algorithm flowchart representing fault identification in general case

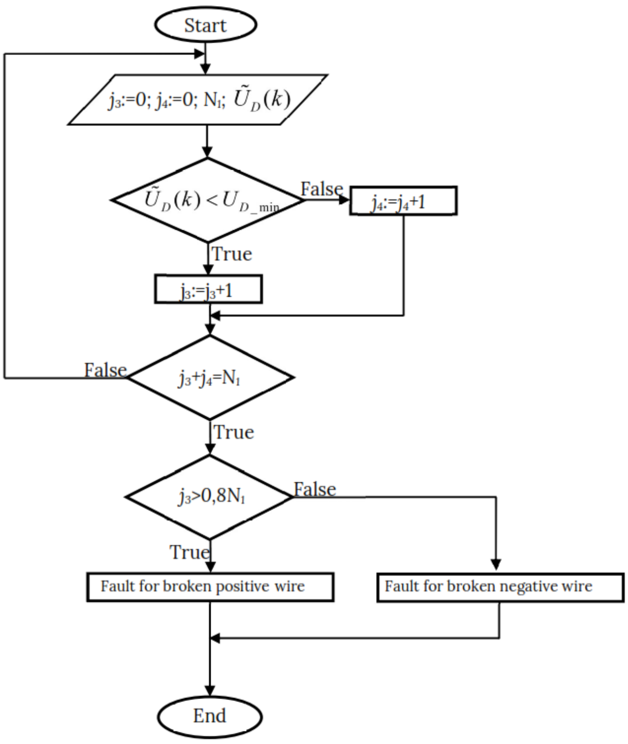

Fig.4. Algorithm flowchart representing fault identification in broken wire case

The value N_1 depend on the accuracy of the algorithm. For the fault type drift or gain change, the parameter calculation expression to build the fault type diagnostic algorithm is as follows:

$$Z_3 = \{\Delta U_0(k) = \tilde{U}_D(k) - \hat{U}_D(k) = const\} = \begin{cases} 0 - & \text{fault for signal driff} \\ 1 - & \text{fault for amplification coefficient changes} \end{cases} \quad (5)$$

Where: $\hat{U}_D(k)$: the calculated value output of sensor.

But first, we need to build an algorithm to determine the value of U_{0TB} to serve as a basis for building a problem diagnosis algorithm.

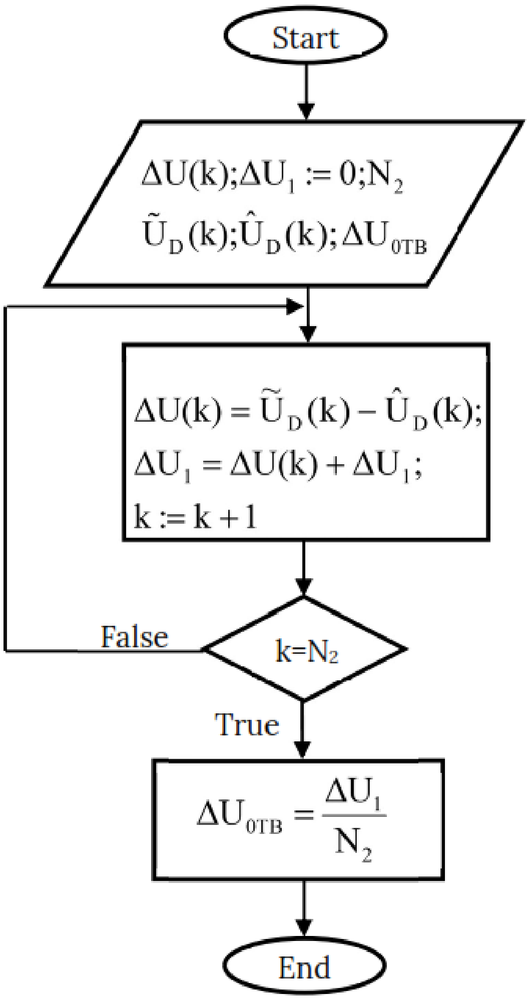

Fig.5. Algorithm flowchart representing determined value U_{0TB}.

