Sensor and Maintenance Strategy Evaluation for Boeing 767 Commercial Fleets

Lukmon Rasaq, North Carolina A&T State University

Korbin Ferguson, North Carolina A&T State University

William Teasley, North Carolina A&T State University

Max Xu, Georgia Tech Research Institute

Kyle E. Blond, Georgia Tech Research Institute

Om Prakash Yadav, PhD, North Carolina A&T State University

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SUMMARY & CONCLUSIONS

This paper presents a framework to evaluate sensor solutions and maintenance strategies using performance metric and genetic algorithm to mitigate future Boeing 767 (B767) Airworthiness Directives (ADs). The results obtained can inform predictive maintenance models and reliability improvements to mitigate the costs of AD for commercial and military B767 operators.

Commercial and military regulators maximize the safety and performance of aviation operations in part by responding to aircraft system failures via ADs. ADs issued by the Federal Aviation Administration (FAA) and United State Air Force (USAF) impart a large business and technical cost on operators. For the B767 and its military derivative, the USAF's KC-46A, historical data provides insight into sensor solutions and maintenance strategies that may mitigate these costs. A reliability study determining the failure modes and mechanisms is presented for ADs relating to the engine given their significant cumulative cost for B767 operations.

We further propose investigation that includes performing mapping metrics as well as investigating sensor solutions and data visualization for further analysis. Consequently, this early detection system may reduce maintenance downtimes by providing early warning to any potential malfunction.

The proposed framework was used for the whole dataset. However, small values of diagnostic result were observed, potentially due to missing value in the dataset. To see the real effect of the diagnostic term result, experiment was further performed on 5 out of 359 failure mechanisms present in the dataset and the result shows higher diagnostic term result for each generation. The proposed genetic algorithm can also be utilized in other applications that involve optimizing the output of the application.

1 INTRODUCTION

Failure modes can be defined as symptoms that eventually show a system has failed. Aircraft systems contain many components and each of these elements has several failure modes that could cause systems failure. To determine the propagation of failure mechanism that could result in failure modes, sensors are required. The sensor's objective is to detect the presence of a failure process or mechanism as quickly as possible so that precautions can be taken to avoid future faults. Moreover, sensors can also be seen as tools that help in diagnosing component failure. Some examples of sensors are flow, level, temperature, pressure, and vibration sensors. To get the highest amount of information regarding a failure, it is always good to use a system of sensors. However, sensors are expensive, and they also have combined weight that could affect the balance of the aircraft. Consequently, a technique for selecting the most appropriate possible sensor needs to be created.

Reeves et al. (2018) discuss sensor performance metrics by looking at a phased mission operation whereby failure occurs at various points in the mission. Additionally, during the phase of mission operation, some components in aircraft systems such as pumps are prone to failure. As a result, prompt identification of components failure is crucial. A factor known as the time dependence factor is used to achieve this. This crucial factor is added to the sensor selection method so that the failure can be identified as soon as it occurs. In addition, the performance metric serves as an indicator that helps to diagnose the failed elements in the system [1].

Over the years, much work has been done around sensor selection. For instance, Kang *et al*. (2000) proposed a technique called fault symptom matrix; wherein columns and rows of matrix commensurate to a distinct component failure and distinct sensor, respectively. The matrix is "1" if a failure can be identified by one sensor and it is "0" if the failure of the

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component cannot be identified by the sensor [2]. Further, Senti *et al*. (2005) proposed a tool called a genetic algorithm (GA) based approach to optimize sensor selection [4]. However, their approach to sensor selection could produce undependable output because the minimum probability of the correct diagnosis is considered.

In addition, Maul *et al*. (2008) proposed a penalty factor in their sensor selection approach [1, 5]. If the number of sensors in the combination of sensors is more than expected, it will be depreciated by the penalty factor [1, 5]. However, if the process of selecting the sensors is replicated by numerous people, it could lead to distinct sensor selection. Additionally, sensor performance metric was proposed by Reeves *et al*. (2017) for sensor selection. Also, in order to be certain that the sensors that have been selected can diagnose the failure and identify failure accurately, Bayesian Belief Network was introduced [6].

