Human Reliability Analysis in the Emergency Evacuation from an Aircraft

Alaide Bayma, Marcelo Ramos Martins
EMBRAER S.A.-Brazilian Company Aeronautical
Analysis, Evaluation and Risk Management Laboratory (LabRisco)
Naval Architecture and Ocean Engineering Department, University of São Paulo, Brazil

Abstract: The reliability of the systems' equipment has advanced a lot over time, however the same cannot be seen about human reliability and many of the causes systems' failures are due to human error. It has been concluded that human error has caused about 80 per cent of all accidents. To deal with this problem, it is proposed analyzing the human interaction within the system to establish a generic causal framework aiming at the study of the human error mechanism. This analysis is proposed through the Bayesian Networks approach supported by Fuzzy Logic whose application is to model the Performance Shape Factors and checking through causal inference and diagnosis, which factors most influence in the performance of the tasks in an environment. This paper presents an application of this approach to analyze the one of task of the emergency evacuation testing of an aircraft, focusing on the quantification of volunteers` human factor contribution regarding cabin design.
Key Words: Human Reliability, Cabin Safety, Bayesian Network, Logic Fuzzy

1. INTRODUCTION

The demand for plane trips has increased worldwide; and it expects substantial growth in the aeronautical industry in the upcoming years.

Although the decrease of fatal accident rates, it has not been noticed the decrease of fatalities in accidents with survivors, therefore, the improvement in survival rates will be highlighted in the upcoming years. In light of these evidences, we can understand that great advances have been achieved with the safety assessment techniques of essential aircraft navigation and performance systems because fatal accident rates have decreased, but this cannot be concluded by reducing fatalities In accidents with survivors.

Survival accidents often result from a hard landing, runway excursion, among others. The runway excursion exit was the most frequent type in 2015. The IATA report "Safety Report 2015 (Inter-national Air Transport Association)" shows that 43% of accidents occurred with an emergency evacuation, fatalities and serious damage to the occupants. By analyzing this scenario, two basic factors may be contributing to this: lack of crew training and cabin design. The aeronautical segments making efforts to raise awareness of safety practice in all details of the development, manufacturing and maintenance process of aeronautical products.

Along with these efforts, several research fronts have emerged to identify opportunities to innovate in the safety of occupants on aircraft under normal and emergency conditions. One of these researches investigated the accidents with survivors and selected passengers' statements that could show the behavior of the aircraft cabin in various accident scenarios, in order to bring to the development product engineers a feedback of working them, according to [2] PISTILLI & BAYMA, 2015.

Survivors' statements we related to: Deformation, Occupant protection, Evacuation and Fire Survival. The sequences of difficulties reported by survivors have been presented in the following order: The structures deformation after the impact, compromising the occupants' protection, consequently these two initial factors has an impact in the evacuation time. With this extended time, the difficulties in-crease with the emergence of the fire and smoke that definitely cause the increase of fatalities in these accidents, which could have a higher survival rate if the difficulties to evacuate the aircraft were mitigated. Regarding the design aspect, manufacturers de-sign aircraft showing compliance with airworthiness safety requirements, and civil approval authorities certify these projects by finding evidence from these showing.

Aircraft structures are designed to withstand certain impact loads according to the air-worthiness requirements so that these structures can withstand certain deformations, and not cause too much damage to the structures, and protect the occupants so that they can evacuate from the aircraft before the possibility of an eminence of fire. The purpose of this research is to provide greater safety and protection to occupants of aircraft, additionally offered by the civil aviation authorities.

To improve the cabin behavior in these emergency situations, one of the aspects that will be presented in this article is the relationship between the occupants with the cabin design items, markings and emergency instructions, that support the evacuation from the aircraft in a time that allows the their survival. An essential aspect of this research is to analyze the human reliability and performance during the procedure to locate and follow the emergency markings in an aircraft emergency evacuation testing and its contribution in the improvement in the design of these markings resulting in the integration be-tween the occupants and the design to improve the level of safety. The main challenge is to consider human integration in the design, to evaluate how much the design influences the errors in the execution of the tasks and to suggest adjustments to the cabin design and mitigate the possible human errors in the emergency evacuation.