The value N_2 depend on the accuracy of the algorithm. After determining value U_{0TB}, we can buid fault identification algorithm in **Fig.3.**

From formula (5), we build an algorithm to diagnose the fault type of the inductor in case the fault is caused by drift or change in gain as follows:

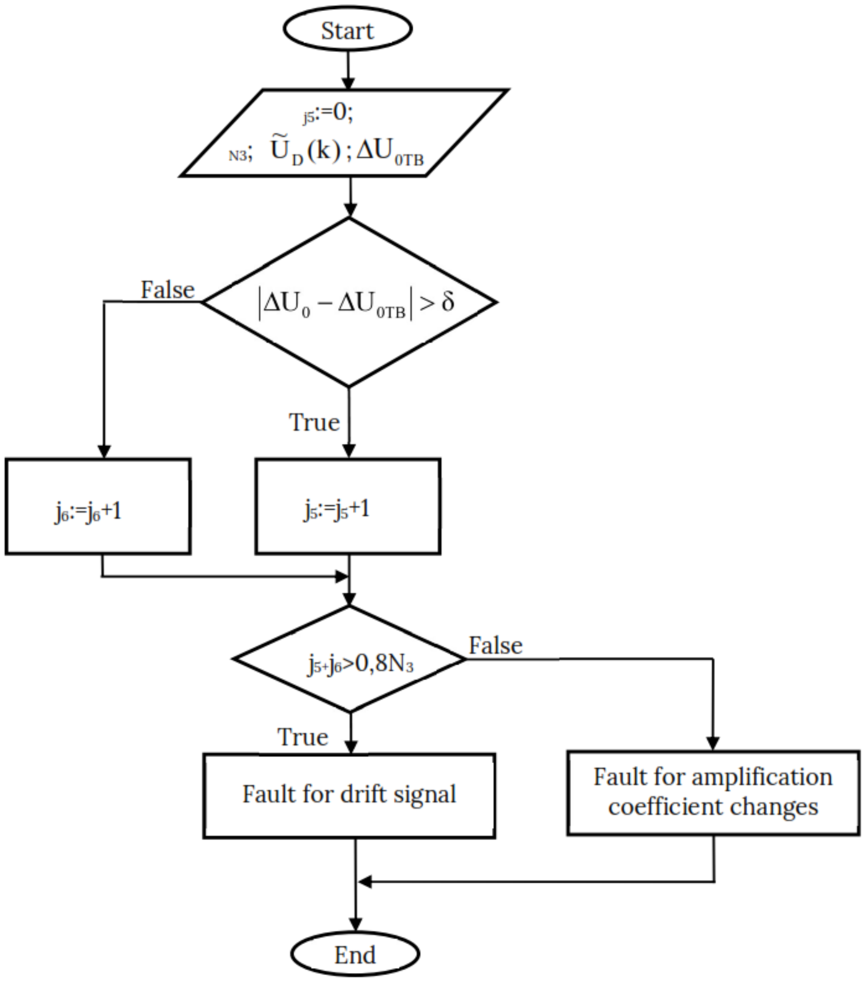

Fig.6. Algorithm flowchart representing determining the identify of drift or change in the transmission gain

Similar to the previous algorithm, the value N_3 depend on the accuracy of the algorithm. Thus, we have perfected the method of identifying fault modes of angular velocity sensor. Inductor block troubleshooting is conducted for transmitters that have been identified as having a remedial problem during the identification process mentioned above. In which sensors have a remedial fault including fault due to drift signal or fault due to gain change.

- For the fault due to drift signal. The physical nature of drift signal is that the actual output value of the sensor deviates from the standard output value by a constant amount over time. The drift value is described by the following expression:

$$\Delta U_o(k) = \tilde{U}_D(k) - \hat{U}_D(k) \quad (6)$$

Where: $\Delta U_o(k)$- Deviation between the actual output value of the sensor and the standard output value;

Thus, after determining the value of $\Delta U_o(k)$ allows us to fixed the output signal from the sensor to see if there is a drift problem. The corrected value is described by the following expression:

$$\tilde{U}_{D.FIXED\_1}(k) = \tilde{U}_D(k) - \Delta U_o(k) \quad (7)$$

Where: $\tilde{U}_{D.FIXED\_1}(k)$- The output value of the sensor has been drift signal corrected.

- For problems due to gain change. The physical nature of the fault due to a change in gain is that the output value of the inductor is always proportional to the reference input value by a constant value and other than 1. If the gain value changes, the gain is described by the following expression:

$$M_1(k) = \frac{\tilde{U}_D(k)}{\hat{U}_D(k)} = const \neq 1 \quad (8)$$

Or we can express through the gain factor as follows:

$$M_1(k) = \frac{\tilde{k}_D(k)}{\hat{k}_D(k)} = const \neq 1 \quad (9)$$

Where: $\tilde{k}_D(k)$- Actual gain of sensor.

$\hat{k}_D(k)$- Standard gain of sensor.

$M_1(k)$- Ratio gain.