The goal of this research work is to use the risk management system of sensor performance metric and genetic algorithm approach to find the best possible combination of sensors (most befitting combinations of sensors) that can be used to detect failure mechanisms in the Boeing 767 and Commercial fleets. This framework could be helpful in not only avoiding critical failure modes in aircraft, but adding to their maintainability and reliability as it may drastically increase the lifetime of crucial systems. This research work consists of data collection, data preprocessing (section 2), risk analysis through Failure Modes, Effect, and Criticality Analysis (FMECA) (section 2.2), and sensor selection (section 2.3) using performance metrics (section 2.3.1) and genetic algorithm (2.4), experiment (section 3), result (section 4), discussion (section 5), and conclusion (section 6).

2 RESEARCH APPROACH AND METHODS

This paper is a collaboration research work between North Carolina A&T State University and Geogia Tech Research Institute. Proper sensor selection is determined based on the values of each term in the performance metric. For example, in aircraft engine control systems, the criticality term value could be higher because the criticality term deals with safety-critical systems such as landing [1]. When the system downtime is costly, the diagnostic term could be higher. For example, when there is problem with the gas rigs and oil, the diagnostic term result could prompt the right sensors, thereby letting us know that the gas rigs and oil should have maintenance priority [1]. Since the performance metric would compute many different combinations of sensors in the aircraft, it could take a while to see the result. Thus, to get the optimal sensor selection, Genetic Algorithm is used.

2.1 Dataset

The data set for this analysis consists of ADs from the ten zones with the highest cost on US operators. Each AD contains information about failure modes and mechanisms, affected components, and recommended corrective actions. Before conducting the FMECA, the data set was carefully reviewed to eliminate any duplicate entries. Each AD and its identified failure modes are condensed and categorized into a generalized set of failure modes to make for ease of analysis. From this generalized set of failure modes were chosen that had either a relatively large presence or a potentially high level of severity.

2.2. Failure Modes, Effects, and Criticality Analysis

Failure Modes, Effect, and Criticality Analysis (FMECA) is a powerful technique used in the aerospace industry to systematically identify and assess potential failure modes of systems, components, or processes. This report presents the FMECA analysis conducted on the available data set of Airworthiness Directives (ADs) to assess the frequency and severity of failures associated with these directives.

FMECA contains a range of mechanisms that were recorded causing the failure mode across the dataset. To assess the severity, each failure mode grouping was assigned a number 1-10 based on its potential effects on passengers or the aircraft. A level of 1 indicates a decrease in comfortability while a level of 9 or 10 indicates loss of life or control of the craft. Additionally, to assess the probability, the frequency of occurrence for each failure mode is evaluated using a category called the Occurrence Factor. The number of ADs that make up each failure mode category is then normalized into a percentage of the complete dataset of zones. This percentage is then ranked by the Occurrence Factor, with 0.001% earning the lowest grade of 1 and 5-10% earning the highest grade of 10. The FMECA matrix was created by multiplying the severity and occurrence ratings. This results in the criticality rating, with the highest scoring failure modes selected as a priority for sensor solution consideration.

2.3 Sensor Selection

During the FMECA analysis, some failure mechanisms were detected such as mechanical malfunctions (e.g., control wiring, wire bundles), friction between wiring, cracking, fracture, and various failures in the fuel system. These failures could be identified or prevented from occurring by using sensors. A tool that can be used to find the most appropriate possible combination of sensors to detect failure is needed. In this paper, we propose the use of a sensor performance metric and genetic algorithms to find the ideal combination of sensors possible that can be used to identify failure mechanism in aircraft as discussed in the following steps [1]:

