Functional Mode Analysis of Safety Critical Systems Using Causal Bayesian Networks (CBNs)

Susmitha Thiyyanoor, R. Krishnaprasad, Manju Nanda and J. Jayanthi

Abstract System Health Management (SHM) is a key technology for detecting, diagnosing, predicting, and mitigating the adverse events during the operation of safety-critical systems. Safety critical systems, specifically Unmanned Aerial Vehicles (UAV) are an important part of today's era whether it is in civilian, commercial, defense, or in military domain. Proper functioning of these sensor systems is very crucial as their faults can result in serious consequences, but they often fail in spite of extensive verification and validation efforts, which raise safety concerns. This paper discusses functional mode analysis of speed and direction sensor to perform SHM using Causal Bayesian Networks (CBN) that can tackle problems associated with system bugs and failures. Sensor parameters from UAV system in real-time is learned, modeled, and analyzed in using Bayesian network. The simulation output graphically shows the influence analysis of sensor parameters on the overall health of the UAV system as a case study. The network performance along with a comparison of actual and predicted values is displayed in the simulation section.

Keywords Safety critical systems · Unmanned aerial vehicles
Functional mode analysis · System health management
Causal bayesian networks · BayesiaLab

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1 Introduction

Safety critical systems are those systems whose failure can cause serious threat to life and property. Unmanned aerial vehicle (UAV) is an important category of safety critical systems and is commonly known as drone or an aircraft without a human pilot. The flight of UAV may be controlled autonomously by onboard computers or by the remote control of a pilot on the ground or in another vehicle. A flight control system that makes the UAV fly or run automatically is called autopilot, have a lot of functions such as guidance, control, and navigation. It act as brain of UAV, this subsystem controls UAV by generating control signals on the basis of desired target information and waypoints. Nowadays space activities including UAVs are characterized by increased constraints in terms of onboard computing power and functional complexity combined with reduction of costs and schedule. This scenario necessarily originates impacts on the onboard software with particular emphasis to the interfaces between onboard software and system/mission level requirements.

System Health Management is an important factor in system level requirement. Health management is performed on the running safety critical systems with the goal to perform diagnosis and prognosis and hence isolates the faults close to their source so that a fault in a sub-system does not lead to a general failure of the global system [1]. A SHM system continuously monitors the behavior of the software and the interfacing hardware or sensor components. Using an abstract model of the software, the SHM can detect unexpected behavior, reason about its root cause, and trigger failure repair or mitigation actions. Only recently, health management systems that monitor software have been developed. The goal of SHM system is to correctly diagnose off-nominal situations with special consideration to sensors that are incorporated in the UAV system. If any of the sensors cause failures in the active stage due to faults, it will affect the functionality of UAV. So every sensor is required to be monitored for its proper functionality which is an important SHM application [2].

Prominent SHM techniques are using Kalman filters, Bayesian Hidden Markov Model approach [3], Artificial Neural Networks (ANN), Causal Bayesian Networks, etc. [4]. Of these, Bayesian Networks can be built from human knowledge, i.e., from theory, or they can be machine-learned from data [5] and holds good for aircraft guidance, navigation, and control [6]. Also, Causal Bayesian Networks can be modeled with their node-arrow structure and due to their graphical structure, machine-learned Bayesian networks are visually interpretable, therefore promoting human learning and theory building.

The paper is organized as follows: Sect. 2 describes the Background work behind the project, Sect. 3 explains the Proposed Approach, Sect. 4 describes the implementation of the system, Sect. 5 shows the Simulation results and finally Sect. 6 gives the scope and conclusion for the proposed system.

2 Background Work

Various SHM techniques exist including Kalman filters, ANN, Causal Bayesian networks etc. Causal Bayesian networks (CBNs) represent multivariate probability distributions and are used for reasoning and learning under uncertainty [7–9]. They are often used to model systems of probabilistic nature [4]. Random variables are represented as nodes in a directed acyclic graph model, while conditional dependencies between variables are represented as graph edges. A key point is that a CBN, whose graph structure often reflects a domain's causal structure, is a compact representation of a joint probability table.

