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Feasibility Demonstration of Diagnostic Decision Tree for Validating Aircraft Navigation System Accuracy

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The current trend in high-accuracy aircraft navigation systems is toward using data from one or more inertial navigation subsystems and one or more navigational reference subsystems. Anenhancement in fault diagnosis and detection is thus achieved via computing the minimum mean square estimate of the aircraft states using, for instance, the Kalman filter method. However, this enhancement might degrade if the cause of a subsystem fault is common to other subsystems providing seemingly independently derived data. One instance of such a case is the tragic incident of Air France Flight 447 in June 2009, where aircraft communication addressing and reporting system message transmissions in the last moments before the crash indicated inconsistencies in measured airspeed. In this research, the authors propose the use of a mathematical aircraft model to work out the current states of an airplane and, in turn, use these states to validate the readings of the navigation equipment through the use of a diagnostic decision tree network. Various simulated equipment failures were introduced in a controlled environment to validate the concept of operation. The results show successful detection and identification of failing equipment in all scenarios run.

Nomenclature

D^I	=	rotational derivative relative to the inertial frame I
$f_{a,p}$	=	aerodynamic and propulsive forces, N
g	=	Earth gravitational constant, m/s^2
m	=	body mass of an aircraft, kg
V_B^E	=	body velocity with respect to Earth, m/s
V_B^I	=	body velocity with respect to the inertial frame I, m/s

I. Introduction

THE work described in this paper is part of a feasibility study to develop an onboard network that can detect malfunctioning equipment, isolate the source and provide helpful recommendations to resolve the issue. It was conducted under a contract to RNC Avionics, Ltd.

To assist the effort for aviation safety and increase navigation accuracy, large aircraft are required to use redundant measuring equipment. The accuracy of the navigation system can be verified by comparing the readings from two or more different equipment groups. For instance, an accurate altitude can be assumed when the altimeter reading of the pilot's panel is identical to that of the flight officer's panel. Otherwise, a search for the defective component is initiated which, in turn, might involve manual procedures such as switching to alternative air data or observing the status of the altimeter for visual defection cues such as a fluctuating pointer [1]. However, manual observations require the pilots to be in a high state of situational awareness where they would be able to comprehend the states of the aircraft and, in turn, make reasonable decisions [2]. This negates the purpose of a decision support system (or redundant measuring equipment) as they are supposed to raise a pilot's situational awareness instead of the other way around.

One fault detection and isolation method that has received much research interest is the detection filter proposed by Beard in the early 1970s, where a fault is associated with a subspace of error state space called the detection space [3]. In this context, Caliskan and Hajiyev have studied four algorithms used to verify the covariance matrix in a Kalman filter (KF) from a performance point of view [4]. However, because all KF based algorithms follow signal-based modeling methods in which only the output signals are monitored, these algorithms can only detect deviations from assumed normal behaviors. The enhancement to fault diagnosis and detection (FDD) is only by ad hoc manner without solid foundation to believe in their generic applicability [5]. Other methods used to enhance fault detection are discussed in [6–9] including both the multiple-model adaptive estimation (MMAE) and the interacting multiple-model (IMM) algorithms.

Little attention has been given to establish a framework to develop an FDD system that deals with navigation systems as a grid of mathematically and physically interrelated quantities in which the accuracy of a reading can be mathematically verified. Such verification could be worked out by a 6 degrees of freedom aircraft mathematical model. When the sensors states and mathematical states of an aircraft do not resemble each other, a search for a fault is provoked which involves qualitative fault isolation. In this research we use the Bayesian diagnostic tree method to point to the most probable culprit of mismatching. The Bayesian diagnostic treealso serves as recursive Bayesian estimators to evaluate the probability density function of a given fault.

II. Six Degrees of Freedom Equations of Motion

When it comes to building a simulation model for a flying body with high-fidelity, the Six Degrees of Freedom (6DoF) is often the popular choice as it can be used to simulate displacement and rotation in three-dimensional space [10]. A flying rigid body (such as an aircraft) in free motion is able to move and rotate freely along any of the three perpendicular axes of a three-dimensional space, hence, providing the six forms of motion.

