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Modelling of Human Factors in Aviation Maintenance Using HFACS-ME (Human Factors Analysis and Classification System- Maintenance Extension) and Bayesian Network

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ABSTRACT

Aircraft maintenance is a complex task involving a skilled human workforce, spare parts, and various other resources. Human factors are an inherent element of the human workforce. Human factors analysis, therefore, becomes an essential aspect of aviation maintenance. Human factors have been identified and classified using various methods in existing literature. However, there is a gap in the study of the interdependency of critical human factors including subfactors, and measuring them effectively to reduce incidents and accidents. This research work proposed a novel approach for human factors modeling using Human Factors Analysis And Classification System Maintenance Extension (HFACS-ME), and Bayesian Network (BN). Inadequate maintenance processes, inadequate documentation, inadequate supervision, Judgement decision, and attention memory were identified as some of the critical human factors in aircraft maintenance. These critical human factors were further analysed and divided into subfactors. The main contribution of the present research work is the methodology of developing a dependency model of the human factors and subfactors to analyse their measured effects on aircraft maintenance. The proposed BN model demonstrated the estimation of the probability of effective maintenance by considering the critical human factors with available facilities, and resources in an aviation maintenance setup.

Keywords: Aircraft maintenance; Bayesian network; Fuzzy AHP; Human factors; HFACS

NOMENCLATURE

ACS	: Accessibility
MEDA	: Maintenance error decision aid
AM	: Aircraft maintenance
MESS	: Maintenance environment survey scale
AME	: Attention memory error
MHZ	: Maintenance hazard
APL	: Application of knowledge
MOD	: Modified
AVL	: Availability
NSL	: Noise level
BN	: Bayesian Network
OBS	: Obstruction
BUL	: Bulletin
OST	: Oversight
CFG	: Configuration
PCD	: Perception
CLR	: Clarity
PER	: Performance
COM	: Communication
PLG	: Planning
DGN	: Design
PRC	: Maintenance process
DOC	: Documentation
PRO	: Procedure
DSN	: Decision
QLF	: Qualification
DTN	: Distraction
QLY	: Quality
ED	: Ergonomic design
RUL	: Rules and regulations
ENV	: Environmental hazard
SIT	: Situational awareness
EOM	: Error of omission
SKL	: Skill level
FAHP	: Fuzzy analytic hierarchy process
SOP	: Standard operating procedure
FMEA	: Failure modes and effects analysis
SQE	: Sequence error
FPD	: Foolproof design
STE	: Skill technique error
GDE	: Guidance
STR	: Stress
HERMES	: Human error risk management for engineering systems
SUP	: Supervision
HFACS-ME	: Human factors analysis and classification system-maintenance extension
TEC	: Technique
HHD	: Hand holding

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TFL	: Trip fall hazard
HKP	: Housekeeping
TFN	: Triangular fuzzy number
HZS	: Hazardous substance
TRG	: Training
JDE	: Judgment decision
TRK	: Trekking
JDG	: Judgement
TSK	: Task
KGE	: Knowledge level
UPD	: Updation
KRE	: Knowledge rule-based error
VIS	: Visibility
MCDM	: Multi-criteria decision-making
WKS	: Workspace
XCH	: Crosscheck correctness

1. INTRODUCTION

Aviation maintenance is a specialised activity involving a skilled human workforce and various other resources. Human factors are an integral aspect of human resources and play a crucial role in effective aviation maintenance. While the system performance characteristics, such as Reliability, Availability, Maintainability (RAM), and quality, have been exhaustively analysed in the literature, human factors remain a critical yet often overlooked aspect in aviation maintenance[1]. About seventy percent of all aviation accidents resulted from human error and out of these, at least fifteen to twenty percent were attributed to maintenance, highlighting the need to analyse these factors[2]. An accident may be caused due to multiple reasons and a precursor or indications are present in most of the cases in the form of incidents and deficiencies in the system[3]. Earlier, the traditional quality control methods were employed, without a specific human factors component to investigate, and manage errors. Later human factor-induced errors in aviation maintenance were analysed mostly through qualitative techniques. Methods such as Maintenance Error Decision Aid (MEDA)[4], Systematic Approach to Human Error Reduction Analysis (SHERPA)[5], Human Error Assessment and Reduction Technique (HEART)[6], Technique for Retrospective/ Predictive Analysis of Errors (TRACE)[7], and Human Error Identification (HEI)[8] were extensively used in human factors Analysis. Identification and prioritisation of human factors have been explored in existing literature, however, they lacked a comprehensive analysis of the interrelation and dependencies of human factors including sub-factors, and effective modeling of their measurable impact on aviation maintenance[9-11]. According to Reason[12], reducing causal factors can effectively lower the probability of maintenance errors manifested due to human factors. Therefore, a better understanding of the human factors was needed for effective error control, specifically identifying its causal mechanism to prevent the reccurrence[13]. The present article provides a more nuanced and precise understanding of the human factors and causal sub-factors, logically maps their dependencies, and allows scientific measurement of their quantitative impact using the Bayesian network (BN) model. The novel approach combines qualitative and quantitative methods and provides a comprehensive understanding of human factors' impact on aircraft maintenance which is an improvement over the general recommendations provided by previous studies.

2. LITERATURE REVIEW

The literature review was carried out in the following three parts.