In the ideal case, the value of the scaling factor is 1 and we denote it as $M_0(k)$. Thus, the difference between the scaling factor in the case of error due to the gain change and the ideal case is expressed by the following expression:

$$\Delta M(k) = M_1(k) - M_o(k) \quad (10)$$

From expressions (8), (9), (10) we see that when determining the scaling factor $M_1(k)$ allows us to correct the output signal from the inductor with the error of the gain change. The correction value is described by the following expression:

$$\tilde{U}_{D.FIXED\_2}(k) = \frac{\tilde{U}_D(k)}{M_1(k)}(M_1(k) \neq 0) \quad (11)$$

Where: $\tilde{U}_{D.FIXED\_2}(k)$- The output value of the sensor has been corrected for gain change error.

The algorithm to determine the value of $M_1(k)$ is as follows:

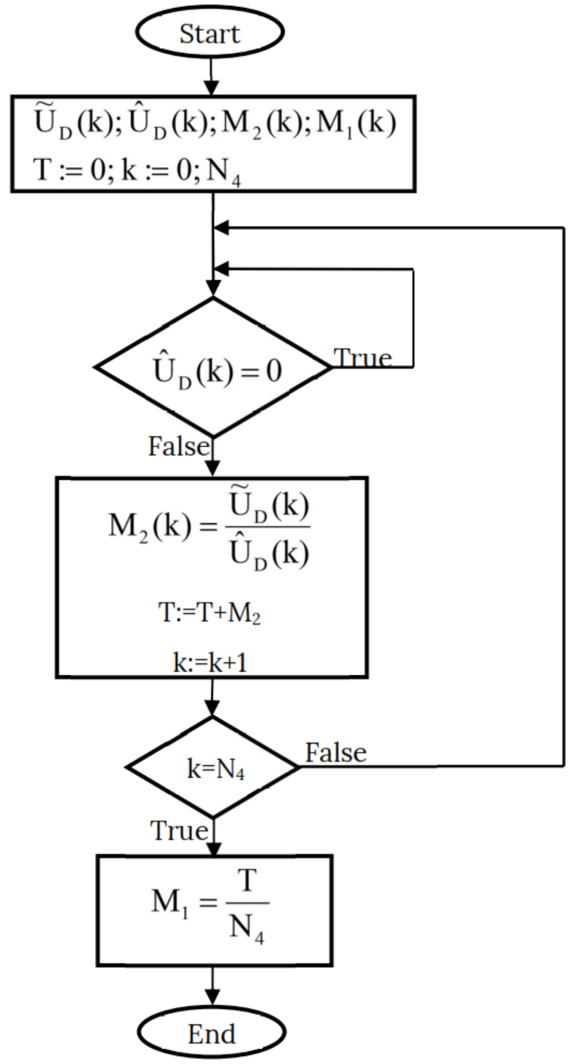

Fig.7. Algorithm flowchart representing determined the amount of gain change

The value N_4 depend on the accuracy of the algorithm. The general algorithm for fixed the sensors block is defined as follows

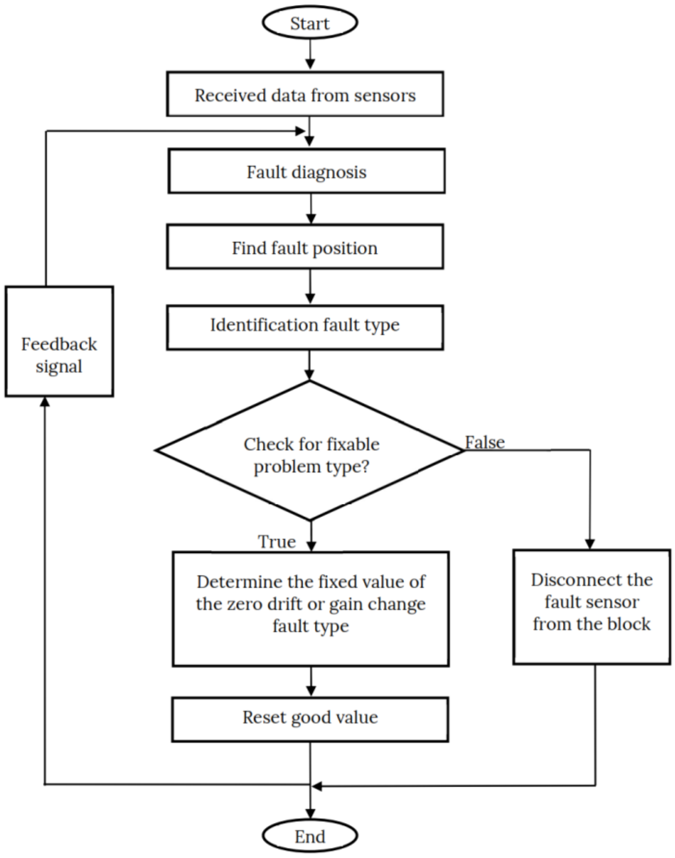

Fig.8. General algorithm flowchart representing fixed fault of sensors

Build detailed algorithm diagram for the system

- For the type of fault due to drift signal. The diagnostic algorithm for fault for sensor with drift problems is not implemented on the basis of expressions 1 to 11 and the mentioned algorithms are as follows:

Where: Block [1] - Algorithm to diagnose a problem on the sensor in the general case;

Block 3 – Algorithm for identification a type of fault in general case.