The 6DoF equation of motion follows from applying Newton's second low of motion to a flying body subjected to aerodynamic and

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thrust forces $f_{a,p}$ and the earth's gravitational field. This can be written as [10]:

$$mD^I V_B^I = f_{a,p} + mg \qquad mD^I V_B^I = f_{a,p} + mg \tag{1}$$

Where m is the body mass and V_B^I is the velocity of it with respect to the inertial frame (I). If the body to be modeled flies relatively close to the earth, the Earth is often assumed to be the reference frame (E), and for these purposes assumed to be flat. To solve the previous equation, one needs to be able to access the forces applied to the body (B) with B taken as the reference frame. This change in reference frames is done through Euler transformation. Thus Eq. (1) can be rewritten as [10]:

$$mD^B V_B^E + m\Omega^{BE} \qquad V_B^E = f_{a,p} + mg \tag{2}$$

The calculation is best carried out using software packages that facilitate state-vector variable integration and matrix manipulation [10]. In this feasibility study, MATLAB was chosen as the simulation environment.

III. Aircraft Modeling

The use of high-fidelity models to simulate aircraft motion in space is required for accurate validation in a nonsimulation environment. The development of such a model requires extensive resources and modeling time. A high-fidelity model of a specific aircraft would require the knowledge of complete aerodynamic and thrust tables, flight control design, mass parameters, and the logic of the navigation and sensor operations. Only then could such a developed model be tested and its reliability thoroughly validated [10]. Unfortunately, such detailed considerations in modeling all onboard equipment would greatly affect the robustness of the model, and limit its application to other aircraft types.

As the focus of this proof of concept study was FDD/qualitative fault isolation and given the time and resource constraints of this study the decision was made to use a generic out-of-the-box model. The selection criteria for the model were primarily on their integration with academically proven simulation environments, such as MATLAB, and trajectory visualizing software packages, such as FlightGear.

AeroSim blocksets of MATLAB/Simulink block library developed by Unmanned Dynamics provide modules for rapid and fast aircraft modeling. A complete aircraft 6DoF model can be defined by generating a configuration script that specifies the aerodynamics and engine parameters for a specific aircraft type. It also provides a parser for importing Flight Gear v. 0.9.2 models such as CESSNA-310. In the development phase of this study, the North American Navion has been chosen to carry out the simulation.

The models of the Aerosim block library are limited to only conventional aircraft with single piston engine and fixed pitch propeller. Nevertheless, this limitation was not deemed to affect the validity of the proof of concept as the design of the system is modular and can be ported to use other aircraft types given an accurate mathematical model.

Figure 1 shows a simplified block diagram of the internal structure used in Aerosim to simulate a complete aircraft. Controls from the pilot joystick are used by the aerodynamics, propulsion, and inertia models to calculate the total forces and moments applied to the aircraft giving the simulated atmospheric conditions and reference frame. These in turn are used to solve the equations of motion and obtain the aircraft position (altitude, latitude, and longitude), orientation (heading, roll, and pitch) and velocity. These vectors are used to update the atmospheric and Earth model as a change in aircraft position might have an impact on the atmospheric conditions (e.g., pressure and gravitational forces). The sensor measurements are then derived directly from the calculated aircraft state. One drawback of the Aerosim library is that there are no models developed to simulate appropriate aeronautical sensors so generic analog and digital sensor blocks were used instead[†] [11]. This lack in specific modeling was also judged not to have a negative impact on the assumption and validity of this feasibility study as the sensors and vector states are treated as black boxes with variations artificially generated through the application of noise and scaling factors.

IV. Current Functional Procedures

To compensate for sensor errors that equipment may encounter during operation, modern aircrafts are fitted with redundant systems that work independently, then the value of the measurements are taken and the value displayed to the pilot is made through a majority rule or least square method. Because in most cases an aircraft in a good condition might only experience a malfunction in a single piece of equipment, this error would be compensated for by the vote of the other redundant systems (assuming two or more redundant systems).

However, majority rule might fail if the cause of the malfunctioning is global in such a way as to affect the other redundant systems that are concurrently working out the same measurement. For example, the measurement of airspeed involves sampling pressure from outside the aircraft using special probes, called pitot probes. If an environmental condition, such as icing, could affect one pitot probes then it is not unreasonable to also expect some impact on the other identical redundant probes.