2.3.1 Performance Metric

The performance metric, $I_{\{s\}}$, is a metric that describes the average of three terms: the percentage of failure that can be detected by the sensors, $DE_{\{s\}}$, the relief of diagnosis of the failure the sensor can detect, $DI_{\{s\}}$, and the effect of the failures detected on the successful completion of the mission, $CR_{\{s\}}$. Additionally, the subscripts s in $I_{\{s\}}$, $DE_{\{s\}}$, $DI_{\{s\}}$, and $CR_{\{s\}}$ signify each sensor or combination of sensors [1]. Mathematically, $I_{\{s\}}$ is defined in equation (1) as follows:

$$I_{(s)} = \frac{DE_{(s)} + DI_{(s)} + CR_{(s)}}{3} \tag{1}$$

The value of the performance metric is a value that falls between 0 and 1, wherein "1" signifies the best sensors meaning as soon as the failure occurs, it identifies all failures. However, "0" means the sensor is not effective or useful to detect the failure type.

2.3.2 Detection Term

The detection term ($DE_{\{s\}}$) deals with the percentage of failure that can be detected by the sensors. In order for the detection term to perform its operation, the initial state of the sensor before the occurrence of failure mechanism, has to be different from the final state of the sensor after the occurrence of failure mechanism [1]. Mathematically, the detection term can be defined in equation (2) as follows:

$$DE_{(s)} = \frac{P_d}{P_{md}} \tag{2}$$

According to Reeves *et al.*(2018), the P_d in equation (2) stands for the total probabilities of occurrence of failure that can be identified by sensor and P_{md} represent the total probabilities of the prevalence of failure that at least one sensor can identify out of the whole possible combination of sensors on the aircraft [1]. Similarly, the value of $DE_{\{s\}}$ falls between 0 and 1 where 1 indicates that all failures can be detected by sensor s as soon as they occur and 0 depicts that no failures occur.

According to Reeves et al. (2018), to know the time at which the components or elements fail and their detection time, a time dependence factor is proposed. The time dependence factor measures the correlation between the component failure and its detection time [1]. By applying the time dependence factor to equation 2, it results in the following in equation 3:

$$DE_{(s)} = \frac{1}{P_{md}} + \sum_{0}^{Nd_{(s)}} P_e \left(1 - \frac{t_d - t_f}{T}\right)\left(1 - \frac{t_d - t_f}{T - t_f}\right) \tag{3}$$

where P_e is the probability of failure event examined, *Nd{s}* is the number of failure components that sensor s can detect, t_d is detection time, t_f is the time of failure, and T is the length of the mission [1]. Additionally, the first expression in parentheses depicts the ratio of detection of failure delay to the total length of the mission. While the second expression in parentheses indicates the ratio of detection of failure delay to the mission time left. If the delay between failure and detection is long, the factor will be small [1]. However, this research work only focuses on using equation (2) for the detection term as there is no time of detection (t_d), time of failure (t_f) and length of mission (T) in the dataset used for this work.

2.3.3 Diagnostic Term

The diagnostic term refers to how sensor s can be utilized to diagnose a failure. To differentiate between distinct failures, the failure traits need to be distinct. Mathematically, the diagnostic term can be defined as the formula in equation 4:

$$DI_{(s)} = \sum_{i=1}^{nrs} Pmli \Big/ \sum_{i=1}^{nrs} Psri \tag{4}$$

According to Reeves *et al*. (2018), the nrs denotes distinct sensor reading, P_{mli} indicates the probability that a failure occurs, and P_{sri} indicates the probability of reading sensor i [1]. Additionally, the component failure is said to be diagnosed properly if the value of $DI_{\{s\}}$ is larger. Based on Reeves *et al.* (2018) study, in order to see the advancement in diagnostic terms, a time factor is examined as shown below in equation 5

$$Factor(T_{step}) = \left(1 - \frac{T_{step} - t_d}{T}\right)\left(1 - \frac{T_{step} - t_d}{T - t_d}\right) \tag{5}$$

Moreover, according to Reeves *et al.* (2018) the first expression in the parentheses in equation (5) indicates the ratio between the time in which the greatest failure diagnostic ability can be reached to the length of the mission. While the second factor indicates the ratio between the time in which the greatest failure diagnostic ability can be fulfilled to the mission time left [1]. For every time step, equation (5) can be modified as shown below in equation (6):

$$\begin{aligned} Value(T_{step}) &= \frac{\sum_{x=1}^{x\max(T_{step})} Pmlx * Factor(T_{step})}{\sum_{x=1}^{x\max(T_{step})} Psrx} \\ &= \frac{N(T_{step}) * Factor(T_{step})}{D(T_{step})} \end{aligned} \tag{6}$$