Many CBN tools exist at present like BayesNet toolbox, Hugin [10], GeNIe and SMILE [11], Netica [12], UnBBayes, OpenMarkov, Direct Graphical Models, etc. But the recent advancement among CBN tools is BayesiaLab 5.4.3 (released in 2015) which is being used in this system. BayesiaLab is a powerful desktop application (Windows/Mac/Unix) with a sophisticated graphical user interface, which provides users a comprehensive "laboratory" environment for machine learning, knowledge modeling, diagnosis, analysis, simulation, and optimization. BayesiaLab leverages the inherently graphical structure of Bayesian networks for exploring and explaining complex problems.

3 Proposed Approach

Functional Mode Analysis or System Health Management (SHM) of UAV sensors using Bayesian Networks has been proposed in this paper. This section consists of the block diagram for the proposed system and the description for the concepts of Knowledge modeling and Machine learning performed using CBN in BayesiaLab.

Probabilistic models based on directed acyclic graphs (DAG) have a long and rich tradition and their variants have appeared in many fields. Within statistics, such models are known as directed graphical models; within cognitive science and artificial intelligence, such models are known as Bayesian networks. The name honors the Rev. Thomas Bayes, whose rule for updating probabilities in the light of new evidence is the foundation of the approach. It addresses both the case of discrete probability distributions of data and the more complicated case of continuous probability distributions. In the discrete case, Bayes' theorem relates the conditional and marginal probabilities of events A and B, provided that the probability of B not equal zero:

$$P(A/B) = P(A) * \frac{P(B/A)}{P(B)} \tag{1}$$

The fact that the significant parameters that influence the sensors in a UAV autopilot also influence the proper functioning of these sensors and ultimately

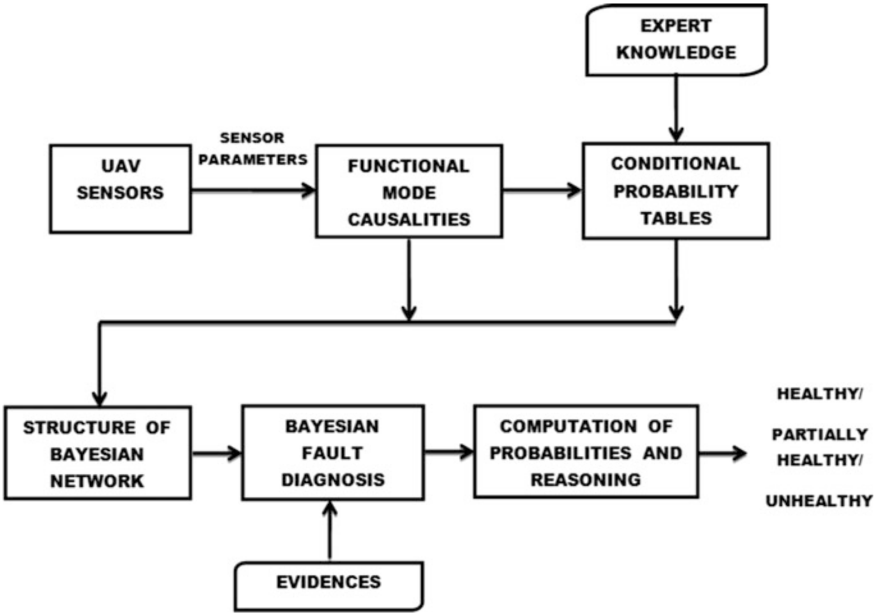


Fig. 1 Implementation of the system

determine the overall health of the UAV system is being exploited. Proposed approach consists of UAV sensor parameters and their derived functional mode causalities, corresponding conditional probability tables (derived from expert knowledge), and the hence derived Causal Bayesian Network. The Bayesian fault diagnosis is then performed on this network by providing evidences and computation of different fault probabilities. Thus, the system can be checked for its different functional modes, i.e., healthy, partially healthy, and unhealthy (Fig. 1).

The implementation of the system mainly constitutes two sections:

3.1 Knowledge Modeling and Evidential Reasoning

Reasoning in complex environments creates cognitive challenges for humans. Subject matter experts often express or model their causal understanding of a domain in the form of diagrams, in which arrows indicate causal directions. This visual representation of causes and effects (known as Knowledge Modeling) has a direct analog in the network graph, in BayesiaLab. The model can then be analyzed by acquiring proper evidences and then executing them. The steps in knowledge modeling can be briefed as below in the flow chart.

In Knowledge Modeling, the complex information is often simplified to form causal relationships between different variables involved in it. In BayesiaLab, the probabilistic relationships between variables in conditional probability tables (CPT) have to be described, which means that no functional forms are utilized.