2.1 Existing Studies on Human Factors

The Human Factors Analysis and Classification System (HFACS) is based on Reason's Swiss cheese model which provides an organisational framework for accident analysis[13]. HFACS was initially developed to identify and analyse aviation accidents. Over time, the model proved to be highly valid and effective, leading to its application in other fields like manufacturing, nuclear, oil and gas, construction, health, safety, etc. Schmidt applied a maintenance extension to HFACS[14]. Human Factors Analysis and Classification System-Maintenance Extension (HFACS-ME) was also used for error classification in air accidents. The findings showed various important associations among operational-level mistakes. and organisational inadequacies[15]. Cacciabau and Vella studied human-machine interactions using Human Error Risk Management For Engineering Systems (HERMES)[16]. Rankine developed Maintenance Error Decision Aid (MEDA) to investigate factors contributing to maintenance errors resulting in incidents and accidents. The approach was successfully used in the identification of organisational and individual errors, although the approach was reactive in nature[4]. Fogarty and Saunders analysed the causes and effects of human factors in maintenance and developed the Maintenance Environment Survey Scale (MESS) to measure a range of individual, environmental, and organisational factors related to maintenance[17].

2.2 Fuzzy AHP

Analytical Hierarchy Process (AHP) a multi-criteria decision-making (MCDM) technique, was found suitable for analysing the aspects such as the interaction of man, machine, and organization[18]. AHP was first proposed by AL Saaty[19]. The classical AHP considers only definite judgments, failing to account for uncertainty and vagueness in decision-making. The use of fuzzy set theory allows more flexible comparisons and intermediate preferences in uncertainties[20]. MCDM, with a fuzzy approach, also enables the analysis of qualitative and incomplete information. Chang proposed a novel method for dealing with the Fuzzy Analytical Hierarchy Process (FAHP). This method involves using triangular fuzzy numbers to establish the relative importance of different factors in the decision-making process. In addition, the extent analysis approach is employed to calculate the synthetic extent values for each of the pairwise comparisons[21]. Kutlu and Ekmekciogli used the fuzzy Analytical Hierarchy Process analysis in the automotive industry[22]. Yilmaz et al. effectively utilised AHP integration for the aircraft selection process[23].

2.3 Bayesian Networks

Bayesian Network (BN) is suitable for investigation of the

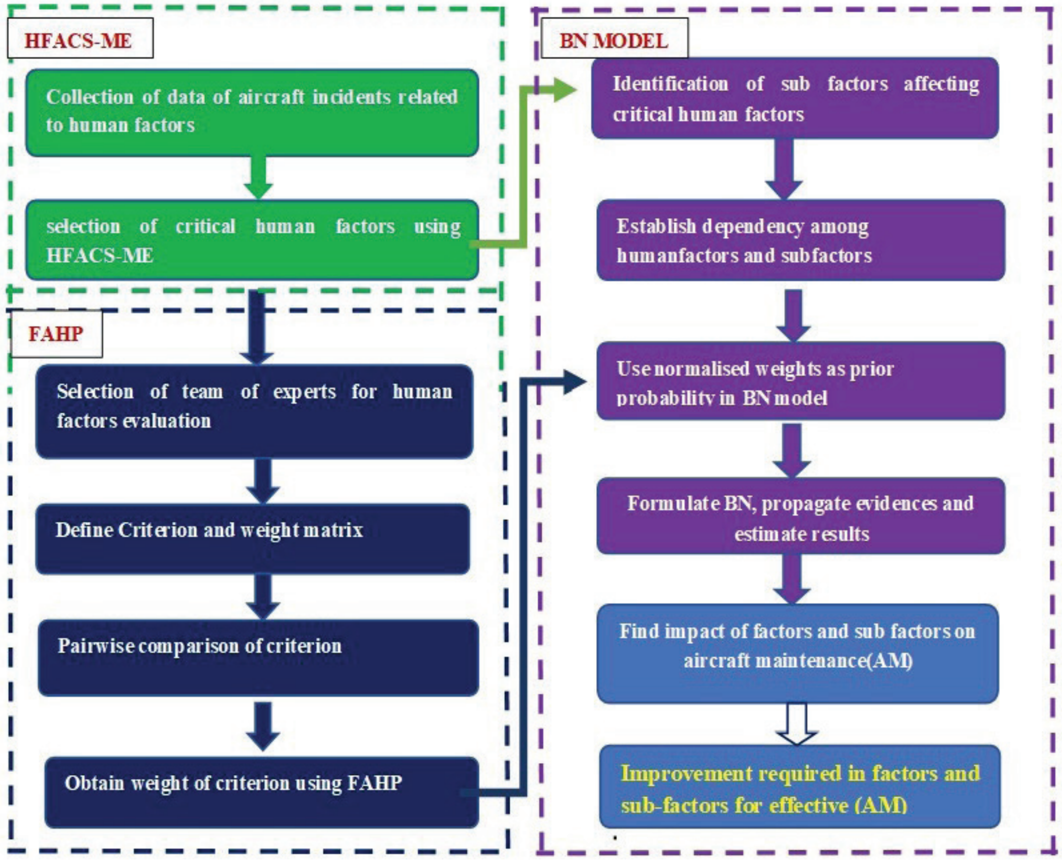

Figure 1. Proposed framework for analysis of human factors.

dependency and casual relationships of multiple variables[24]. BN is capable of modeling dependability among contributory factors and performing quantitative analyses to obtain measured results[25]. BN can aid in predictive and diagnostic reasoning for effective interventions[26]. Bayesian networks have been extensively used to model various situations in industries, as documented in the literature[27-29], however, the application of BN in modeling human factors in aircraft maintenance was found to be limited in aviation maintenance. No specific work was found on human factors in aircraft maintenance using HFACS with the BN and AHP. A gap was, therefore, identified to analyse human factors using integrated qualitative and quantitative techniques to enable effective control measures to mitigate accidents in aviation maintenance.