Therefore it is of high interest to be able to calculate the conditional probability of a malfunctioning sensor, given that another sensor has malfunctioned using the same process for measurement. Figure 2 shows a simple Bayesian network representation of two sensors (labeled $S1$ and $S2$) working out the measurement of a quantity in an influential environment (E). In this case, it is safe to assume the conditional probability of having a wrong reading given that E has occurred identically for both sensors, that is:

$$P(S1|E) = P(S2|E) \tag{3}$$

We are most interested in calculating the probability that the second sensor might be malfunctioning given that $S1$ has malfunctioned and E has occurred, i.e., we want to calculate: $P(S2|E, S1)$ $P(S2|E, S1)$. One way of calculating that is:

$$\begin{aligned} P(S2|E, S1) &= (P(S1|S2, E)P(S2|E))/(P(S1|E)) \\ &= (P(S1|E)P(S2|E))/P(S1|E) = P(S2|E) \end{aligned} \tag{4}$$

The result of Eq. (4) means that if there exists evidences for the occurrence of environment E, then the probability of one sensor malfunctioning has no statistical influence on the other. Both sensors would be influenced by E to the same probabilistic degree, whereas if E is assumed not to have a global influence, then the probability of having two wrong readings out of three is

$$P(2 \text{ out of } 3) = P_{S1}P_{S2} \tag{5}$$

The probability of two wrong readings out of three for sensors that have independent ways of working out a reading is dramatically lower than the probability of two wrong readings for those sensor types with a similar way of calculating a measurement. Thus, it is desirable to have a validating system that uses–to the maximum extent possible- independent methods of calculating the current states of an aircraft.

V. Base of Aircraft Data and Total Energy Model

Base of Aircraft Data (BADA) provides performance operation data and aerodynamics parameters for about 151 types of aircraft. These parameters are the results of developing a mathematical model for a given aircraft using the total energy model (TEM)[‡] [12]. Consequently, the parameters can be used to check if an aircraft is operating within a set of recommended speed, rate of climb or descent (ROCD), or fuel flow. This could in turn provide a way of

[†]Additional data available at http://www.u-dynamics.com/aerosim/aerosim_ug.pdf [retrieved 30 January 2010].

[‡]Additional data available at http://www.eurocontrol.int/eec/gallery/content/public/document/eec/report/2009/003_BADA_3_7_User_manual.pdf [retrieved January 2010].