Block 5 - Algorithm to calculate the value U_0TB.

Block 6 - Algorithm for specific identify of problems caused by drift or change in gain.

- For the fault form due to the change of gain factor. Troubleshooting diagnostic algorithm for faulty sensor due to gain change is performed on the basis of expressions 1 to 11 and the algorithms in [1] are as follows:

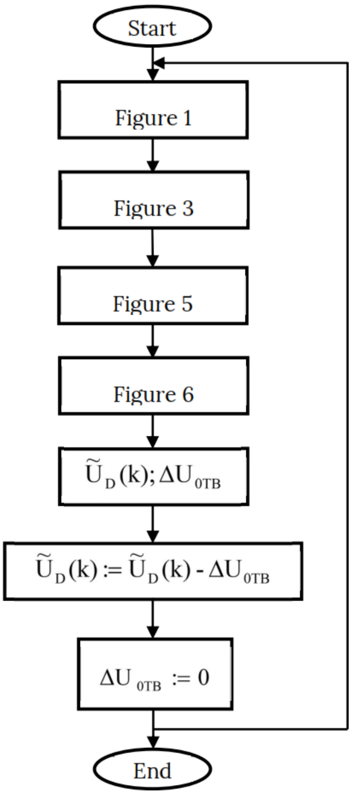

Fig.9. Algorithm flowchart representing fixed fault in driff signal case

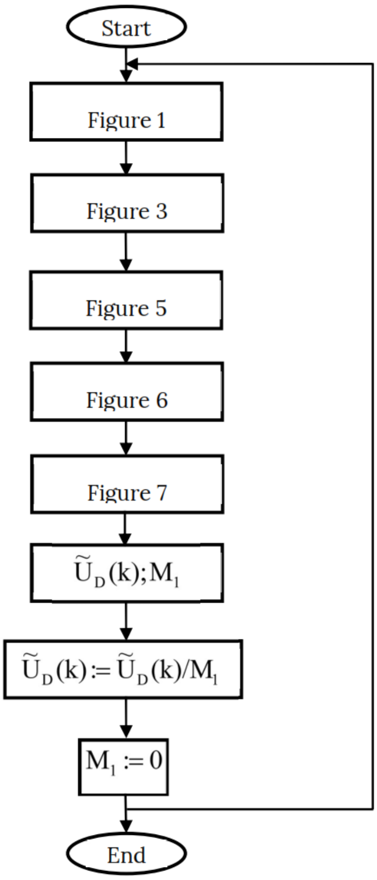

Fig 10. Algorithm flowchart representing fixed fault in amplification coefficient changes case.