2. OBJECTIVE

In order to know the human reliability in the integration to the design will be applied the analysis by Bayesian Network sup-ported by Fuzzy Logic to evaluate how much the design that makes evacuation possible, contributing with the occupants (test volunteers) in the execution of the tasks of locating and following the markings of emergency. The result of this research and the validation of a method that can be another tool for the development of cabin interior designs promoting a better integration between occupant-cabin, mitigating human failure, allowing evacuation in time to guarantee occupant survival with less serious injuries.

3. HUMAN RELIABILITY ASSESSMENT

A human error is an action or decision, which was not intended, which involved a deviation from an accepted standard and which led to an undesirable outcome. It is necessary the study of human interactions with the system for predicting or mitigating the effects of errors impact in the system. The human interactions with systems result in physical activities that require action can be classified as errors of omissions (slips and lapses). The interactions with system that result in mental activities that require analysis can be classified as errors of commissions (mistakes). Skill-based errors, i.e. slips and lapses, occur in very familiar tasks, which carry out without much need for conscious attention. Slips are failures in carrying out the actions of a task, for example picking up the wrong component from a mixed box, operating the wrong switch or misordering steps in a procedure. Lapses of memory cause us to forget to carry out an action, to lose our place in a task or even forget what we intended to do. Mistakes are a more complex type of error where we do the wrong thing believing it to be right. Rule-based error, i.e. mistakes, occur when our behavior are based on remembered rules and procedures. Knowledge-based, i.e. mistakes occur when the operator has to resort to an expert judgment unsupported by rules and procedures.
Human reliability is the opposite of human error. It is the probability of successfully performing a task. Human Reliability Assessment (HRA) is a structured and systematic way of estimating the probability of human errors in specific tasks according to [10] KIRWAN et al, 1994. HRA gives a benchmark for safety cases and design briefs, enables comparison of alternative designs or organizational solutions and identifies the weaker human links in a system so that the appropriate control measures can be introduced. As shown in Fig. 1, the diagram details the steps of HRA.

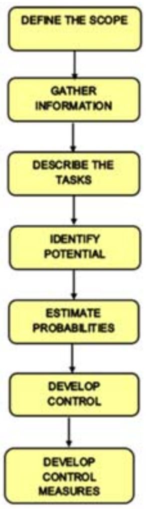


Figure 1 – Human Reliability Analysis

3.1 MAN-MACHINE SYSTEM AND INTERFACE

The term man-machine system denotes a system in which people have a monitoring and/or control function. The term man is used in the generic sense. The term man-machine interface refers to points of inter-action between people and the system. Thus, a dis-play, a control, written materials, or any other item a person observes or uses is a man-machine interface. Man-man interfaces refer specifically to person-to-person communication or other interaction, the term man-machine interface includes man-man interfaces.

3.2 PERFORMANCE SHAPE FACTOR

In modeling human performance, it is necessary to consider those factors that have the most effect on performance. Many factors affect human performance in such a complex man-machine system. Some of these performance-shaping factors (PSFs) are external to the person and some are internal. The external PSFs include the entire work environment especially the equipment design and the written procedures or oral instructions. The internal PSFs represent the individual characteristics of the person his skills, motivations, and the expectations that influence his performance.

4. CAUSAL FRAMEWORK

The study of human error mechanism in the inter-acting with the equipment, the procedure, or the de-sign varies according to the characteristics of the person, the environment and the organizational management. According to [8] WEBB and LAMOUREUX, the human error causal framework de-scribes the causal mechanisms of human error occur-ring during the procedure of emergency evacuation from aircraft. As shown in Fig.2, in this human error causal framework, the factors influencing human re-liability will be divided into two categories the external and internal factors. The external factors are the organizational factors, situational factors, and the internal factors are the individual factors and abilities. The organizational factors are related to aircraft crew operational activities such as training, demonstration of safety items, communications and so on. The error causal framework proposed the organizational factors affect individual factors of volunteers (passengers) such as knowledge of instructions, social behavior and so on. The situational factors are related to aircraft design interior such as marking, safety card, visibility and task criticality. The situational factors affect volunteers' abilities for performing the tasks of localizing and following the exit markings. Abilities are the direct cause of human error, have the most direct impact on human reliability.