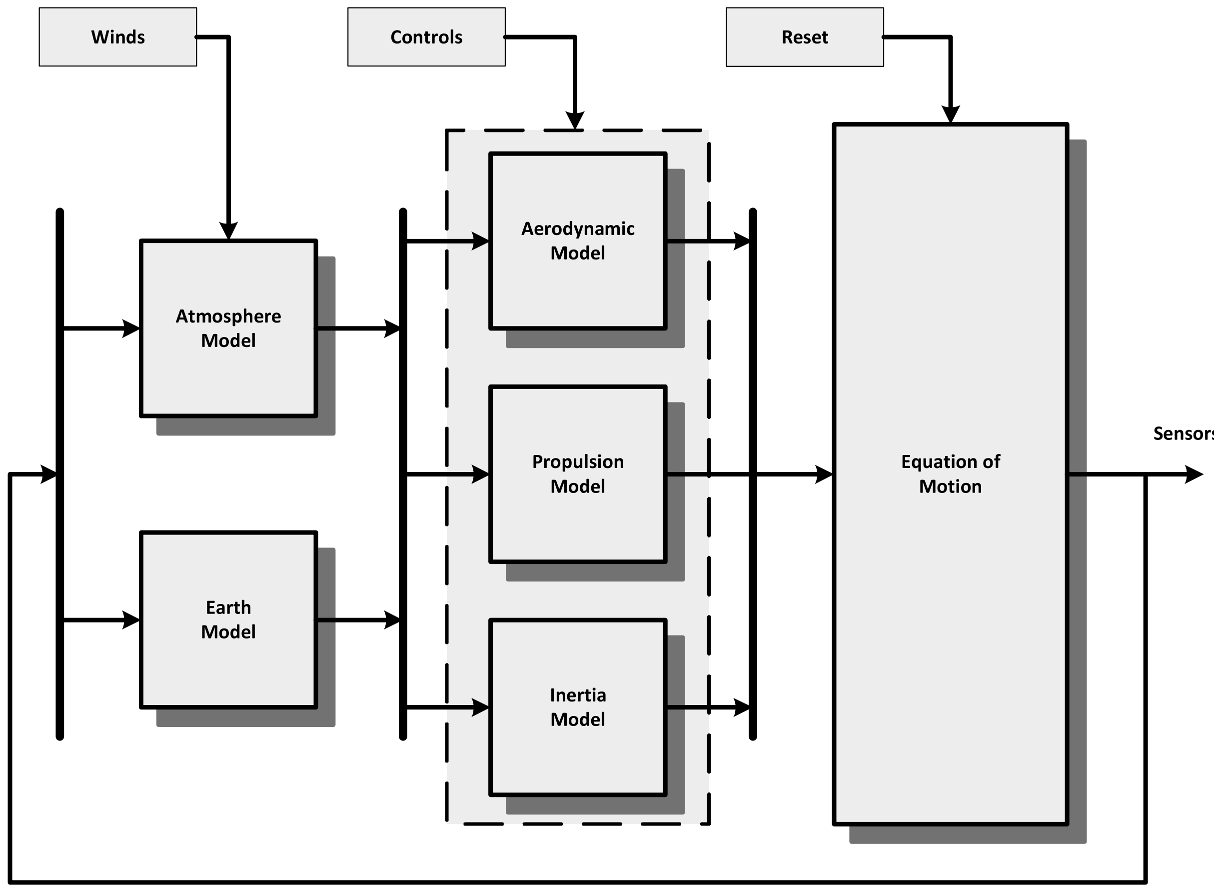


Fig. 1 The internal structure of the complete aircraft block, adopted from [11].

validating a current onboard situation in case the data being logged for any of these parameters goes beyond safe, recommended, or normal range. In this paper, this process will be labeled *BADA check* or *is exceedance*. This type of validation could detect exceedances in real time rather than by the end of the trip as the one described in [13]. As a side benefit, because the checking is performed against recommended operational data, commercial airliners would greatly benefit from the resultant fuel saving and maintenance as pilots comply with recommended speed, ROCD, and so on.

VI. Assumptions and Proposed Design

The diagnostic decision tree network developed in this feasibility study is based on two assumptions:

1) The airplane is in good and airworthy condition so that the source of a problem could be traced back to one or two causes at most.

2) Each group of parameters used as input to the mathematical aircraft model (called Math Engine) has some impact on the calculated parameters of the airplane vector state. This is borne out in aerodynamic theory: wind speed affects ground speed, position, and Euler angles, and control surfaces (for pitch, roll, and yaw) affect ground speed position and Euler angles.

The reasoning of the proposed diagnostic decision tree is a natural extension from the two previous assumptions. If any sensor reading used as input to the Math Engine (ME) is impacted by a malfunctioning then we would expect to find all the calculated parameters from the ME to differ from those of the onboard sensors (due to the second assumption). Since the probability that this “disagreement” is due to malfunctioning of all equipment onboard is extremely low (due to the first assumption), the more logical explanation is that one of the ME input parameter is wrong.

Figure 3 shows the proposed algorithm for diagnosing differences in readings of different equipment/subsystems. It starts with a simple check of whether every sensor’s reading of the primary system (PS) is similar to that of the redundant system (RS) and that of the ME. Readings are considered similar if the error is within a tolerated value which can be set appropriately. If all readings are similar, then the confidence that everything is working fine would increase, nevertheless this could be a false negative as the network might have failed to detect anomalies in an equipment reading. Therefore, a more expensive test is performed to check for false negative which was accomplished by adding *is exceedance* checks in which the readings from equipment are compared with the recommended operation levels taken from BADA.

However, if the readings differ, then the next observation that has to be noted is the proportion of disagreed cases that have been detected. If only one case of disagreement is detected, then it is most likely that the ME output is true (this is evident by ME = PS = RS for the other parameters). The reading that is in disagreement with the calculated ME value is highly likely to be the culprit.