2.4 Research Gap

The available literature has adequately explored the identification of human factors in aviation. However, there has been limited research on the interplay of human factors, sub-factors, and their measured influence on aircraft maintenance. The presented article is an effort to fill the research gap in the analysis of human factors.

2.5 Objectives

The present article aims to analyse human factors and subfactors, mapping their inter-dependability and measurable effects on aircraft maintenance.

3. METHODOLOGY

The present study proposed an integrated approach of HFACS-ME and BN model for the evaluation of human factors and their measured impact on aircraft maintenance. Ten critical human factors identified and prioritised during the authors' previous work were further analysed and divided into their respective sub-factors, and dependency among factors and subfactors was established. A BN model to assess the impact of factors and subfactors on aircraft maintenance was formulated. FAHP is used for determining the normalised weightage of the human factors and sub-factors and was used as prior probabilities in the BN model. The measured impact of human factors and sub-factors on aircraft maintenance was analysed using the BN model. The percentage improvement required for each factor for effective aircraft maintenance was evaluated. The proposed framework for the analysis of human factors using HFACS-ME, FAHP, and BN is presented in Fig. 1.

3.1 Identification of Critical Human Factors

The ten critical human factors were identified and prioritised in the earlier study[3] using the FMEA-Fuzzy AHP-TOPSIS approach, the result of the study is reproduced for reference in Table 1.

The recommendations to mitigate human factors in aircraft maintenance given by earlier studies in the literature are generic and do not indicate any measurable effects of human factors on aviation maintenance[9-11]. A system can be improved

Table 1. The rank of critical human factors affecting aircraft maintenance[3]

Rank	Critical human factors in aircraft maintenance
1	Inadequate maintenance process
2	Judgement/decision-making error
3	Inadequate documentation
4	Inadequate supervision
5	Attention/memory error
6	Knowledge/rule-based error
7	Inadequate design
8	Obstructed workspace
9	Environmental hazards
10	Skill/technique error

by breaking it down into measurable components because what can be measured can be improved. Therefore, it is necessary to measure the impact of human factors to effectively control and mitigate the incidents caused due to these factors in aircraft maintenance.

Mapping the interrelation between organisational, workplace, and human factors is essential to understand their interplay and dependency. In the next section, we analysed the ten critical human factors identified in Table 1, with respect to their possible subfactors and interdependencies among them.

3.2 Analysis of Critical Human Factors

The ten critical human factors that affect aircraft maintenance from Table 1, are discussed along with their causal sub-factors in this section. Each of these human factors has its own sub-factors that can have an impact on it. The critical human factors and their possible sub-factors with their relationships were analysed to cover their potential influences on aircraft maintenance. The following paragraphs provide a detailed explanation of each factor and its sub-factors.

3.2.1 Maintenance Process (PRC)

Maintenance process signifies the sequence of events involved and executed in a particular maintenance activity[6]. Inadequate process was the most common human factor affecting the effectiveness of aircraft maintenance. Good planning, regular trekking, and oversight, availability of standard operating procedures, and task complexity would affect the process of the task. Hence, there are many sub-factors that can cause the process to be adequate or inadequate[11], such as:

- Planning (PLG)
- Tracking (TRK)
- Standard operating procedure (SOP)
- Oversight (OST)
- Procedure (PRO)
- Task complexity (TX)

3.2.2 Judgement and Decision Errors (JDE)

Aviation maintenance is a highly demanding task and is thus prone to judgement and decision errors, especially under time constraints. Inadequate situational awareness or wrongly perceived maintenance situations would adversely affect the maintenance quality. The following sub-factors could contribute to JDE:

- Decision (DCN)
- Perceived situation (PCD)
- Situational awareness (SIT)
- Judgement (JDG)

Correct perception of events during maintenance activities, adequate situational awareness on the shop floor, the right decision, and good judgement even under time constraints would be desired for effective maintenance.

3.2.3 Documentation (DOC)

There are two aspects of documentation in aviation maintenance. Availability of standard documents required to undertake maintenance activity like OEM specifications, service bulletins, technical manuals, maintenance schedules, SOPs, and other rules and regulations governing maintenance activities. The other documents that are required to be updated after a maintenance activity is undertaken, to serve as future maintenance records like aircraft or aero engine logbook, component log, functional check record, etc. The following sub-factors could affect the documentation:

- Bulletins (BUL)
- Availability (AVL)
- Clarity (CLR)
- Quality (QLY)
- Updation (UPD)

The availability of requisite documents is essential for maintenance. Good clarity and high quality of available maintenance documents are also equally important. Maintenance documents are required to be updated regularly to remain relevant.

3.2.4 Supervision (SUP)

Continuous supervision is essential for effective maintenance. The following sub-factors affect the supervision:

- Guidance (GDE)
- Training (TRG)
- Performance (PER)
- Qualification (QLF)
- Handholding (HHD)

Adequate guidance and regular training are required to be imparted by the supervisor. Continuous tracking of performance and enhancement of qualification needs to be instituted by the supervisor for effective maintenance outcomes.