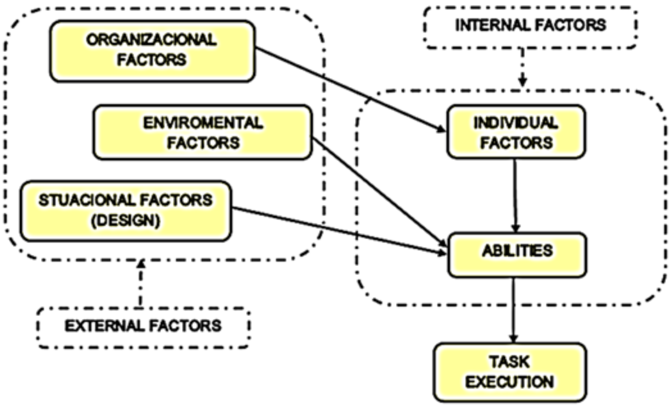


Figure 2 – Human Error Causal Framework

4.1 PERFORMANCE SHAPING FACTORS SELECTION

The first task of human reliability analysis is to find out a set of human factors related to the operation performance. Consequently, the study of the Performance Shaping Factors (PSF) was involved. PSF were proposed by [11] SWAIN and GUTTMANN built Technique for Human Error Rate Prediction (THERP) for qualitative and quantitative analysis of human reliability. Since the 1990s, there have been a lot of discussions about developing PSF. A large number of different factors influences the human reliability; it is very difficult to consider all the PSF. PSF are not independent of each other, it is necessary to make a selection of PSF in order to avoid the possibility of double counting. Considering characteristics of the Bayesian network, the general requirements of selecting PSF are summarized as follows: a) The PSF with major impact should be covered as much as possible. b) The PSF, which are the root nodes of Bayesian network, should be independent of each other. c) The same class of PSF should also be independent as far as possible. d) The selected PSF should be measurable or evaluable. Ac-cording to the selection requirements, taking into ac-count the size of model, some simplifications are made appropriately. The PSF chosen for the HRA model are shown in Table 1.

Table 1 – Performance Shaping Factors

PERFORMANCE SHAPING FACTOR SELECTION				
EXTERNAL			INTERNAL	
ORGANIZATIONAL	SITUATIONAL (DESIGN)	ENVIRONMENTAL	INDIVIDUAL	ABILITIES
Safety Instructions Demonstration	Markings	Noise	Knowledge of Instructions	Attention
Communication	Visibilty		Social Behavior	Perception
	Safety Card		Time Concerning	Interpretation
	Criticality			Decision Making
				Lidership

4.2 BAYESIAN NETWORK APPROACH TO HUMAN RELIABILITY ASSESSMENT

Bayesian networks are causal networks, probabilistic dependency graphs, are graphical models for reasoning based on uncertainty, where nodes represent discrete or continuous variables, and the arcs represent the direct connection among them. The networks represent conjunctions of probabilities and present the dependencies among the variables of a domain, according to [3] MATURANA & MARTINS, 2010. A Bayesian network is a directed acyclic graph, which is defined by a qualitative component and one quantitative. Qualitative component is represented in the graph topology and quantitative component is formed by the conditional probabilities, according to [4] SCHLEDER & MARTINS, 2012. The Bayesian network organizes the knowledge of the domain relating causes and consequences of the all events involved and combines causal and probabilistic knowledge (diagnoses). The network is composed of nodes and arms, the node set Vi = {V1, V2, …Vn} represent the variables, and the arms represent the influence in the nodes. The nodes where from the arches are called of parents, root, prior nodes, and the nodes of evidences F1 …Fn. The nodes where arrive the arches are called of sons nodes, the nodes of hypothesis. For each Vi variable of the one son node that has parents nodes F1, …Fn there is a conditional probability $P(Vj\backslash F1 \cap F2 \cap F3 \cap \ldots Fn)$. Given the probabilities of parents nodes (F1, F2 …Fn), and the conditional probability of each son node (Vi), the probability distribution of son node can be calculated.

$$P(Vi)=\sum P(F1 \cap F2 \cap ..Fn \cap V1=\sum P(F1).P(F2/F1).P(Fn/F1 \cap F2 \cap ..Fn-1).P(V1/F1 \cap F2 \cap ..Fn) \quad (1)$$