However if all of the readings differ from each other, then it leads to the conclusion that one (or two) of the inputs to the ME are incorrect. A check of all the input parameters of the ME is needed. It

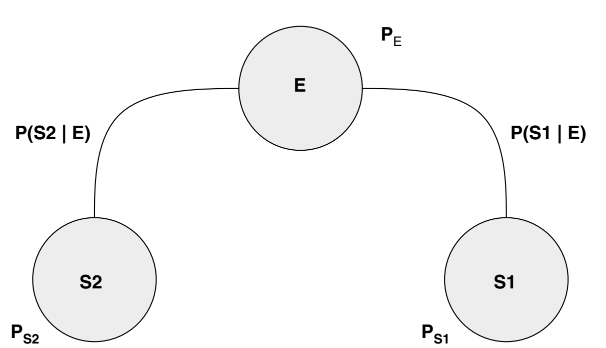


Fig. 2 Bayesian network for two sensors *S*1 and *S*2 in environment *E*.

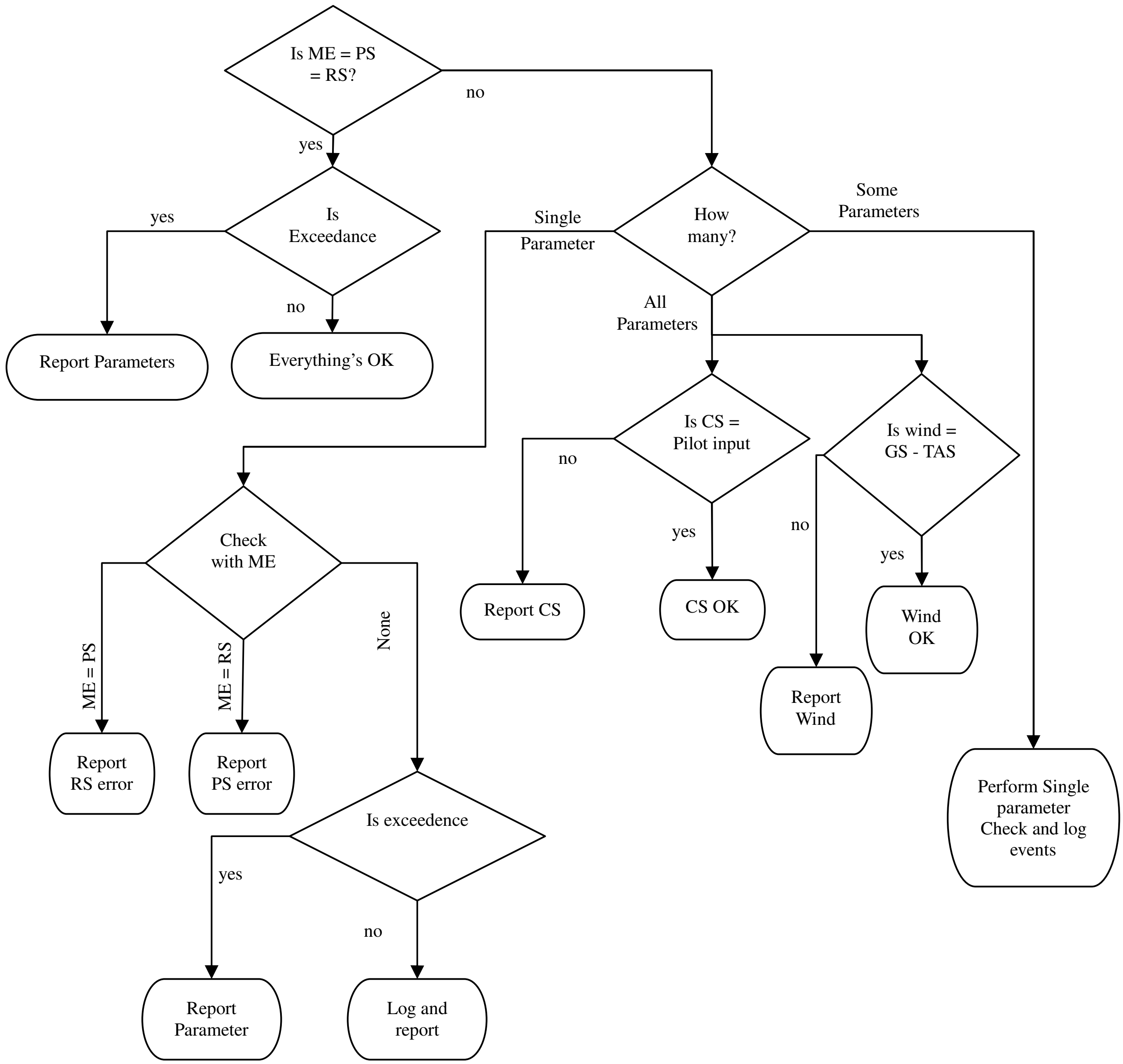


Fig. 3 The proposed investigation engine.

is possible to check the control surface (CS = pitch, roll, yaw) by comparing its values with those extracted from the pilot CS input. Checking the other parameters to make sure they follow the same procedure is not implemented in this study. For example, it is fairly easy to check if the wind speed is measured correctly by this simple equation:

$$\text{Wind} = \text{GS} - \text{TAS} \tag{6}$$

where GS is the ground speed, and TAS is the true air speed.