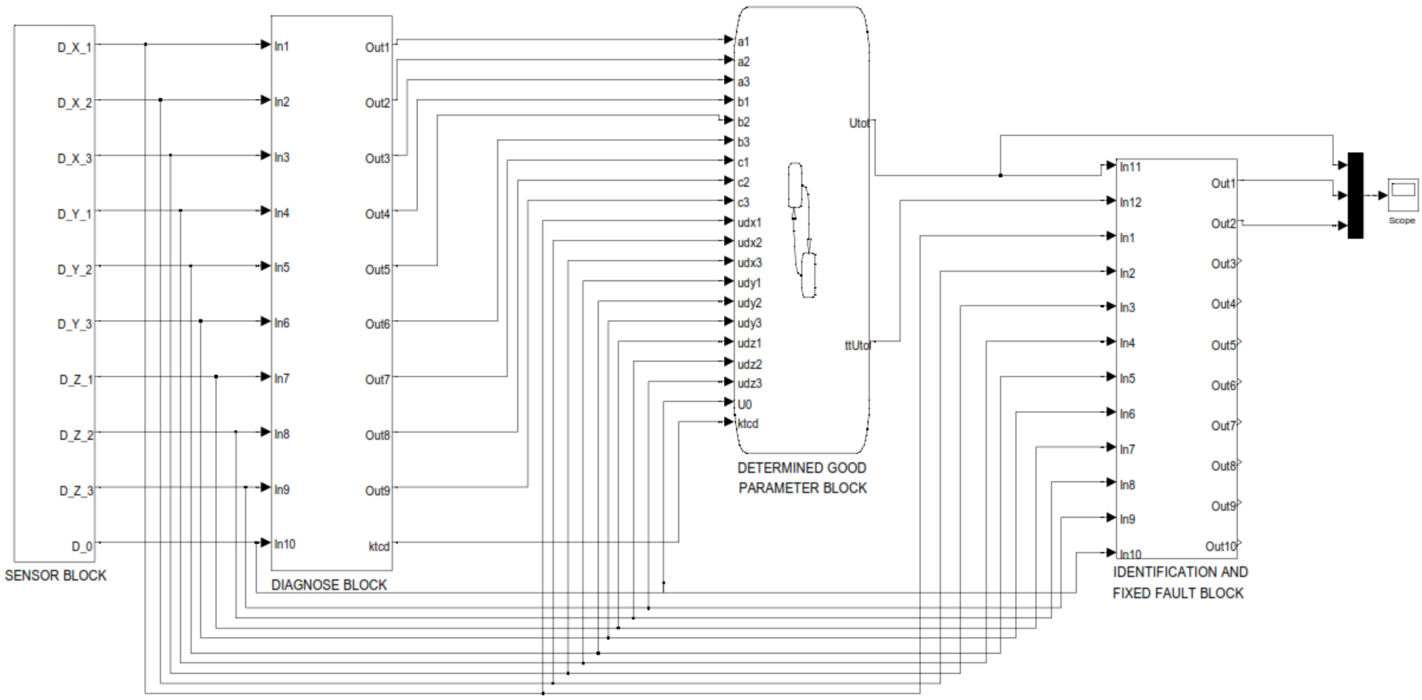

Fig 11. General simulation diagram for diagnosing, identifying and fixed fault of angular velocity sensors

Where:

Block 1 - Algorithm to diagnose a problem on the sensor in the general case

Block 3 – Algorithm to identificate a type of fault in general case.

Block 5 - Algorithm to calculate the value . U_{0TB}

Block 6 - Algorithm for specific identify of problems caused by drift or change in gain.

Block 7 - Algorithm for determined the amount of gain change

3. Results

On the basis of diagnostic results for the automatic identification and fixed fault algorithm on MATLAB Simulink simulation done by the current authors. The parameters are assumed that:

$$U_{D\_max} = 550$$
$$U_{D\_min} = -550$$
$$N = N_1 = N_2 = N_3 = N_4 = 100 \quad (9)$$
$$\delta = 0.5$$

On the basis of diagnostic results, continuing to simulate the automatic error identification algorithm. Based on the flowchart, the algorithm determines the type of the drift problem or the change in the gain of the sensor (Figure 6). Suppose we have determined that fault sensor is SENSOR_X1, which is good SENSOR_X2 sensor. The schematic diagram of fault identification is shown in Figure 12.

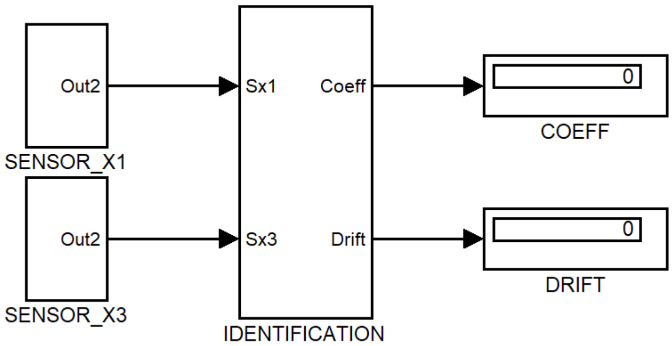

Fig 12. Fault identification simulation diagram

The automatic fault identification process is divided into 2 stages: Stage 1 calculates the parameters for the identification process using formulas 1 to 6 and algorithm 5 and algorithm 6. Diagram The simulation is shown in Figure 13.

Where algorithm 5 is represented in block CAL_U0TB and algorithm 6 is represented in block IDENTIFICATION. Simulation is performed in the two cases of sensor SENSOR_X1 with signal drift fault by changing the drift coefficient and the signal gain of the inductor, respectively. Running the simulation program gives us the results shown in Figure 14.