First stage nodes represent the parameters, second stage nodes represent the healthy and unhealthy mode of the sensors, and third stage nodes represent the overall functional modes of the system. Arrows specify the conditional dependency between the nodes. Necessary knowledge is assigned as Conditional Probability Tables to the nodes of the system. Switching on to the Validation mode helps users to check the functionality modes of the system by giving suitable hard and soft evidences.

3.2 Machine Learning

The earlier work gives a concept that can be helpful for many research works but it does not facilitate real-time processing of input data from the parameters of interest to determine the functionality modes of the sensors and thus the system. Human expert knowledge is useful for identifying causal relations, but proves to be inefficient in real time. Most of the research works face the challenge of handling with the real-time data acquired from on board during active run of the system. Machine Learning comes into play at this instinct where real-time processing is a must.

Machine Learning is implied in this system to learn and then establish the predictive importance of a range of variables with regard to a target variable. The domain is the UAV Autopilot system and we wish to examine the relationships between sensor parameters and the overall functionality of the system. The real-time data from the UAV sensors is acquired as input to the Bayesian Networks as excel spread-sheets (or Comma Delimited file). The highly optimized learning algorithms that can quickly uncover structures in datasets are considered in BayesiaLab for the process of testing and learning. Naive Bayes algorithm which is a Supervised Learning approach, a causal dependency is formed between the "Class" node and the other nodes. It was found to be more useful for the sensor data because the target variable which is the functionality mode of the sensor will always have a causal dependency on every parameter that defines the sensor. The relationship between the Target node and other nodes is viewed by highlighting the Mutual Information between them which reflects the predictive importance of the parameters on the target node.

Machine learning has many benefits over knowledge modeling, of which the most important one is real-time processing capability. Also in machine learning, a detailed analysis and comparison of different parameters on the target node can be obtained which is absent in Knowledge modeling. It also helps in interpretation of real-time data in different perspectives: Target Interpretation tree, Adaptive Questionnaire, Mapping, etc.

4 Implementation

Implementation of the proposed system is shown in this section. It describes the procedures for knowledge modeling in BayesiaLab and designing of test data for machine learning. Also selection of different functional modes based on whether the parameters are in the proper nominal range or not is also explained here in this section.

4.1 *Knowledge Modeling and Evidential Reasoning*

The proposed work relies on considering the Speed and Direction Sensor and its different parameters. The parameters of interest and their nominal ranges of operation are Output Ambient Temperature (−40–150 °C), Output Current (30–85 mA), Magnetic Offset (−60–60), Output Frequency (0–40 kHz), Output Air Gap (0.75–3 mm), and Duty Cycle Variation (40–60%). Each of these parameters individually contributes to the health of the sensor and thus the overall health of the system. The effect of variation of these parameters from their nominal values in health of the sensor is described as: Healthy—if all sensors are healthy or 0 unhealthy sensors; partially healthy—if 1–3 sensors are unhealthy; Unhealthy—if 4–6 sensors are unhealthy.

Now, similar to the Speed and Direction sensor, 5 other sensors were also identified which are gyro sensor, accelerometer, angle of attack, altimeter, and differential pressure sensor. The overall functionality mode of the system (whether Healthy, Partially Healthy or Unhealthy) is determined by the functional mode analysis of each sensors. Figure 2 shows the overall modeled CBN for the proposed system.

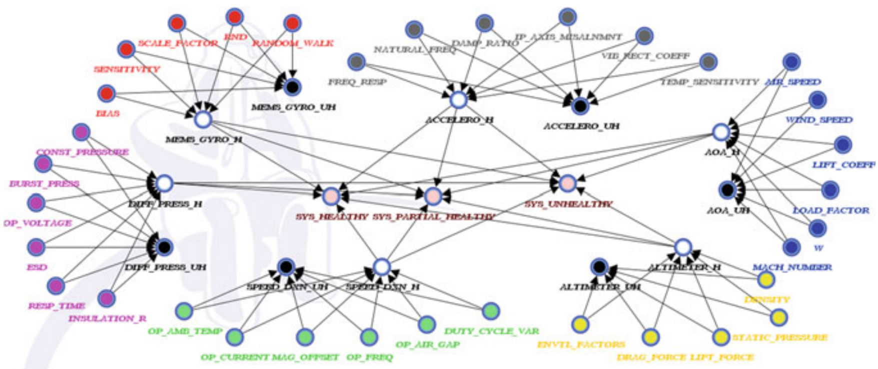


Fig. 2 Knowledge modeling

4.2 Machine Learning

On a top-level, real-time data from software and hardware sensors is learned and then presented as the nodes of the Bayesian network, which in turn performs its reasoning (i.e., updating the internal health nodes) and returns information about the health of the software. Machine learning of sensor data is explained below. Prior to that, designing of test data is to be discussed.