Ranging i=1 up to n (number of state of each son node (Vi). P(F1), P(F2),..P(Fn) are independents, then the sum of probabilities of product (Marginal Probability of Vi) is:

$$P(Vi) = \sum P(F1).P(F2).P(Fn).P(V1/ F1 \cap F2 \cap ..Fn) \quad (2)$$

The total probability distribution is:

$$P(V)=P(V1,V2,...,VN) =\prod P(Vi \mid F \text{ parents } (Vi)) \quad (3)$$

Where P(V) = Total probability of network; V1, V2, ...Vn = Probability distribution of variables of net-work; P(V1, V2, ...Vn) = Represent a input in the do-main; P(Vi\F parents (Vi)) = probability of occur a Variable (i) son, given occurred the probability of variable parent of son node. After having the domain of probabilities of events, the Bayesian analysis can be completed for updating a priori event (F) (parents event) based on evidences of probabilities of son node (V). The updating of priori probability (P(F)) is known as posteriori probability given a probability of evidence (P(V)) of an event of a son node. This relation is known as Bayes Theorem according to [1] MARQUES & BAYMA, 2016.

$$\frac{P(F/V) = P(F \cap V) = P(F).P(V/F)}{P(Vi)} \qquad (4)$$

4.3 FUZZY LOGIC MODELING

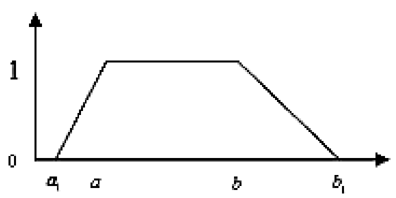
As mentioned previously, the probabilities conditional can be acquired by Fuzzy Logic Tool. The Fuzzy Logic Modeling are utilized in modeling of uncertainties for which statistical data are not available. This modeling is applied in artificial intelligence. Fuzzy logic is a multiple values logic, which allows intermediate values defined between conventional evaluations as true / false, yes / no, low / high, etc. Notions such as too much or too fast can be formulated mathematically and processed by computers. The fuzzy logic is based on the fuzzy set theory. A set fuzzy can be defined as a collection of elements in a universe of information, where the limit of the set contained in the universe is ambiguous, vague and diffuse, according to [5] MESQUITA & NASCIMENTO, 2010 This set is defined as:

$$A: X \ \ [0,1] \qquad (5)$$

This type of set allows its members to have differ-ent degrees of pertinence (pertinence function) in the interval [0,1]. A fuzzy set on a classical set X is characterized by its pertinence function and can be de-fined as follows:

$$A=\{(x, \mu A\ (x)) \mid x \in X\} \qquad (6)$$

Where μA (x) represents the degree to which x be-longs to A. The pertinence function μA (x) quantifies the degree of pertinence of elements x to the fundamental set X. A mapping of an element to a value of 0 means that the member is not included in that particular set, 1 means that the member is included in that particular set. The pertinence functions more used are: Function "S", Trapezoidal, Triangular, Gaussian and Sigmoidal. In this paper was used trapezoidal function for achieving the conditional probabilities in (1). The Trapezoidal function can be observed in the Fig. 3 below.



$$\mu_A(x) = \begin{cases} 0 & for\ x \le a_1 \\ \frac{x-a_1}{a-a_1} & for\ a_1 \le x \le a \\ 1 & for\ a \le x \le b \\ \frac{b_1-x}{b_1-b} & for\ b \le x \le b_1 \\ 0 & for\ b_1 \le x \end{cases}$$

Figure 3 – The Trapezoidal Function

The operations between fuzzy sets are defined as an extension of the operations and relations of classical theory such as union, intersection, and complement, can be applied to Fuzzy sets. The operation used in this paper was the intersection.