3.2.5 Attention and Memory Error (AME)

The manifestation of attention and memory errors is not desirable for effective maintenance. Miscommunication or lack of communication, attention distraction, and stress could lead to sequence errors and errors of omission in maintenance activities. The various sub-factors that contribute to AME could be:

- Communication (COM)
- Distraction (DTN)
- Stress (STR)
- Sequence error (SQE) Error of omission (EOM)

3.2.6 Knowledge and Rule-Based Error (KRE)

Adequate trade knowledge and awareness of relevant rules and regulations is a prerequisite for effective maintenance. Technicians should be proficient in the application of professional knowledge. The following sub-factors may contribute to knowledge and rule-based errors:

- Knowledge (KGE)
- Rule (RUL)
- Application of Knowledge (APL)

3.2.7 Design (DGN)

If the design of equipment is not good, it will be challenging to render effective maintenance. The design of equipment may be affected by the following sub-factors.

- Modification (MOD)
- Configuration (CFG)
- Accessibility (ASC)
- Foolproof Design (FPD)
- Defect Not Cleared (DNC)

Adequate accessibility and good configuration are the basic tenets of equipment design. Foolproof design can reduce the probability of failure. Modification ensures the upgradation of the equipment. Similarly, if the earlier reported defects on the equipment are rectified then maintenance quality is expected to be good.

3.2.8 Workspace Obstructions (WKS)

Good visibility and an obstruction-free workspace without any hindrance to maintenance are highly desirable for effective maintenance. The following subfactors can affect the workspace.

- Visibility (VIS)
- Obstruction (OBS)
- Maintenance Hindrance (MHD)

3.2.9 Environmental Hazards (ENV)

The environmental hazards need to be controlled for effective maintenance. The sub-factors under adverse environmental conditions could be as follows.

- Housekeeping (HKP)
- Noise (NSE)
- Trip and Fall Hazard (TFL)
- Hazardous Substance (HZS)

Maintaining a clean and quiet workplace is crucial. It is important to identify and fix any potential trip and fall hazards. Additionally, hazardous chemicals such as acids, fuel, oil, and lubricants should be stored separately to ensure the safety of maintenance technicians' health.

3.2.10 Skill and Technique Error (STE)

It is important to have skilled aircraft maintenance technicians performing maintenance work. If technicians lack the necessary skills and fail to perform proper maintenance, it may result in damage and additional malfunctions within the system. The following sub-factors may lead to skill and technique errors:

- Skill (SKL)
- Technique (TEC)
- Cross-check (XCH)

The maintenance will be effective if the technician possesses the right amount of skill and applies the correct techniques during maintenance activities. The cross-checking of executed tasks is essential to avoid skill and technique errors in aviation maintenance.

The factors mentioned above can have a direct impact on the quality of maintenance. These ten critical human factors are interdependent on each other and also on their respective sub-factors. The interdependencies of these factors may be mapped as follows.

- Inadequate process (PRC) can be a common effect of Inadequate documentation, inadequate supervision, high task complexity, knowledge, and rule-based error, attention and memory error, decision and judgment error, obstructed workspace, and unfavourable environmental conditions.
- Inadequate supervision (SUP) may result in inadequate process, inadequate documentation, knowledge and rule-based error, judgment and decision error, and obstructed workspace.
- Environmental hazards and obstructed workspace may result in inadequate process, judgment, and decision error, skill and technique error, and attention and memory error.

3.3 Fuzzy AHP

Fuzzy AHP was utilised in this study to obtain the normalised weights of the human factors and sub-factors. The normalised weights were used in the formulation of BN model as the prior probabilities. The experts, qualified aircraft maintenance engineers were consulted, to evaluate human factors in aircraft maintenance. These experts were current on the system and had equal weightage in the calculation, as they had similar qualifications and experience. Table 2 provides the description and Triangular Fuzzy number (TFN) spectrum for the weight of human factors used in FAHP.

Table 2. Description and TFN for criterion weight of human factors in FAHP

Description	Symbol	Triangular Fuzzy Number (TFN)
Absolutely strong	(AS)	2, 5/2, 3
Very strong	(VS)	3/2, 2, 5/2
Strong	(ST)	1, 3/2, 2
Slightly strong	(SS)	1, 1, 3/2
Equal	(EQ)	1, 1, 1
Slightly weak	(SW)	2/3, 1, 1
Weak	(WK)	1/2, 2/3, 1
Very weak	(VW)	2/5, 1/2, 2/3
Absolutely weak	(AW)	1/3, 2/5, 1/2

3.4 Pairwise Matrix For Knowledge and Rule-Based Error (KRE)

A sample calculation of normalised weight vector for Knowledge Rule-Based Error (KRE) is explained in this subparagraph. Similarly, calculations for other human factors and subfactors were carried out. Table 3 presents the

Table 3. Linguistic variables and corresponding TFN

Criteria	**Knowledge**			**Rule**			**Application of knowledge**		
Knowledge	EQ	EQ	EQ	ST	SS	SW	VS	WK	SS
	1	1	1	0.72	0.89	1.17	1	1	1.17
Rule	WK	SW	SS	EQ	EQ	EQ	WK	WK	EQ
	0.89	1.17	1.5	1	1	1	1	1.7	1.5
Application of knowledge	VW	ST	SW	ST	ST	EQ	EQ	EQ	EQ
	0.89	1	1	0.72	0.89	1	1	1	1

linguistic variables and corresponding TFN corresponding to experts' opinions on how the subfactors knowledge, rule, and application of knowledge impact KRE. These opinions were captured using linguistic variables and corresponding TFN. The experts' comparative judgments were consistent, as the consistency ratio[19] (CR) was less than 0.1.