For all points in the mission, x_{max} indicates the number of sensors reading, and T_{step} indicates the time step [1]. Thus, the $DI_{\{s\}}$ can be modified into equation (7) as follows:

$$DI_{(s)} = \frac{\sum_{t=td\min}^{t=T} \sum_{i=1}^{nrs(t)} \left(N(T_{step\max}) * Factor(T_{step\max})i\right)}{\sum_{i=1}^{nrs(t)} D(T_{step\max})i} \tag{7}$$

Based on Reeves *et al.* (2018) survey, the $T_{stepmax}$ is the highest value of T_{step}, nrs(t_d) stands for the number of differences at individual time step, and t_{dmin} signifies the initial time at which the detection time was noticed [1]. However, this research work only focuses on using equation (4) as the diagnostic term as there is no time step (T_{step}), maximum time step ($T_{stepmax}$), time of detection (t_d), and length of mission (T) in the dataset used for this project.

Similarly, the value of the diagnostic term is between 0 and 1; where 1 show that all the failure of a component as soon as they occur create different readings of the sensor and it is closer to 0 when the failure of the component output the same readings of the sensor [1].

2.3.4 Criticality Term

Criticality term ($CR_{\{s\}}$) deals with the ability of a sensor to identify failure in the performance of a system [1]. Similarly, the $CR_{\{s\}}$ follow the idea of Cheok et al. (1998), Fussell-Vesely metric. This metric considers the sensors that can be used to identify failure [9]. Mathematically, the criticality term is defined as follows in equation 8:

$$CR_{(s)} = \frac{Q_{sys} - Q_{sys}(q_s = 0)}{Q_{sys}} \tag{8}$$

where Q_{sys} is the system's failure probability; the formula in equation (8) shows that the system's failure probability, $Q_{sys}(q_s = 0)$ which is considered when the system is functioning well is removed from the failure of the system Q_{sys} [1]. According to Reeves *et al.* (2018), this value is then normalized by the system failure probability Q_{sys} [1].

2.4 Genetic Algorithm

To optimize the result derived from the performance metric, we need to use genetic algorithms. According to Holland JH's book (1992), a Genetic algorithm (GA) is an optimization algorithm that works based on natural selection. The GA chooses items from the present population and uses that item as the parent that can produce children for the next generation [10]. The population grows towards the best solution after consecutive generations. Moreover, problems that are not suitable for other optimization algorithms can be solved with a GA. For example, GA can be used to optimize tasks that have a discontinuous objective function. At each step, the GA uses pragmatic rules which include selection, crossover, and mutation to produce the next generation from the present population. In terms of the sensor selection problem, the sensors stand for chromosomes and every sensor has a gene. When a sensor is selected, it stands for 1, however, when a sensor is not selected, it is referred to as 0. For example, suppose there are 20 sensors in an application, the string: 11001000000000010001 indicates that sensors 1, 2, 5, 16, and 20 are selected [1].