The intersection between two Fuzzy set A and B with pertinence functions μA(x) and μB(x) respectively, it is a Fuzzy set C, described as follows:

x ϵ U : μc =mim [μA (x), μB(x)] (7)

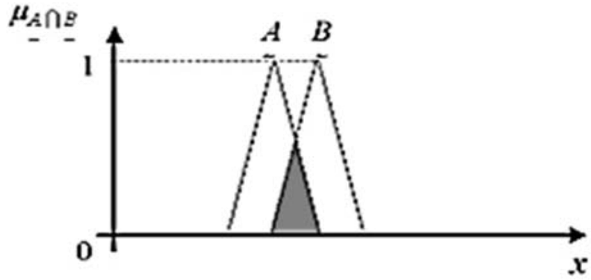


Figure 4 - Intersection of Two Fuzzy Sets

The fuzzy logic is performed by substituting am-bivalent pertinence functions (0 or 1) by fuzzy pertinence functions that is defined in the interval [0,1]. Be the fuzzy sets A and B, with elements x ϵ A and y ϵ B. The preposition If x is A, then y is B has pertinence function μA B(x,y) ϵ [0,1]. The pertinence function μA B(x,y) measures the degree of truth of preposition.

4.4 BAYESIAN NETWORK MODELING OF PSF

As previously, stated, human errors occur due to influence of organizational factors, situational factors, individual factors and abilities. All these factors are represented by PSFs mentioned in the Fig. 5 below.

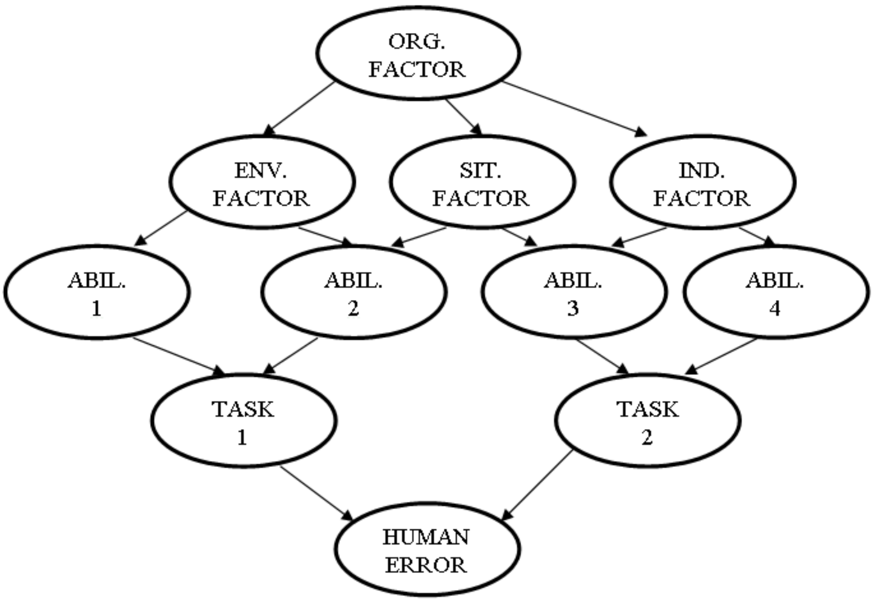


Figure 5 - The Bayesian network model for HRA in the Emergency Evacuation from an Aircraft

As shown in Fig.5, demonstration and communication are belong to organizational factors, while knowledge, time concerning social behavior, attention, perception, interpretation, decision making and leadership belonging to individual factors, marking, safety card, criticality, visibility and noise are belong to situation factors.

4.5 BAYESIAN ANALYSIS

According to statistical data of testing and expert assessment based on Fuzzy Logic tool, the probabilities associated with each node can be acquired. Based on the Bayesian network model as shown in Fig.3 causal inference and diagnostic analysis can be discussed.

4.6 CAUSUAL INFERENCE

An Assumption can be two states. For example, there are two states of factor “Knowledge (φ)”: adequate (φ1) and inadequate (φ2). Analogously, the factors “Marking” (d) and “Visibilty” (c) also have two states: adequate (d1) inadequate (d2) and adequate (c1) inadequate (c2) respectively. The intersection of these three factors result in the factor “Perception (V)” with the same two states adequate (V1) and in-adequate (V2). With the probabilities of the nodes “knowledge”, “Marking” and “Visibilty” the conditional probabilities of the intermediate son node “Perception”, the probability of “V1” state of factor “Perception” is:

$$P(V1)= P(\varphi i)[\ P(dj)[\ P(ck)P(V1)|\varphi i,dj,ck)] \tag{8}$$

Similarly, the probability of “inadequate” state of factor "Perception" is:

$$P(V2)= P(\varphi i)[\ P(dj)[\ P(ck)P(V2)|\varphi i,dj,ck)] \tag{9}$$

The discrete probability distribution of factor “Perception” is acquired. In the same way, we can get the discrete probability distributions of all factors and finally get the human reliability.