Suppose M_{gi}^{j} is a TFN in the i_{th} row and j_{th} column of the criterion assessment, then

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} a_{ij}, \sum_{j=1}^{m} b_{ij}, \sum_{j=1}^{m} c_{ij} \right) \tag{1}$$

where a, b, and c, are TFN elements. As per AHP, M_{gi}^{j} can be calculated from Eqn (1) as given in Eqns (2-4).

C_1=(1+0.72+1,1+0.89+1,1+1.17+1.17)=(2.72,2.89,3.34) (2)

Similarly,

C_2=(0.89+1+1,1.17+1+1.17,1.5+1+1.5)=(2.89,3.34,4.0) (3)

C_3=(0.89+0.72+1,1+0.89+1,1+1+1)=(2.61,2.89,1). (4)

Column wise sum of M_{gi}^{j} is given in Eqn. (5) and the inverse is calculated in Eqn (6).

$$\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j} = (2.72+2.89+2.61, 2.89+3.34+$$

$$2.89, 3.34+4.0+1.0) = (8.22, 9.12, 8.34) \tag{5}$$

and

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} = \left(\frac{1}{8.34}, \frac{1}{9.12}, \frac{1}{8.22} \right) \tag{6}$$

Therefore, the fuzzy synthetic index F_i can be given from Eqn. (7) as presented in Eqn. (8-10).

$$F_i = \sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} \tag{7}$$

$$F_1 = (2.72, 2.89, 3.34) \otimes (0.12, 0.11, 0.12) = (0.33, 0.32, 0.40) \tag{8}$$

$$F_2 = (2.89, 3.34, 4.0) \otimes (0.12, 0.11, 0.12) = (0.35, 0.37, 0.48) \tag{9}$$

$$F_3 = (2.61, 2.89, 1.0) \otimes (0.12, 0.11, 0.12) = (0.31, 0.32, 0.12) \tag{10}$$

The magnitude of $F_2(x_2,y_2,z_2) \geq F_1(x_1,y_1,z_1)$ is presented in

$$(F_2 \geq F_1) = \left\{ \begin{array}{ll} 1 & \text{if } x_2 \geq x_1 \\ 0 & \text{if } y_1 \geq y_2 \\ \dfrac{(x_1 - z_2)}{(y_2 - z_2) - (y_1 - x_1)}, & \text{Otherwise} \end{array} \right\} \tag{11}$$

where, (x_2,y_2,z_2) and (x_1,y_1,z_1) are TFN. The relative magnitude of fuzzy synthetic extent can be given in Eqn. (12).

$$M(F \geq F_1, F_2, ..., F_k) = M\left[(F \geq F_1), (F \geq F_2)...(F \geq F_k) \right] = minM(F \geq F_i), i = 1, 2, ...k. \tag{12}$$

The degree of possibility for all the F_i were calculated from Eqn. (12) and given in Eqn. (13-15).

$$\mathrm{M}\left(F_1 \geq \mathrm{F}_2\right) = 0.5 \textit{ and } \mathrm{M}\left(F_1 \geq \mathrm{F}_3\right) = 1,\ \min \left\{ \mathrm{M}\left(F_i \geq \mathrm{F}_k\right) \right\} = 0.5 \tag{13}$$

$$\mathrm{M}\left(F_2 \geq \mathrm{F}_1\right) = 1 \textit{ and } \mathrm{M}\left(F_2 \geq \mathrm{F}_3\right) = 1,\ \min \left\{ \mathrm{M}\left(F_i \geq \mathrm{F}_k\right) \right\} = 1 \tag{14}$$

$$\mathrm{M}\left(F_3 \geq \mathrm{F}_1\right) = 1 \textit{ and } \mathrm{M}\left(F_3 \geq \mathrm{F}_2\right) = 1.2,\ \min \left\{ \mathrm{M}\left(F_i \geq \mathrm{F}_k\right) \right\} = 1 \tag{15}$$

The weight vector obtained from the fuzzy synthetic index is given in Eqn. (16) and the normalised weight vector is given in Eqn. (17).

Weight vector $W' = (0.5,\ 1,\ 1)$ (16)

Normalised weight vector for knowledge and rule-based error is $W = \left(\frac{0.5}{2.5} = 0.20,\ \frac{1}{2.5} = 0.40,\ \frac{1}{2.5} = 0.40 \right)$ (17)

Similarly, the normalized weight vectors of all the other human factors and sub-factors were calculated. The favourable state of factors/subfactors for aircraft maintenance (AM) and their respective normalised weights obtained from fuzzy AHP are given in Annexure I.

3.5 Formulation of the Proposed BN Model

The ten critical human factors, along with their potential causes and dependencies, have been examined in section 3.2 to ensure comprehensive coverage of all possibilities that could affect aircraft maintenance. Various classical methods like Fault Tree Analysis (FTA), Markovian Analysis (MA), Artificial Neural Network (ANN), and Bayesian Network (BN) were utilised in the existing literature to model these kinds of interdependencies. However, FTA is not suitable for cases with multiple modes of failures and even MA is rigorous and complicated for such cases. Machine learning techniques like Artificial Neural Networks (ANN) are capable of modeling and learning from data but need huge database and a long training duration. In comparison, BN provides good performance, accuracy, and simplicity. It provides multiple quantitative results with simple operations.