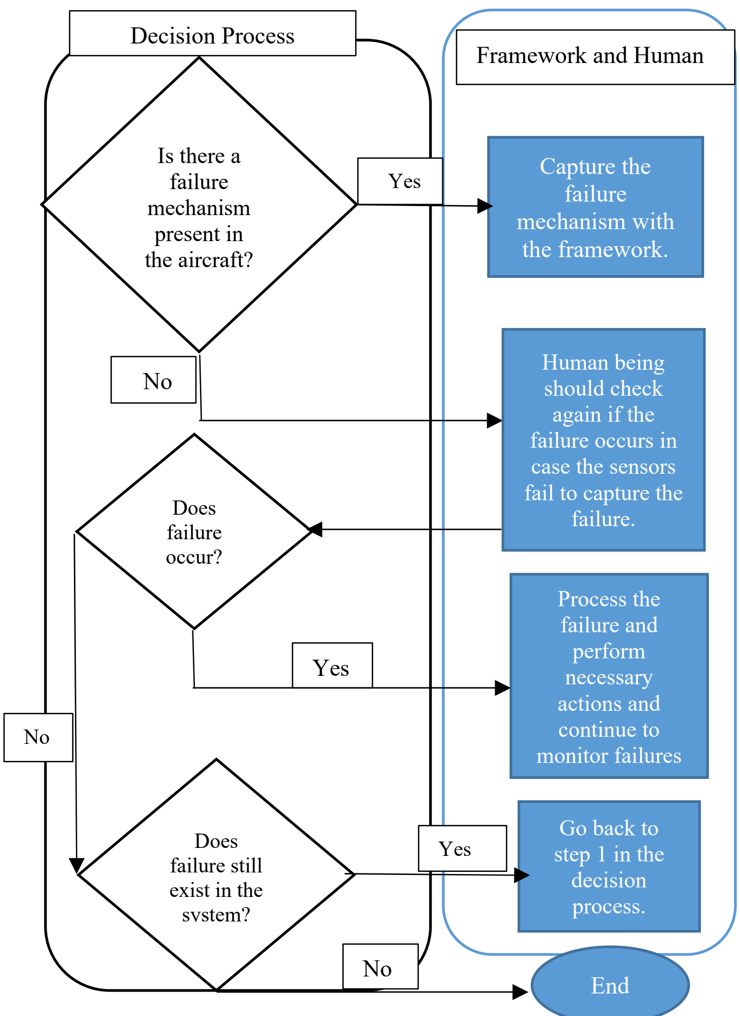

Figure 1. Proposed Sensor Selection Framework

Figure 1 depicts how the proposed sensor selection framework works. Humans are included in the framework because some sensors might not be able to capture some failure. So, it is advisable for humans to be visiting some critical places in the aircraft perhaps like every 10 minutes.

3 EXPERIMENT

Firstly, all the failure mechanisms in the dataset were examined and the programming language used for the experiment is a python programming language. Additionally, all the functions which include performance metric, detection term, diagnostic term, and criticality term were evaluated. To assess the best possible combination of sensors (most satisfactory sensor selection), the fitness function (performance metric) was passed into a specific type of genetic algorithm called pyGAD. In the pyGAD module, different parameters such as num_generation, fitness_func, initial_popuplation, sol_per_pop were passed into the module. These parameters were chosen based on the given problem. For example, nums_parent_mating represents the number of solutions to be selected as parent, also, within the population, sol_per_pop represents the number of chromosomes which further represent the number of sensors in our research work, num_genes represent the number of genes in the chromosomes.

5 out of the whole 359 failure mechanisms: water accumulation, malfunction, unserviceable relay, seal failure, damage to wire were examined with the performance metric and genetic algorithm methods to be able to see better diagnostic term result. The two experiments were performed based on 20 generations.

Additionally, 10 sensors which include pressure sensor, temperature sensor, flow sensor, vibration sensor, strain gauge sensor, level sensor, proximity sensor, light sensor, sound sensor, and humidity sensor are used for these experiments. Each of these sensors measure different characteristics. For example, in the dataset used for this experiment, some failure mechanisms such as fuel leak occur in the dataset and this type of problem can be detected with a sensor device such as pressure sensor as the pressure sensor measures the level of the fuel. Also, in the dataset, there are some mechanical malfunctions; this type of problem can be detected by strain gauge sensor. The strain gauge changes the tension, pressure, and force into electrical resistance which can be measured. Moreover, in the dataset, there are some water accumulation failure mechanisms. This type of failure can be measured by level sensor and pressure sensor. The level sensor works in such a way that the pressure on the sensor's surface is changed to the height of the liquid when the sensor is put in the measuring liquid. The vibration sensors also monitor features such as acceleration, and speed.