4.7 DIAGNOSE

The diagnose is a bottom-up inference process that based on a Bayesian network model. According to evidences had known, the reasons causing certain consequence will be analyzed and the probabilities will be calculated. In this paper, there are two states of “Human Error (H)” in the Bayesian network model: H2 (No - Human Error) and H1 (Yes - Human Error). Their probabilities can be computed from the causal inference. If assuming that human error has happened, we can get that Human Error = Yes. Un-der this condition, according to Eq. (4), the posterior Probability “inadequate” state of “Marking” is:

$$\underline{P(d2/H1) = P(d2\cap H1)=P(d2).P(H1/d2)} \atop P(Hi) \tag{10}$$

Similarly, the posterior probabilities of all the root nodes can be calculated.

5 APPLICATION AND RESULTS

5.1 CASE STUDY

The emergency evacuation procedure consist of several tasks one of them is to follow the route signal over wing. This paper aims to model through Bayesian Network the tasks of the development test of following the route signal over wing of an aircraft and find out which human performance factors that most influence to human error in performing the tasks. Volunteers participated of testing as passengers and flight attendants.
The main steps of this test were: the passengers has taken seat, the flight attendant made a speech explaining that the test simulated an emergency situation, the second flight attendant made demonstration of safety items, and she has stated to passengers to evacuate from aircraft, after-wards the passengers performed the tasks of following the route signals over wing as fast as they can. After testing, the volunteers were taken to a room where they answered several specific questions about their performance in the test. These information were used for getting of probabilities associated with every root node and conditional probabilities associated with each son node supported by logic Fuzzy. The conditional probabilities of son node "Perception" are as shown in Table 2. The probabilities tables of other nodes are not presented here due to the space restriction.

Table 2 – Conditional Probabilities of Node "Perception

KNOWLEDGE $P(\varphi i)$	MARKING P(di)	VISIBILITY P(ci)	PERCEPTION $P(Vi/\varphi i,di,ci)$ $P(V1/\varphi 1,d1,c1)$	PERCEPTION $P(Vi/\varphi i,di,ci)$ $P(V2/\varphi 2,d2,c2)$
$P(\varphi 1)$=0.84 ADEQUATE	P(d2)=0.55 INADEQUATE	P(c1)=0.79 ADEQUATE	0.81	0.19
		P(c2)=0.21 INADEQUATE	0.58	0.42
	P(d1) =0.45 ADEQUATE	P(c1)=0.79 ADEQUATE	0.42	0.58
		P(c2)=0.21 INADEQUATE	0.41	0.59
$P(\varphi 2)$=0.16 INADEQUATE	P(d2)=0.55 INADEQUATE	P(c1)=0.79 ADEQUATE	0.59	0.41
		P(c2)=0.21 INADEQUATE	0.58	0.42
	P(d1)=0.45 ADEQUATE	P(c1)=0.79 ADEQUATE	0.42	0.58
		P(c2)=0.21 INADEQUATE	0.19	0.81

With the probability distributions of root nodes "Knowledge", "Marking", "Visibility" and the conditional probabilities of node "Perception", according to (8), the probability of "adequate" V1 and V2 of factor "Perception" are:

$P(V1)= P(\varphi i)[P(dj)[P(ck)P(V)|\varphi i,dj,ck)]$
$P(V1)=0.56$

Similarly, $P(V2)=0.44$

The Bayesian Network below was acquired by software GeNIe 2.1 Academic. The computation is shown in Fig.6.