One-fifth (20%) of the data are chosen as test data from which the software learns the system. There are six parameters considered for the sensor.

Hence, $2^6 = 64$ combinations of data is used as Test set and thus, $64 * 5 = 320$ data combination is included in the database as input to the CBN and remaining data is said to be Learning Set.

The data set input is shown in Fig. 3. The dataset is then Machine-Learned after certain pre-processing steps like Discretization, Normalization, etc. The Learning algorithm applied is Naïve Bayes algorithm that best suits such applications where there is a single target that depends on several sub-factors. Figure 4 shows the machine learned CBN for the overall system as per Naïve Bayes algorithm.

The obtained outputs and differences are shown in the next section. In Knowledge Modeling, only just reasoning is possible, whereas in Machine learning, detailed analysis of data is possible which comes under three categories:

4.2.1 Performance Analysis

The relationship between the Target node and other nodes is viewed by highlighting the Mutual Information between them which reflects the predictive importance of

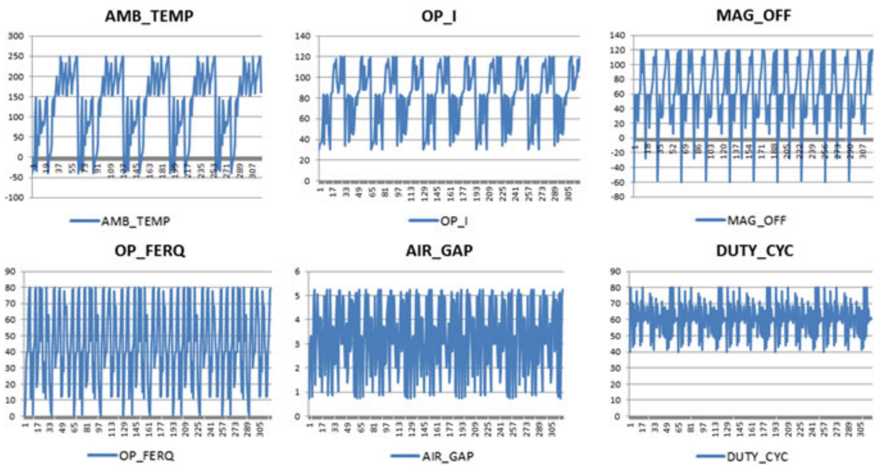


Fig. 3 Data set input for machine learning

Fig. 4 Machine learned Causal Bayesian Network

the parameters on the target node. The network performance is analyzed to know how the Naïve Bayes learning algorithm predict the states of the Class variable, Healthy or Unhealthy. Network performance on the target is shown in the Simulation Results.

To mitigate any sampling artifacts that may occur in such a one-off Test Set, we can systematically learn networks on a sequence of different subsets and then aggregate the test results. For this, we perform K-Folds Cross Validation (to iteratively select K different Learning Sets and Test Sets and then, learn the networks and test their performance) and is also shown in Simulation Results. Next step is Structural coefficient ("significance threshold" for network learning) Analysis. This analysis shows Structure/Target Precision Ratio which is a very helpful measure for making trade-offs between predictive performance versus network complexity.

4.2.2 Model Inference

The main objective of the proposed system is to derive a correlation between different parameters of the network and the target. Target Correlation, is obtained by sorting the parameters based on their Mutual Information with the target node "Class."

4.2.3 Interactive Inference

Interactive Inference is a special feature that helps the user to review the individual predictions made based on the model. The user can give evidences to check for the different functionality modes that hold for the system. Adaptive Questionnaire is an important category of Interactive inference where only individual cases are under review. End user can check any number of evidences and the probability distribution of the target node gets updated as a result. Not only the target node, but also all other nodes get updated upon setting evidence, reflecting the omnidirectional nature of inference within a Bayesian network. The process of updating can be continued until an acceptable level of certainty regarding the diagnosis is achieved.