VII. Experiments Setup

This research is conducted through setting up a simulation environment in MATLAB. The complete aircraft block from AerSim blockset is used to simulate an aircraft. The sensors and states outputs were labeled PS and RS, which represent a generalized way of identifying a reading from either of two independent sources, for example, a barometer or a GPS reading. Because the objectives of this study did not include investigating the systematic or environmental causes of malfunctioning equipment but rather to validate the readings, aircraft subsystems (equipment) were treated as black boxes, and errors in equipment readings were simulated by the addition of random noise and/or by multiplying a reading by a scaling factor. The output of the investigation engine was monitored to determine if the faulty equipment in which the error was introduced was correctly detected.

To test the operation of the network, scenarios have been created where a malfunctioning equipment event was introduced while the output of the investigation engine was logged. Figure 4 shows the block diagram representation of the overall Simulink model developed in this study. The aim of these scenarios was to test the accuracy of the developed investigation engine, and its ability to pinpoint the faulty equipment whenever a fault was introduced. The simulations used a deterministic environment in which the investigation engine operated at perfect (100%) accuracy and output either 0, for no fault detected, or 1, for fault detected. The sampling frequency was every 0.008 s.

VIII. Scenario One: Fault in Primary System Pitch

The first scenario that was run was to test the operation of the network when simulating a malfunction in the sensor equipment responsible for displaying the current pitch attitude. The simulation

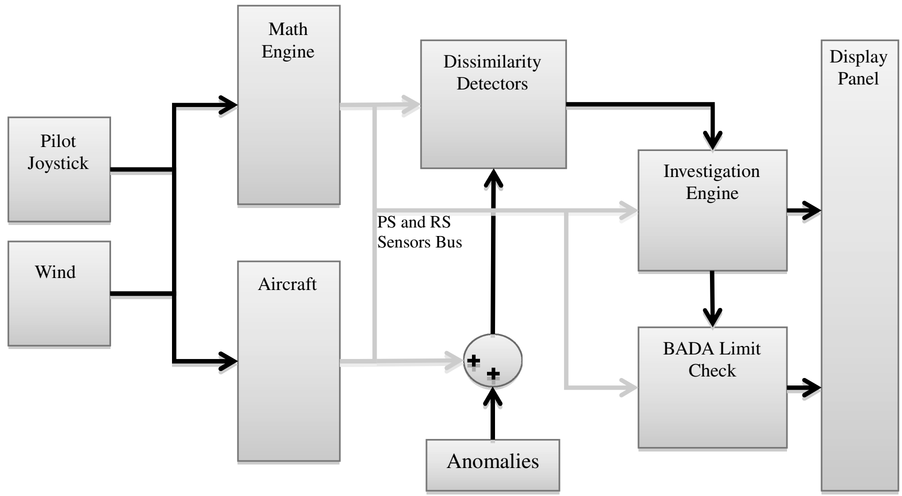
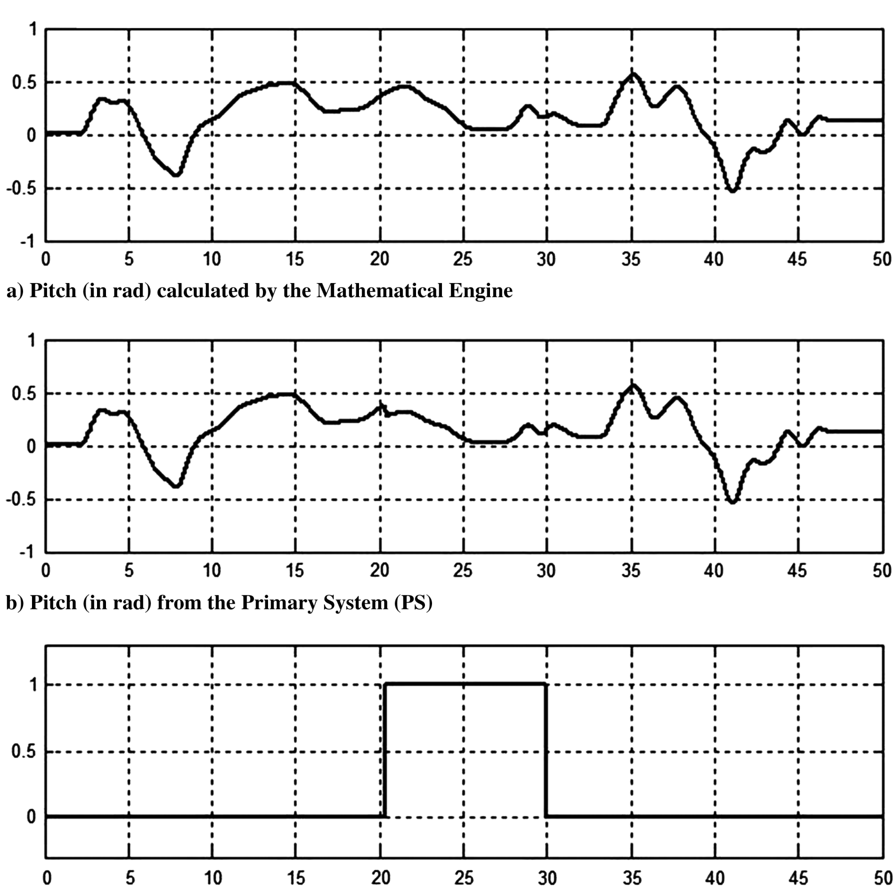