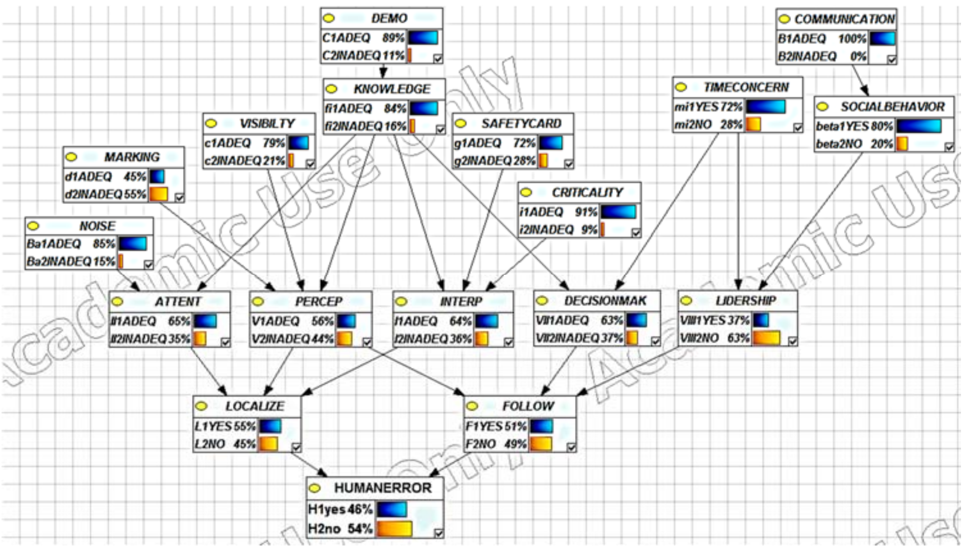


Figure 6 - The Bayesian Network Model

As shown in Fig.6, the human reliability can be found equal to 0.54 and the probability of human er-ror is 0.46. Assuming that human error happened, the posterior probabilities of all nodes can be calculated according to (4) with Bayesian Network. For example the posterior probability of "inadequate" state of factor "Perception" is:

$$P(V2/H1) = \frac{P(V2).P(H1/V2)}{P(Hi)} \qquad (11)$$

$= (0.44x0.51)/0.46= 0.49$

The software GeNIe 2.1 Academic was used to calculate the posterior probabilities of all nodes, the computation result is shown in Fig. 7

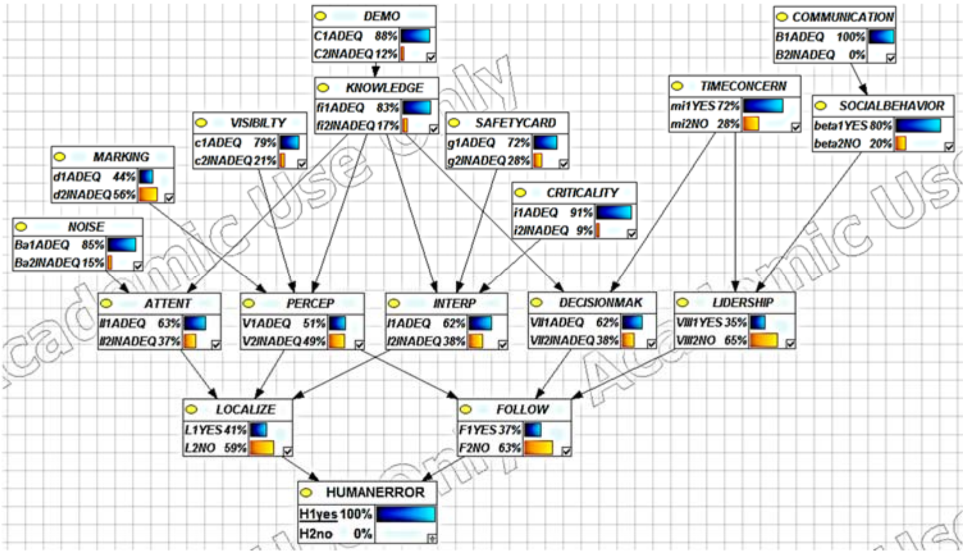


Figure 7 - The Bayesian Network Model for Diagnose

Assuming that Human Error happened as Fig.7, the table 3 presents the posterior probabilities of "in-adequate" state of other abilities nodes.