Due to the subjective nature of human factors, it can be quite complex to mathematically model their dependencies on each other and on aircraft maintenance. Therefore, a BN

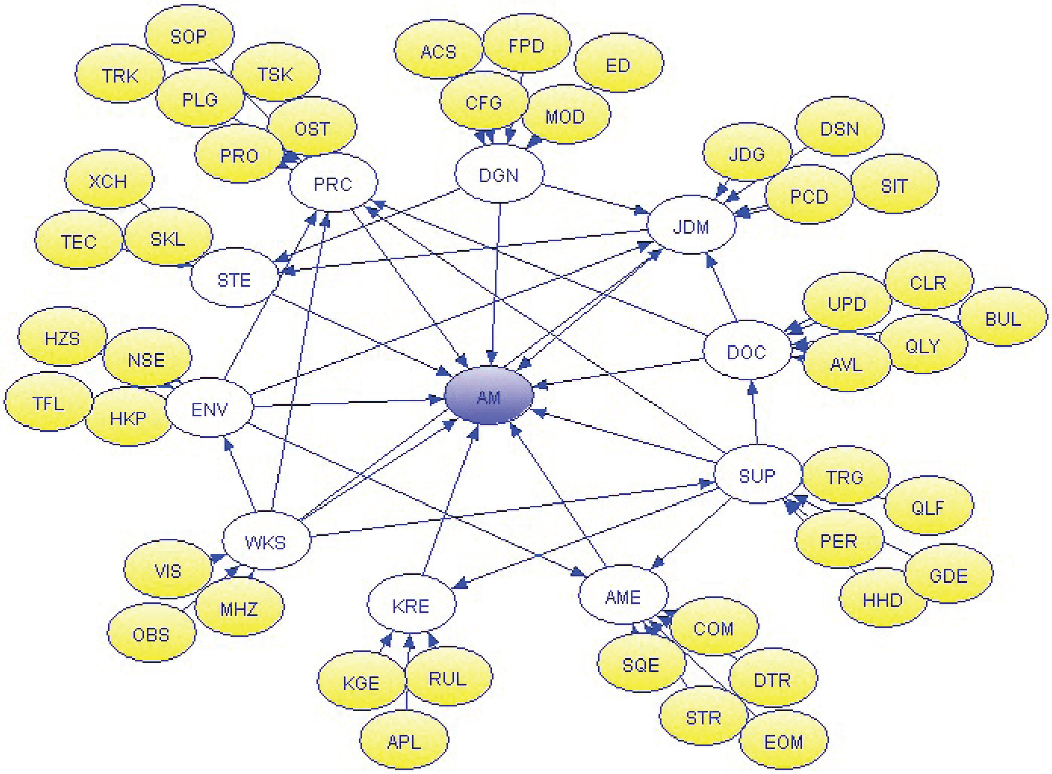

Figure 2. Proposed BN model.