Fig. 4 Block diagram representation of the proposed network.

time was set to 50 s, and throughout the simulation, the value of the aircraft pitch attitude was constantly changed by means of a pilot joystick. Figure 5a shows the theoretically calculated pitch altitude whereas 5b shows a graph of the pitch altitude sensor's reading. During time 0 to 20.5 s, the two values resembled each other and the investigation engine's port: Fault in PS Pitch was zero (Fig. 5c). However, when a malfunction was introduced into the primary system's pitch sensor at time $t = 20.5$ s, the investigation engine was successful in pinpointing the faulty equipment. The fault was held for 10 s time, during which the investigation engine's output port *fault in PS pitch* stayed at 1, producing a positive result for the test scenario.

IX. Scenarios 2: Fault in Primary 2and Redundant Speed Sensors

The second scenario demonstrates the superiority of the network over current systems when using two sensors to independently calculate the same physical quantity. Once again, the simulation was set up to run for 50 s, and Fig. 6a shows the theoretically calculated airspeed values against time. Figures 6b and 6c show the airspeed's sensor reading on the PS (e.g., the pilot panel) and Redundant System RS (e.g., the copilot panel), respectively. Before time $t = 20$ s there was no malfunction simulated, so the three graphs of ME, PS, and RS airspeed readings were the same. After time $t = 20$ s, a malfunction