Table 3 - Prior and Posteriori Probabilities of Abilities Nodes

NODES ABILITIES	PRIOR PROBABILITIES INADEQUATE	POSTERIOR PROBABILITIES INADEQUATE	VARIATION (%)
ATTENTION	0.35	0.37	5.71
PERCEPTION	0.44	0.49	11.4
INTERPRETATION	0.36	0.38	5.55
DECISION MAKING	0.37	0.38	2.70
LIDERSHIP	0.63	0.65	3.17

The node "Perception" presented the most influence with the evidence that human error happened. Following this reasoning and assuming that "Perception" is inadequate, the posterior probability of parents nodes, "Marking", "Visibility" and "Knowledge" can be calculated according to (4) with Bayesian Network. For example the posterior probability of "inadequate" state of node "Marking" is:

$$P(d2/V2) = \frac{P(d2).P(V2/d2)}{P(Vi)} \qquad (12)$$

$=(0.55x0.59)/0.44 = 0.73$

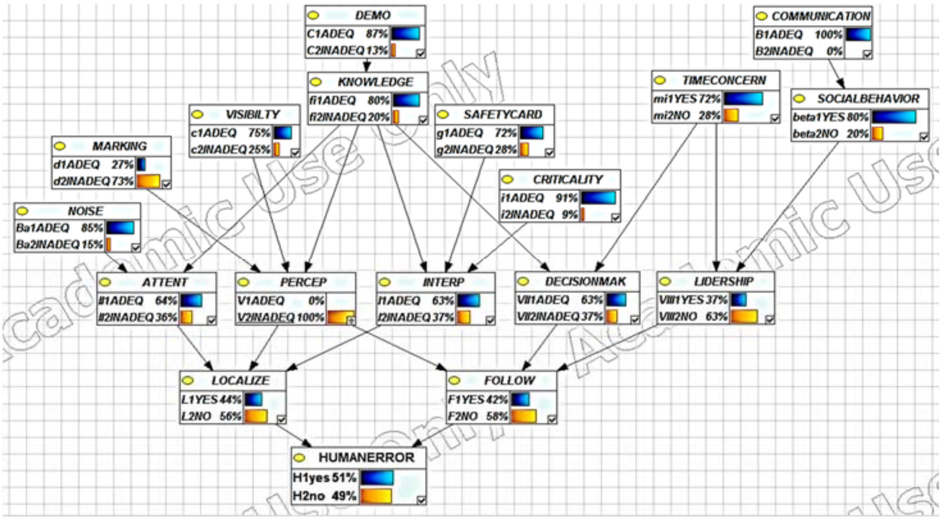


Figure 8 - The Bayesian Network Model for Diagnose Perception

Assuming that "Perception" is inadequate as Fig.8, the table 4 presents the posterior probabilities of "in-adequate" state of other parents nodes, Situational factor – Design.

Table 4 - Prior and Posteriori Probabilities for Situational Factor - Design

NODES SITUATIONAL FACTOR DESIGN	PRIOR PROBABILITIES INADEQUATE	POSTERIOR PROBABILITIES INADEQUATE	VARIATION (%)
MARKING	0.55	0.73	32.7
VISIBILITY	0.21	0.25	19.0
KNOWLEDGE	0.16	0.20	25.0

The table 4 presents the posterior probabilities of "inadequate" state of parents nodes of node "Perception", the same can be done for nodes "Attention", "Interpretation", "Decision Making" and "Lidership for knowing the variation of parents nodes of them. Regarding node "Perception" can be noted that there are significant changes in the posterior probabilities of inadequate" state of "Marking", Visibility" and "Knowledge" when human error happened. It might suggest that "Marking", Visibility" and "Knowledge" are significant influencing factors to human reliability. In order to avoid human errors, more attention should be paid to improve de-sign development of aircraft cabin safety regarding exit markings and visibility, and strategy for capturing the passengers attention during the short time when demonstration of safety items are presented prior each flight.

5 CONCLUSIONS

Human error is an important factor influencing in the emergency evacuation from aircraft, however the Human Reliability Analysis is still the stage of introducing. This paper proposes a Bayesian Network approach to analyze one of task of the emergency evacuation testing of an aircraft focusing in the volunteers shape performance influencing. This analysis is based on quantification of each Performance Shape Factor for knowing the influencing in the human error in the performing of task to localize and to follow the exit marking over wing of aircraft. The most important is to know the influencing of each one, the values of probabilities are so not relevant. The case example shows that the proposed methodology can integrate organizational factors, situational factors, and individual factors to quantitatively measure the human reliability in performing of one of task of the emergency evacuation. Moreover according to the diagnostic analysis, the most significant factor leading to human error can be identified, and some design improvements can be made for prevention of human error. This approach provides forceful support for improving the human reliability of design development of cabin safety.

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