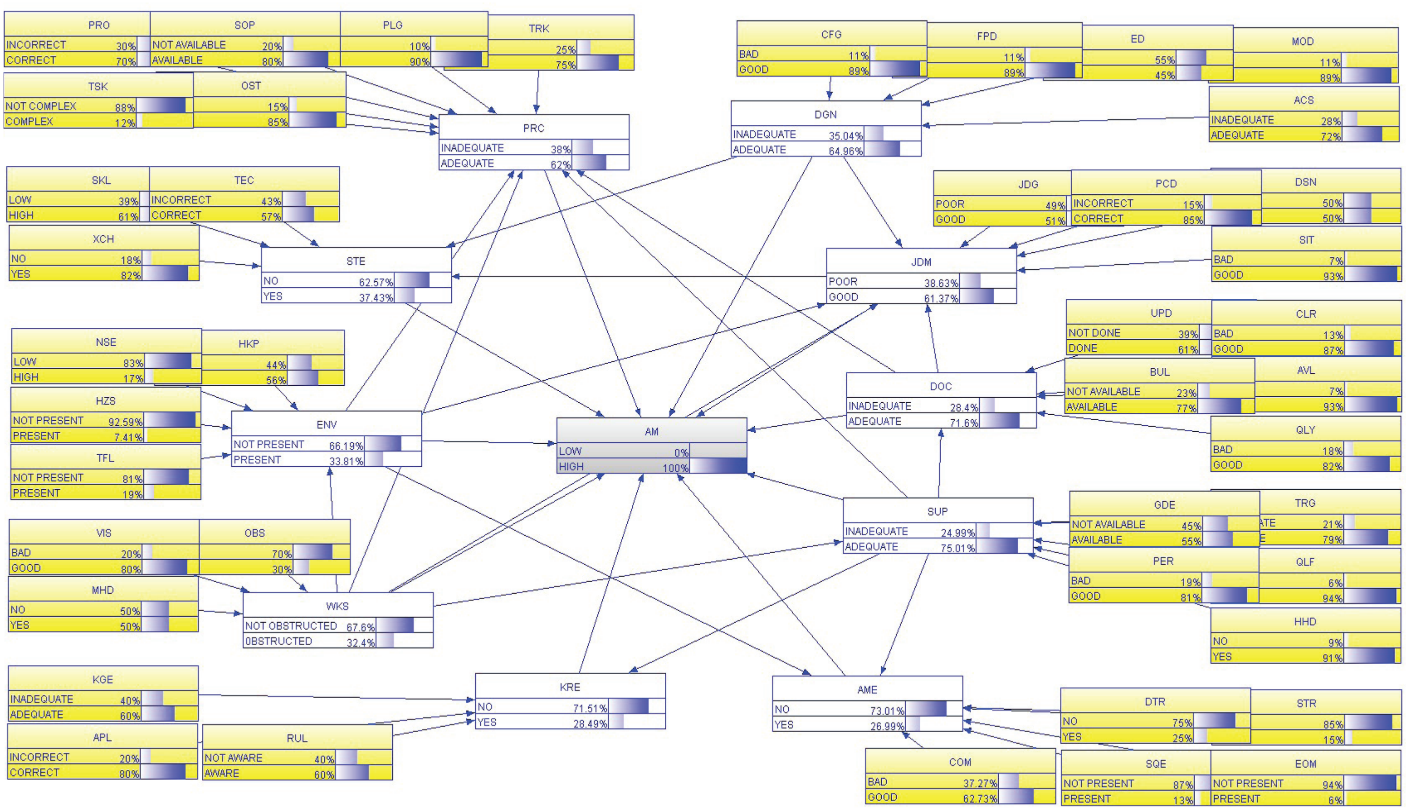

Figure 3. Bayesian network for aircraft maintenance.

model is used to analyse the critical human factors, subfactors, and their effects on aircraft maintenance. Formulation of BN requires a clear understanding of causal human factors including subfactors, and their dependency on each other. A Bayesian network diagram comprises nodes and arcs, the nodes represent the variables and the arcs indicate the relationship between them. These variables can exist in multiple states. Each factor and sub-factor was assigned two states *i.e.* factors favourable or unfavourable for aircraft maintenance. The proposed BN model is given in Fig. 2.

4. RESULTS AND DISCUSSIONS

The impact of human factors and sub-factors on aircraft maintenance is measured in this section using the proposed BN model. We have considered two states of Aircraft Maintenance (AM) in the study, effective and non-effective. Here effective maintenance signifies maintenance free from incidents caused due to human factors. The proposed BN model is utilised to analyse the human factors and their impact on aircraft maintenance as percentage effects, in two ways by providing respective evidences:

The probabilities of human factors favourable to effective aircraft maintenance, and improvement required in each human factor in percentage for effective maintenance.

In a particular maintenance setup, the BN model was formulated as shown in Fig. 2. Prior probabilities of human factors required in BN were obtained from FAHP using experts' opinions given in Annexure I. The impact of factors and subfactors on AM was examined by using the effective AM as evidence and propagating it in the network. The percentage effect of critical human factors and subfactors being favourable on aircraft maintenance is shown in Fig. 3.

It was observed from Fig. 3 that SUP is affecting AM most followed by AME, DOC, KRE, WKS, ENV, DGN, STE, PRC, and JDE respectively, and improvement in these factors significantly improved aircraft maintenance. A noticeable

Table 4. Probability of favourable factors and percentage improvement required for effective maintenance

Critical Factors	Probability of factors favourable to AM (in %)	Improvement required in factors to effective AM (in %)
PRC	62	38
JDE	61.37	38.63
DOC	71.6	28.4
SUP	75.01	24.99
AME	73.01	26.99
KRE	71.51	28.49
DGN	64.96	35.04
WKS	67.6	32.4
ENV	66.19	33.81
STE	62.57	37.43

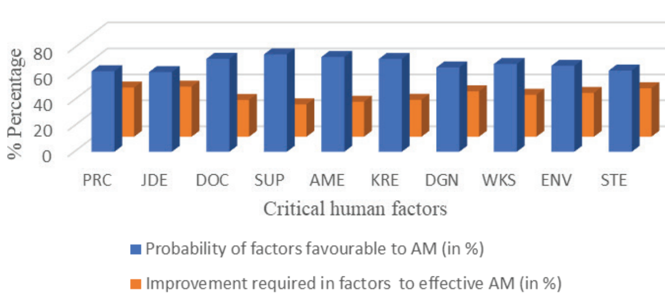

Figure 4. Improvement required in critical human factors for effective maintenance.

Table 5. Impact of favourable factors and percentage Improvement required for effective maintenance

Critical factors	Sub factors	Probability of factors favourable to AM (in %)	Improvement required in factors to effective AM (in %)
PRC	OST	85	15
	PLG	90	10
	TRK	75	25
	PRO	70	30
	TSK	88	12
DGN	MOD	89	11
	CFG	89	11
	ED	66	34
	ACS	72	28
	FPD	89	11
JDE	JDG	51	49
	DSN	50	50
	PCD	85	15
	SIT	93	7
DOC	UPD	61	39
	BUL	77	23
	CLR	87	13
	AVL	93	7
	QLY	82	18
SUP	GDE	65	35
	TRG	79	21
	PER	81	19
	QLF	94	6
	HHD	91	9
AME	COM	62	38
	DTN	75	25
	STR	85	15
	SQE	87	13
	EOM	84	16
KRE	KGE	60	40
	RUL	60	40
	APL	80	20
WKS	VIS	80	20
	OBS	70	30
	MHZ	50	50
ENV	NSL	83	17
	HKP	56	44
	HZS	92	8
	TFL	81	19
STE	SKL	61	39
	TEC	57	43
	XCH	82	18

change in effective maintenance could be observed even by improving a single factor, for example, when subfactors of documentation (DOC), namely bulletin (BUL), availability (AVL), clarity (CLR), upgradation (UPG), and quality (QLY), all were considered in favorable state for Aircraft Maintenance (AM) and the beliefs were propagated in the network, it improved the effective aircraft maintenance by 5 %. Thus, using the proposed model, the percentage of individual factors to be favourable for effective maintenance can be estimated for the available resources as well as the constraints in a particular maintenance setup by processing suitable evidence.