Target Interpretation Tree is the next significant inference, and is explicitly shown in the form of a static graphical tree. The Target Interpretation Tree is induced once from all cases and then prescribes in which sequence evidence is be sought for gaining the maximum amount of information towards a diagnosis. Mapping is another inference category where the size of the nodes is proportional to the Mutual Information with the Target Node given the current set of evidence.

5 Simulation and Results

This section lists the obtained simulations and results. Simulated results for machine learning are classified under 3: (i) Performance Analysis; (ii) Model Inference; and (iii) Interactive Inference which are also described below.

5.1 Knowledge Modeling and Evidential Reasoning

In Knowledge modeling, the information about the health of the system is extracted from the posterior distribution, specifically from health nodes. The simulated outputs are briefed below in Fig. 5.

Figure 5 shows 3 sections: (i) the probabilistic distribution of each parameter of Speed and Direction sensor. Initially, all probabilities are normalized which shows an effect on healthy and unhealthy nodes of the sensor. (ii) Shows the effect of hard evidences on the healthy and unhealthy nodes of the sensor. (iii) Shows the effect of soft evidences on the healthy and unhealthy nodes of the sensor.

Fig. 5 Simulated output for evidential reasoning in BayesiaLab

5.2 Machine Learning

In machine learning, all sensor data, which are usually time series, must undergo a pre-processing step, where certain (scalar) features are extracted. These values are then discretized into symbolic states or normalized numeric values before presented to the Causal Bayesian model. The optimization criteria in BayesiaLab's learning algorithms are based on information theory based on which desired simulated results are obtained.

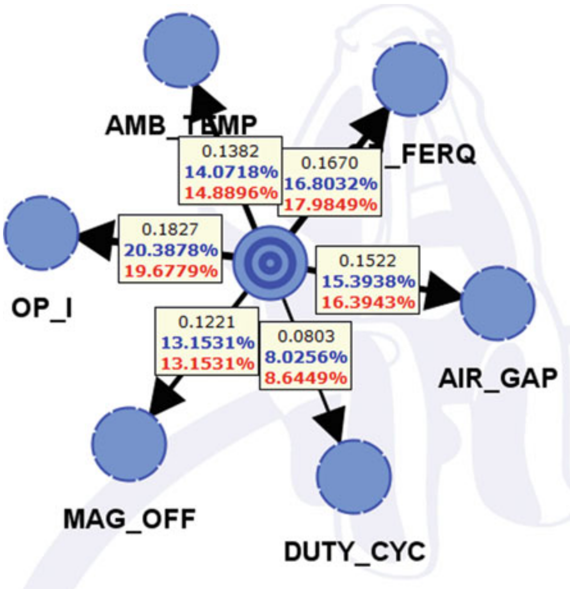
Figure 6 shows the Mutual Information between the parameters of the sensor and the target "CLASS", which shows the healthy and unhealthy modes of the sensor.

Figure 7a shows the overall performance can, which is expressed as the Total Precision, and is computed as total number of correct predictions (true positives + true negatives) divided by the total number of cases in the Test Set, i.e., (17 + 41) ÷ 64 = 90.625%.

Figure 7b shows that with different samples of data considered, the system proves good as it shows a total precision of (81 + 204) / 320 = 89.06%.

Figure 8 shows different parameters of the sensor that are sorted in the decreasing order of correlation with the target. The correlation is calculated based on the Mutual Information between different parameters and the target node. It is clear from the figure that OP_I has more correlation with the target followed OP_FREQ and so on. It is also verified that slight variations in the parameter probabilities induce effective variations in the target node too.

Fig. 6 Machine learning technique to obtain mutual information between CLASS variable and different parameters