4 RESULT

The FMECA analysis identified several critical failure modes based on their criticality ratings. These critical failure modes were associated with components that showed either a high frequency of failure or had severe consequences on aircraft airworthiness. Specific failure modes that rank high in the severity assessment include Ignition/Fire/Combustion, Fluid Leak, Arcing/Electrical Failure.

Furthermore, Table 1 shows the result of the performance metric, detection term, diagnostic term, and criticality term on the whole dataset for different generations. Table 1 also shows that the larger the combination of sensors, the higher the value of the performance metric, detection term, diagnostic term, and criticality term respectively. For example, the combination of 9 sensors gives higher detection term and criticality term as compared to the combination of 7 sensors for the detection term and criticality term. This means that the combination of 9 sensors can detect all the failure mechanisms correctly. Additionally, the performance metric was optimized by the pyGAD model for efficient combinations of sensor that can be used to identify the failure mechanisms correctly. From Table 1, it was also observed that the diagnostic term output in each of the generations was very small when the missing values in the failure mechanism column were included. This caused smaller diagnostic values in each generation.

Figure 2 shows the performance of the proposed framework on 20 generations. From figure 2, it was observed that as the generation increases the value of the fitness (performance metric) increases.

Table 1 Best possible combination of sensors that can be used to detect failure mechanism in the dataset. The legend will be used for reference in the following information to denote the sensors in each generation.

Legend:
Pressure Sensor [A] | Temperature Sensor [B] | Level Sensor [C] | Stain gauge Sensor [D] | Flow Sensor [E] | Vibration Sensor [F] | Proximity Sensor [G] | Light Sensor [H] | Sound Sensor [I]

Sensors	Numbers	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$	Generation
A, B, D, E, G, H, I	7	0.5065	0.5845	0.0128	0.9220	1
A, B, D, E, F, G, H, I	8	0.5348	0.6676	0.0147	0.9220	3
A, B, C, D, E, F, G, H, I	9	0.5894	0.7989	0.0179	0.9518	5
A, B, C, D, E, F, G, H, I	9	0.6231	0.8979	0.0197	0.9518	17
A, B, C, D, E, F, G, H, I	9	0.6255	0.9048	0.0199	0.9518	20

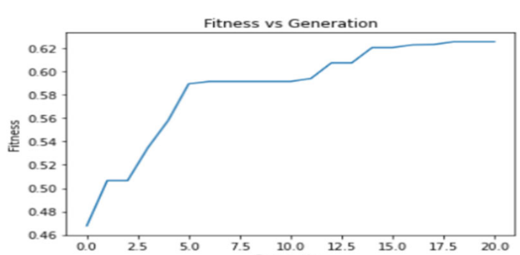

Figure 2. The performance of the proposed framework based on 20 generations on the whole failure mechanism present in the dataset.

Furthermore, to see better performance of the diagnostic term, 5 out of the 359 failure mechanisms were considered. The result of this experiment can be shown in Table 2.

Table 2 Best possible combination of sensors to detect 5 failure mechanisms out of the whole 359 failure mechanism present in the dataset.

Sensors	Numbers	$I_{\{s\}}$	$DE_{\{s\}}$	$DI_{\{s\}}$	$CR_{\{s\}}$	Generation
A, C, E, F, I	5	0.7646	0.7218	0.7218	0.8502	1
A, B, D, E, F, H, I	8	0.9594	1.0000	1.0000	0.8782	11
A, C, D, E, G, I	6	0.8255	0.7992	0.7992	0.8782	4
A, B, C, D, E, G, I	7	0.9594	1.0000	1.0000	0.8782	7
A, B, C, D, E, G, H, I	8	0.9594	1.0000	1.0000	0.8782	18

From Table 2, for each generation, it was observed that there is an increase in the diagnostic term as compared to the diagnostic term in table 1 and this is because there is no account for any missing value in the second experiment as the second experiment was based on 5 out of 359 failure mechanisms present in the dataset. Additionally, from Table 2, it was observed that ideal combination of 7 sensors can identify the failure mechanisms instead of 8 sensors since they both have the same $I_{\{s\}}$, $DE_{\{s\}}$, $DI_{\{s\}}$, and $CR_{\{s\}}$. Consequently, these 7 combinations of sensors help to minimize cost and weight in the aircraft. In addition, these selected sensors can be placed in different locations on the aircraft to maintain the right balance on the aircraft.