In the second scenario, we consider a situation where the organisation wants an improvement in aircraft maintenance and require feedback on factors affecting AM. Percentage improvement required for each factor on propagating effective maintenance as evidence in the proposed BN model, the obtained results, indicated that SUP, DOC, AME, KRE, DGN, PRC and JDE impact AM in this order. The results of the second case show that treating the proposed factors/sub-factors in proportion to the acquired Bayesian network can significantly improve AM. The probability of critical human factors in a favourable state and the percentage improvement required for each factor is shown in Table 4.

The percentage improvement required in critical human factors for effective maintenance obtained from the proposed BN model is presented in Fig. 4 in graphical form. The precise measurable effects of each human factor and subfactor on aircraft maintenance could be achieved using the proposed BN model. Modifying each factor in the proposed model changes the probabilities of others, making it useful for simulating different possible situations and demonstrating the versatility and robustness of the BN model.

The probability of critical human factors and the subfactors in a favourable state and the percentage improvement required for each factor is shown in Table 5. It was observed that sub-factors such as availability of SOP, good PLG, continuous TRK, and OST play important role in effective maintenance and require significant improvement.

In comparison to the general recommendations of the previous studies, the proposed Bayesian Network model offers a precise and scientifically valid solution. It presents the percentage impacts of various factors on aircraft maintenance, allowing for effective control and interventions to mitigate aviation accidents. The proposed BN model can identify dependencies and recognize factors influencing aircraft maintenance. The main contribution of this methodology is its ability to measure the impact of human factors and calculate the required improvements for effective maintenance.

5. CONCLUSION

In this study, HFACS-ME was effectively combined with BN to analyse the impact of human factors in aviation maintenance. Analysis of human factors indicated that improvement in supervision, documentation, judgment decision-making, attention and memory error, and knowledge and rule-based errors results in effective aircraft maintenance. Analysis of human factors using the proposed model can provide measured guidance that helps in effective aircraft maintenance and necessary control strategies to reduce accidents in aviation.

6. LIMITATIONS AND FUTURE SCOPE

It is important to note that the weightage of factors, sub-factors, and expert opinions, may vary in different fields and with different individuals. As a result, our proposed model involves a degree of subjectivity that should not be disregarded. Modeling of Reliability, Availability and Maintainability (RAM) factors may be considered in future studies.

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In the current study, he guided in reviewing the manuscript and providing insight into formulation and results.

Annexure I

Details of human factors and subfactors

Factors/ subfactors	Abbreviation	State for aircraft maintenance		Normalised weights obtained from FAHP
		Favourable	Unfavourable	
Knowledge rule-based error	KRE	No	Yes	0.07
Maintenance Process	PRC	Adequate	Inadequate	0.2
Judgment decision Error	JDE	No	Yes	0.12
Documentation	DOC	Adequate	Inadequate	0.1
Supervision	SUP	Adequate	Inadequate	0.13
Attention memory error	AME	No	yes	0.04
Design	DGN	Adequate	Inadequate	0.16
Workspace	WKS	Not obstructed	Obstructed	0.06
Environmental hazard	ENV	Not present	Present	0.04
Skill technique error	STE	No	Yes	0.08
Standard operating procedure	SOP	Available	Not available	0.3
Oversight	OST	Yes	No	0.1
Planning	PLG	Good	Bad	0.15
Tracking	TRK	Yes	No	0.12
Procedure	PRO	Correct	Incorrect	0.25
Task	TSK	Simple	Complex	0.08
Modified	MOD	Yes	No	0.11
Configuration	CFG	Good	Bad	0.11
Ergonomic Design	ED	Yes	No	0.45
Accessibility	ACS	Good	Bad	0.28
Fool proof design	FPD	Yes	No	0.05
Judgement	JDG	Good	Bad	0.51
Decision	DSN	Right	Wrong	0.27
Perception	PCD	Correct	Incorrect	0.15
Situational awareness	SIT	Good	Bad	0.07
Updation	UPD	Updated	Not updated	0.39
Bulletin	BUL	Available	Not available	0.23
Clarity	CLR	Good	Bad	0.13
Availability	AVL	Yes	No	0.07
Quality	QLY	High	Poor	0.18
Guidance	GDE	Available	Not available	0.45
Training	TRG	Adequate	Inadequate	0.21
Performance	PER	Good	Bad	0.19
Qualification	QLF	High	Low	0.06
Hand holding	HHD	Yes	No	0.09
Communication	COM	Good	Bad	0.41
Distraction	DTN	No	Yes	0.25

Factors/ subfactors	**Abbreviation**	**State for aircraft maintenance**		**Normalised weights obtained from FAHP**
		Favourable	**Unfavourable**	
Stress	STR	Low	High	0.15
Sequence error	SQE	No	Yes	0.13
Error of omission	EOM	No	Yes	0.06
Knowledge level	KGE	High	Low	0.4
Rules	RUL	Aware	Unaware	0.4
Application of knowledge	APL	Correct	Incorrect	0.2
Visibility	VIS	Good	Poor	0.2
Obstruction	OBS	No	Yes	0.3
Maintenance hazard	MHZ	No	Yes	0.5
Noise level	NSL	Low	High	0.17
Housekeeping	HKP	Good	Bad	0.56
Hazardous substance	HZS	Not present	present	0.08
Trip fall hazard	TFL	Not present	Present	0.19
Skill level	SKL	High	Low	0.39
Technique	TEC	Correct	Incorrect	0.43
Crosscheck correctness	XCH	Yes	No	0.18