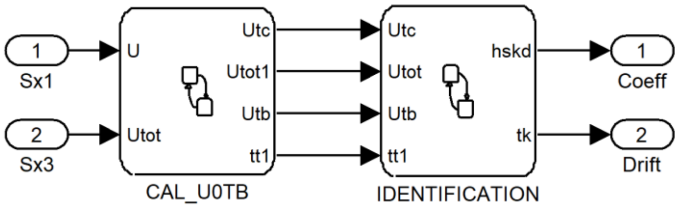

Fig 13. Block diagram of the fault identification block

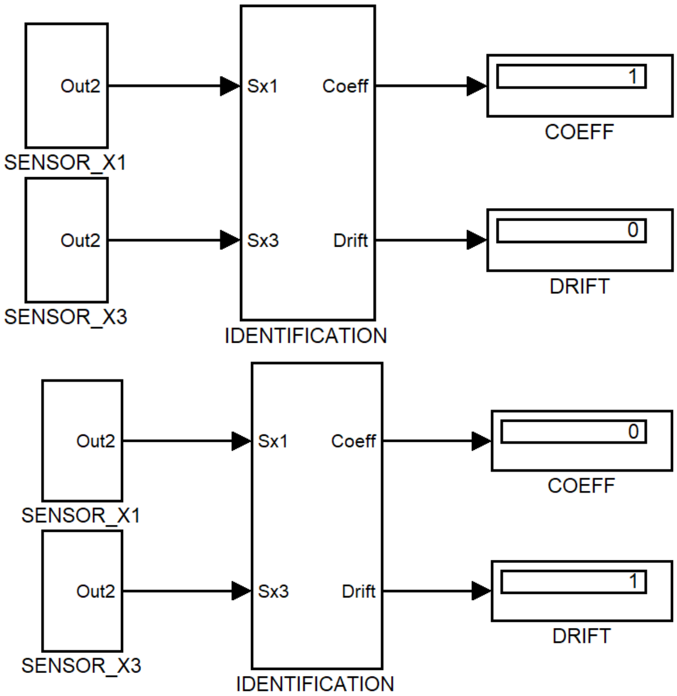

Fig 14. Fault identification simulation results

From the fault identification results in case of drifting sensor, we see that the output signal of the gain is zero - there is no error due to the gain change, the output signal of drift not equal to 1- is there a problem due to drift error. This proves that the drift fault detection system does not work well and can meet the requirements when there is no signal drift fault or gain change. Next, we simulate the process of automatically repairing the fault of the inductor, the simulation diagram is shown in Figure 15.

In which the troubleshooting block consists of 7 input signals and 2 output signals. Hskd-Fault signal due to gain change, tt2-end signal of fault identification due to gain change, Utc-signal from inductor fault , Utot- signal from inductor is working well, tk- signal is there any drifting problem, Utb-Average error value of inductor signal has problem and good sensor, tt3-signal of process end drift fault identification. 2 output signals are 2 signals that have been fixed.

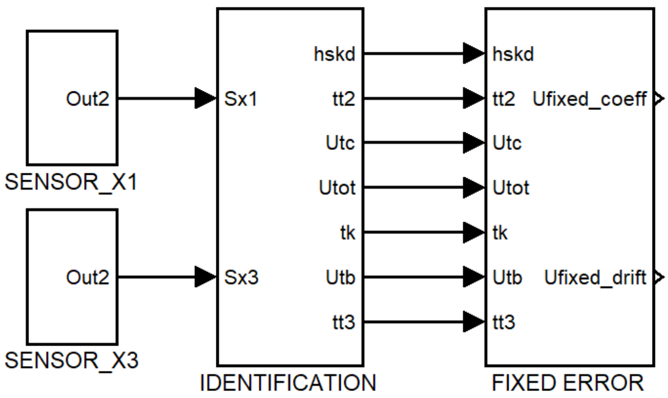

Fig 15. Diagram to simulate the process of automatically identifying and fixing fault

To simulate the process of automatic troubleshooting, we simulate in two cases: sensor has a problem due to a change in gain; Is there a problem with the transmission due to drift? For the case of sensor, there is a problem due to the change in gain. We assume that the SENSOR_X1 inductor has problems due to gain changes or has problems due to no-signal drift, the SENSOR_X3 inductors are good inductors. The simulation diagram and simulation results are shown in Figures 17, 18, 19. The output value of the sensor has been multiplied by the factor k in Figure 19.

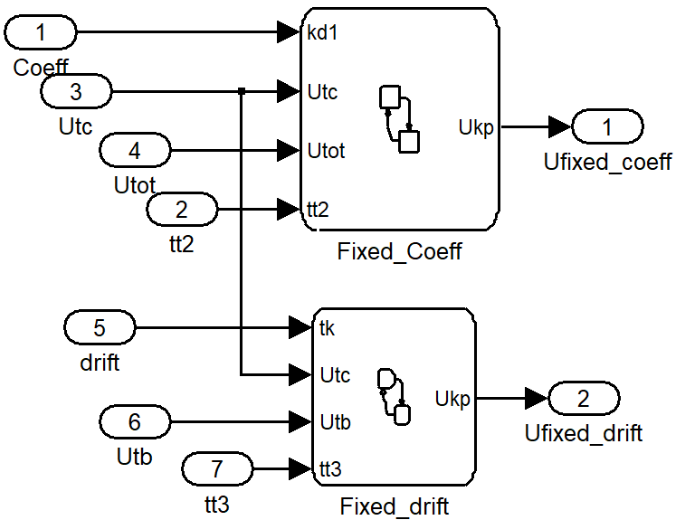

Fig 16. Automatic fixed fault signal block diagram

Where: 1-Fixed fault sensor signal; 2-Good sensor signal; 3-Fault sensor signal. Based on the simulation results, we can see that initially the troubleshooting signal coincides with the signal of the faulty transmitter due to the delay time to calculate the fault identification and fixed fault. After this delay, the rectified signal has the same form as that of the well-functioning sensor. This proves that the algorithm to fix the problem caused by changing the gain coefficient shown in Figure 10 is completely correct.