5 DISCUSSION

In general, to spend less on sensors and to avoid unnecessary weight, it is safe to use the performance metric as it is used to find the best (appropriate) possible combination of sensors that can be used to identify failure in aircraft. Additionally, the result of each term of the performance metric can be used to select the suitable sensor for a particular application. There are some applications that require more of a particular term than the others. For example, in a safety-critical system, the result of the critical term will be more crucial than the other two terms as the problem deals with more critical behavior. When the application downtime is high, the result of the diagnostic term is more crucial than the other two terms.

In addition, it was noticed that the result of 5 out of the 359 failure mechanisms considered in the dataset shows higher diagnostic term. Consequently, the missing values present in the dataset could affect the diagnostic term result.

6 CONCLUSIONS

This paper proposed sensor selection by using performance metric and genetic algorithm (GA). In addition, the code was written with python programming. Two experiments were performed using the proposed framework and it shows that there is a gap in diagnostic terms between the first experiment and second experiment due to some missing values in the dataset. From the experiments, it was observed that the combination of 7 or more sensors produced higher performance metric. Hence, human lives are crucial; we need urgent ways of mitigating risks in aircraft by using different sensors based on the performance metric and genetic algorithms.

Future research work is planned to build machine learning algorithms that can be used to predict failure mechanisms to prevent it from damaging the aircraft.

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BIOGRAPHIES

Lukmon Rasaq, B.Sc, MSc, Ph.D (in view)
North Carolina A & T State University
1601 E Market St, Greensboro, NC 27411

e-mail: larasaq@aggies.ncat.edu

Lukmon Rasaq is a researcher and a Ph.D student studying Industrial and Systems Engineering. His research area includes network optimization, evolution of economic networks, human activity recognition, Machine Learning, Deep Learning, and Natural language processing (Speech to text, sentiment analysis).

Korbin Ferguson, Undergraduate Research Assistant
North Carolina A & T State University
1601 E Market St, Greensboro, NC 27411

e-mail: kwferguson@aggies.ncat.edu

Korbin Ferguson is a sophomore undergraduate student studying Mechanical Engineering with plans to go into the Aerospace field.

William Teasley, BSc Industrial and Systems Engineering

e-mail: wjteasley@aggies.ncat.edu

William Teasley received his bachelor's degree in May 2023.

Max Xu, Research Intern

e-mail: Max.Xu@gtri.gatech.edu

Max Xu is a research intern at GTRI, and he is also a member of the electronic systems laboratory, air national guard program office, and strategic sustainment team.

Kyle E. Blond, PMP, LSSBB
Strategic Sustainment Team (SST)
Georgia Tech Research Institute (GTRI)
260 14th Street NW
Atlanta, Georgia 30318 USA

e-mail: kyle.blond@gtri.gatech.edu

Kyle E. Blond is an aircraft sustainment researcher at GTRI and leads GTRI's SST. He is also a Doctorate of Systems Engineering candidate at Colorado State University and Aircraft Maintenance Officer in the United States Marine Corps Reserve. His research specialties include aerospace industrial enterprise systems and aircraft maintenance operations.

Om Prakash Yadav
1601 E Market St
Greensboro, NC 27411

e-mail: oyadav@ncat.edu

Om Prakash Yadav is a Professor and Chair in the Department of Industrial & Systems Engineering at North Carolina Agricultural and Technical State University, USA. He earned his Ph.D. in Industrial Engineering from Wayne State University in Detroit, USA. He has authored or co-authored more than 150 research articles in different areas namely reliability, risk assessment, and design optimization. His research interest includes reliability modeling and analysis, risk assessment, robust product/process design, optimization techniques, lean manufacturing, and Six Sigma methodologies. Om's research work has been published in Reliability Engineering & System Safety, Quality, and Reliability Engineering International, Journal of Risk & Reliability, and so on.