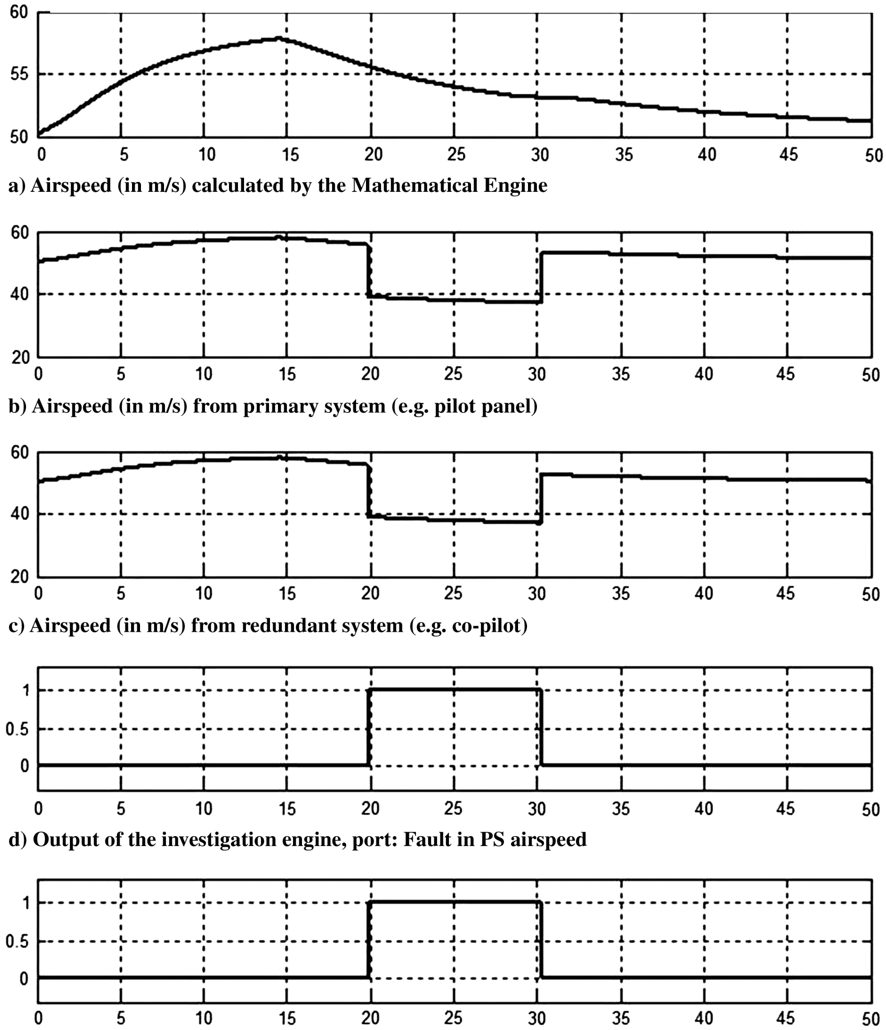


a) Pitch (in rad) calculated by the Mathematical Engine

b) Pitch (in rad) from the Primary System (PS)

c) Output of the investigation engine, port: Fault in PS Pitch

Fig. 5 Simulation results of scenario one.



a) Airspeed (in m/s) calculated by the Mathematical Engine

b) Airspeed (in m/s) from primary system (e.g. pilot panel)

c) Airspeed (in m/s) from redundant system (e.g. co-pilot)

d) Output of the investigation engine, port: Fault in PS airspeed

e) Output of the investigation engine, port: Fault in RS airspeed

Fig. 6 Simulation results of scenario two.

was simulated on both the PS and RS sensors so as to indicate the same incorrect reading. Routinely, such fault might be hard to detect as, for example, both the pilot and the copilot would each confirm the same reading ignorant of the presence of a malfunction in both systems. Since the mathematical engine relies on equations to estimate the correct airspeed value, it will report a dissimilar airspeed value which, in turn, is supplied to the investigation engine to identify the source of the malfunction. Figures 6d and 6e show output ports *fault in PS airspeed sensor* and *fault in RS airspeed sensor*, are changing from 0 to 1 during the time of the fault indicating a successful diagnosis.

Because of the separation of the decision-making engine from the type of information input, the scenarios outlined (1 and 2) are inherently generic and thus can be applied to monitor any quantity being reported by two systems where it is crucial to also be able to determine which if any system is producing trustworthy information.

X. Conclusions

The research in this paper focused on the development of a fault detection system to increase pilot situational awareness. To overcome the constraints of fault detection / validation systems regarding the use of erroneous data, we independently validated sensor readings against a mathematical model output for the respective type of aircraft. The identification algorithm for malfunctioning equipment was based on a Bayesian Decision Tree, which when a sensor malfunction was simulated the network correctly recognized and identified the malfunctioning element(s). The output of the investigation engine port further allows the identification of the subsystem producing erroneous or non-nominal readings.

Because of the early encouraging results of the system further enhancements are being developed, including the use of the JSBSim open source library of aircraft models, which allows for a wider range of aircraft models including commercial airliners (e.g., Boeing B737). JSBSim represents one attempt to standardize the way of parameterizing aircraft aerodynamics into one xml file that can be parsed by different simulation and visualizing software packages including MATLAB, FlightGear, and OpenEaagles flight simulators. In addition, it would be of value to simulate the same scenarios that were conducted in this research under a probabilistic environment and monitor the detection rate.

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