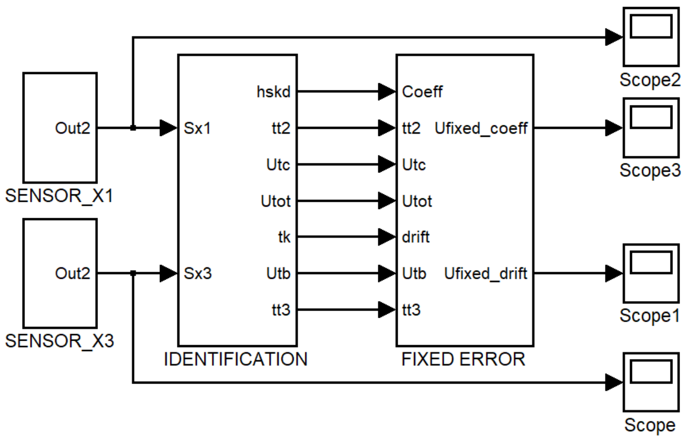

Fig 17. Diagram to simulate the automatic fixed fault signal process

4. Conclusions

From an industry standpoint, any sophisticated model-based solution for aviation systems should be clearly shown in terms of added value. Any modifications to an established and well-proven scheme must include a feasible technological solution that improves performance while maintaining resilience. New methods and technologies are risky, and they must be thoroughly validated and verified before being implemented in real-world systems. Hundreds of aircraft have been mass-produced in the civil aircraft industry for several decades. Some improvements can be planned throughout the aircraft building process, such as expanded range, increased maximum take-off weight, and passenger capacity.

vOne critical need in this context is that the new design be adaptable to different aircraft types and systems. For the adaptability of a novel solution in the context of mass production, easy-to-tune high-level input parameters are required. A small number of tuning parameters is preferable to reduce the validation and verification operations necessary for certification. Identify and isolate aircraft faults while maintaining aircraft performance operations and safety as a minimum requirement for today's technology. This fault diagnosis system should not be a black box; condition monitoring and comprehensive diagnosis results should be made available to engineering consulting services. It should be able to assist engineers in accumulating knowledge for reconfiguration activities (including diagnosis regulations) and improving the creation of innovative aircraft.

In the context of this research, the faults identification and repair algorithm is entirely accurate. After recognizing the fault pattern, the algorithm automatically compensates for the signal that coincides with the original signal form of the inductor working well. Based on the proposed method, it is possible to build an automatic fault identification device and repair some faults on the aircraft to ensure the system's safety in all working conditions. The proposed algorithm is only suitable for some typical fault types, not considering random factors, noise, calculation speed, and other sensor faults. However, the algorithm needs improvement to speed up the computation to meet the shortest and most efficient time. The actual implementation of the algorithm can use the FPGA platform. The author will overcome the study's limitations in future investigations. Further studies will extend to other sensors in aircraft and use a more intelligent identification method.