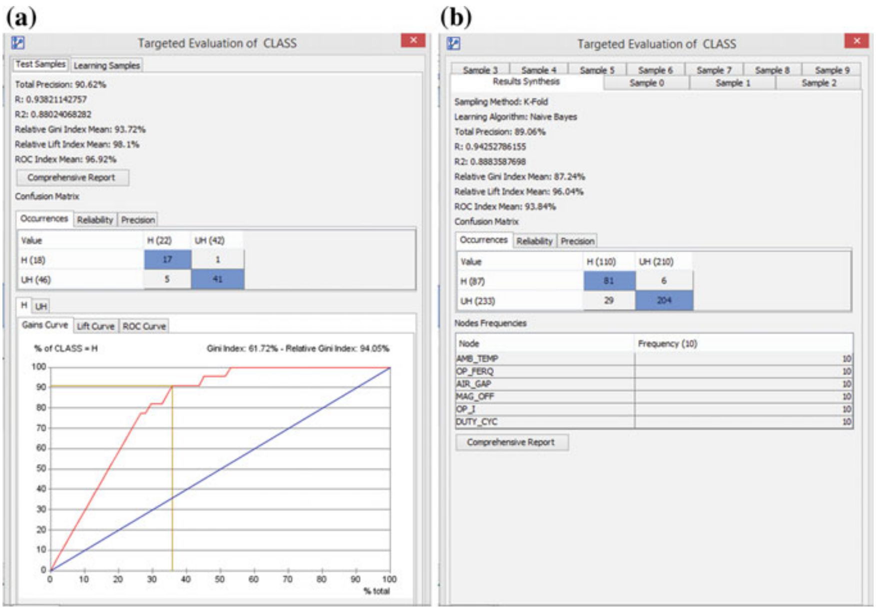


Fig. 7 **a** Network performance based on the target, **b** K-fold validation

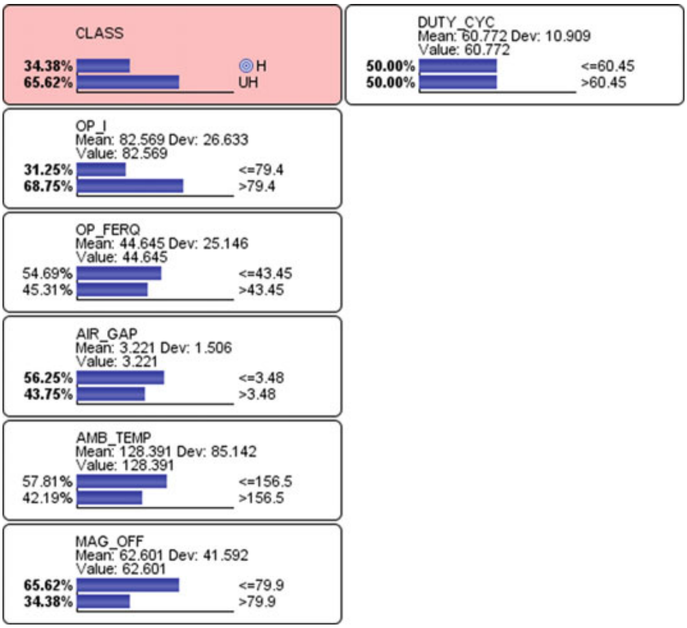


Fig. 8 Target correlation based on mutual information

Figure 9 shows the Adaptive Questionnaire section in which a third person can provide his/her evidences which are known to him/her. He/she need not know the system design. With the known evidences, even if only individual cases are under review, the system provides proper diagnostic support.

Figure 10 shows the Target Interpretation Tree which is induced from the cases shown in the monitor:

AMB_TEMP = p{ <=156.5:28.95%; >156.5:71.05%};
OP_I = <=79.4;
MAG_OFF = > 79.9;
OP_FREQ = p{ <=43.45:54.39%; >43.45:45.61%);
AIR_GAP = > 3.48;

The tree picturizes the effect of these evidences on the parameter DUTY_CYC and how its information is to be sought for gaining the maximum amount of information towards a diagnosis.

Figure 11 shows the mapping of target node with respect to other parameter nodes by applying Node analysis. The size of the nodes is determined by their Mutual Information with the Target node.

These simulation results under machine learning show the effect of the real time individual parameter values on the health of the Speed and Direction sensor. The

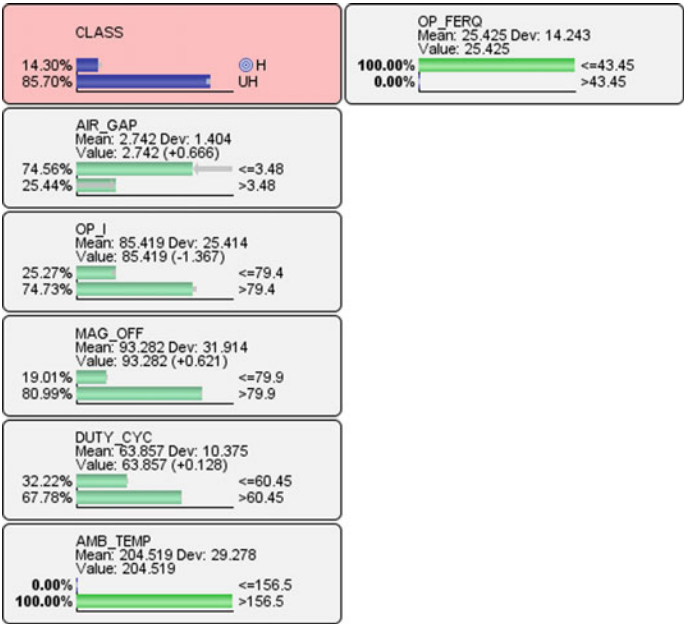


Fig. 9 Adaptive questionnaire

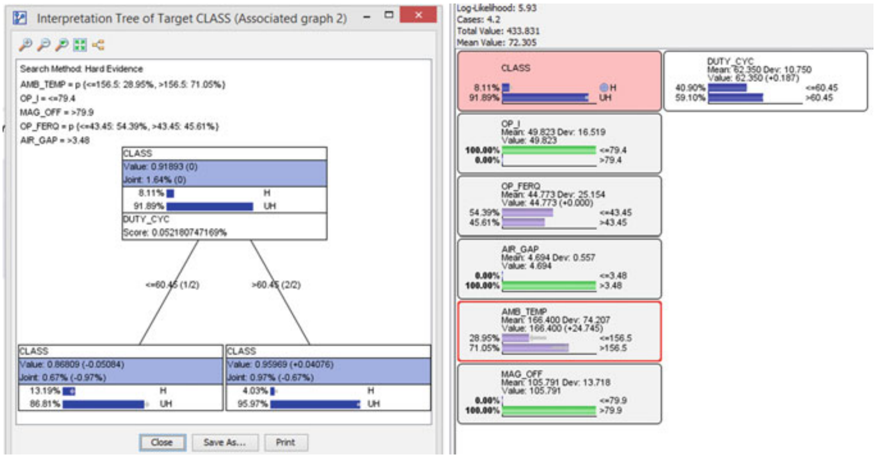


Fig. 10 Target interpretation tree

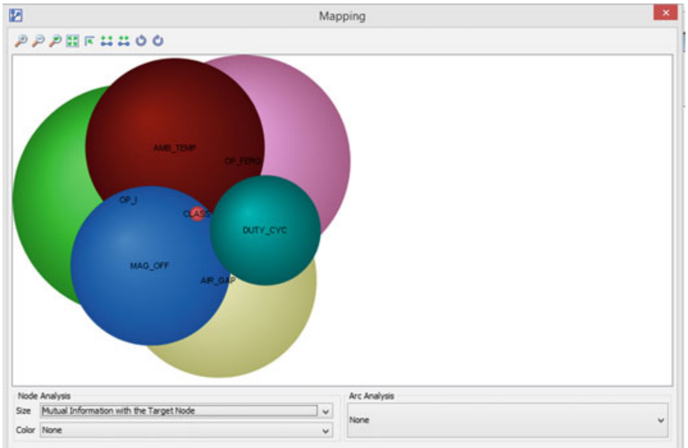


Fig. 11 Mapping

different outputs give the correlation of these parameters on the functional mode of the sensor and this correlation is being calculated using the concept of Mutual information in Bayesian Networks. The system also facilitates in interaction between an end user and the system through its features like Target Interpretation tree and Adaptive Questionnaire.

6 Conclusion & Future Work

System Health Management of safety critical systems is an important concept and is put to extensive research works for the past years. Irrespective of their complexity, many Fault Detection and Recovery techniques were tried out on UAVs. SHM is a key technology for detecting, diagnosing, predicting, and mitigating the adverse events during the operation of safety-critical software systems. Since size and complexity of software for even tiny autonomous systems increase dramatically, we think that powerful on board means for real-time fault detection and diagnosis can provide a crucial additional layer of reliable functioning. Causal Bayesian Networks, because of their numerous advantages prove to be useful in the area of SHM.

The concept of Functional Mode Analysis for SHM to be implemented using Causal Bayesian Networks has been discussed here. Knowledge Modeling and Machine Learning were tried out and irrespective of the various advantages modeling offered, machine learning was found to be more useful for practical real-time applications as they learned the system behavior on their own and facilitated for further analysis purposes.

The research work can be extended to robustly handle unexpected and un-modeled failures that can cause threat to both life and property. It can also be extended to artificially model Bayesian models when specific anomalies are found in the system.

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