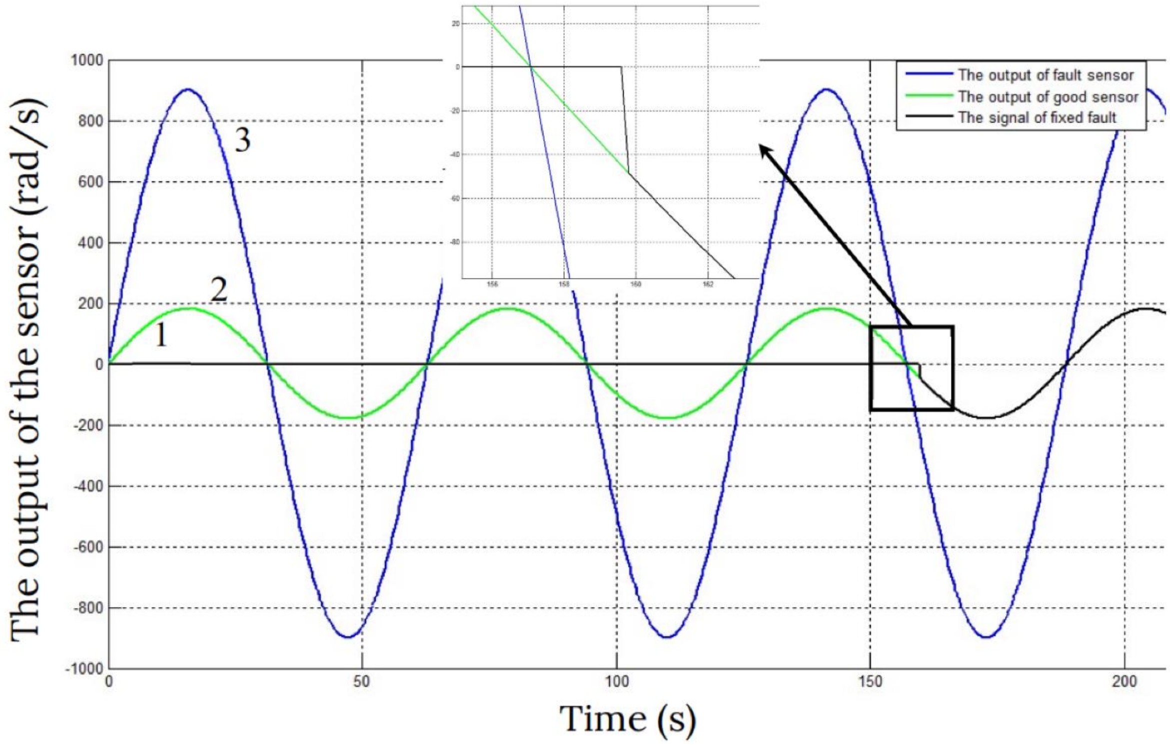

Fig 18. Simulation results of automatic repair of fault s for damage caused by signal gain changes

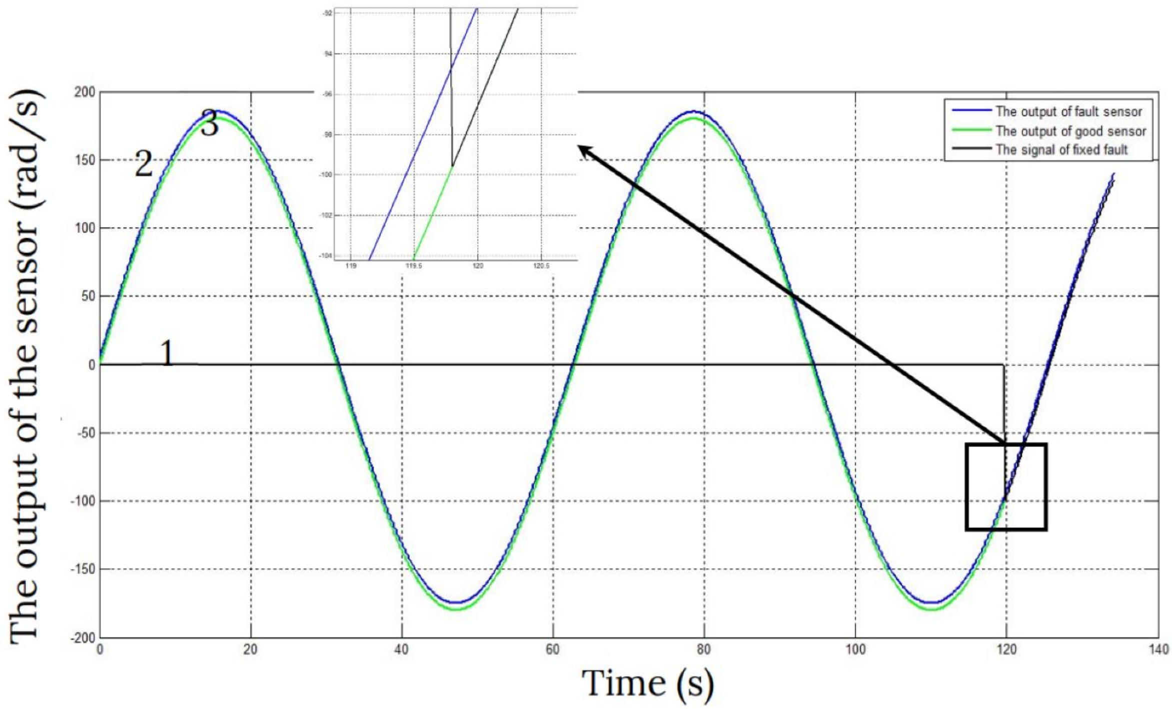

Fig 19. Simulation results of automatic repair of fault s for drift fault

Abbreviations

AV : Aerial Vehicles
UAV : Unmanned Aerial Vehicle
FDD : Fault Detection and Diagnosis

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