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 $ISEVIEK$  **IFAC-PapersOnLine 49-12 (2016) 133–138** 



## Risk Assessment using Bayesian Belief Networks and Analytic Hierarchy Process **applicable to Jet Engine High Pressure Turbine Assembly applicable to Jet Engine High Pressure Turbine Assembly J. C. Pereira\*, M. D. Fragoso\*, M. G. Todorov\***

**J. C. Pereira\*, M. D. Fragoso\*, M. G. Todorov\* J. C. Pereira\*, M. D. Fragoso\*, M. G. Todorov\***

\*Department of Systems and Control, National Laboratory for Scientific Computing, Petropolis, RJ 25651-075, Brazil (e-mail: jpereira@ lncc.br, frag@ lncc.br, todorov@ lncc.br) (e-mail: jpereira@ lncc.br, frag@ lncc.br, todorov@ lncc.br)

engine failure. The selection and use of an adequate analysis method to ensure software, hardware and operation reliability is very important. This paper proposes a framework for identifying undesirable events related to software, hardware and operation failure, which might occur during HPT (High Pressure Turbine) assembly process, based on Analytic Hierarchy Process (AHP) and Bayesian Belief Network (BBN). Experts estimate the risks and the associated risk factors, which are loaded into Bayesian Belief (BBTV). Experis estimate the risks and the associated risk factors, which are foaded into Bayesian Benef<br>Networks to assess the probability of occurrence of undesirable events. AHP is utilized to rank the relative importance (impact) of risks. The combination of probabilities and the impacts identifies the most significant risks. The novelty of the paper is the combination of Bayesian Belief Networks with most significant risks. The novelty of the paper is the combination of Bayesian Belief Networks with AHP to select the most significant risk. The model has practical implications and allows decision makers to identify critical failure risks, in order to allocate resources to improve the quality and safety of the jet engine manufacturing and overhaul system. **Abstract:** In the jet engines manufacturing/overhauling process, risk analysis is essential to prevent  $\alpha$  to see the most significant risks, the model of model resources to impliove the quality and safety of the jet

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Keywords: Risk assessment, Bayesian Belief Network, Analytic Hierarchy Process, HPT rotor assembly.

## 1. INTRODUCTION 1. INTRODUCTION

The jet engines manufacturing industry in general faces a variety of risks, many capable of compromising the viability of an organisation. The leadership needs to understand the risks through probabilistic risk analysis, so that decisions are not taken in real time without considering the probability and severity of adverse consequences on the reliability, safety and quality of the product. Depending upon the risk, they can be avoided, shared, transferred, minimised or mitigated with suitable strategies (Mishra, 2012). suitable strategies (Mishra, 2012). The manufacturing of jet engines is very complex and

The manufacturing of jet engines is very complex and depends on several variables related to Hardware, Human Beings, Software and the Environment. The total number of parts in a jet engine can reach several thousand items. Dangers, risks, and many critical elements are present in the thousands of activities necessary to put these parts together to manufacture or overhaul a jet engine (Pereira et al., 2014). In order to identify the primary failure cause factors, a qualitative risk analysis is critical. Stakeholders normally use their knowledge and experience to propose ideas and solutions for redesigning processes. solutions for redesigning processes.  $T$  objective of this paper is to present a method to  $p$ 

The objective of this paper is to present a method to classify possible risks of undesired events during the assembly of the most critical module of a jet engine, which is the High Pressure Turbine Module. This module is assembled using a Stack Prediction System. Stack Prediction System.

The assembly process demands a precise measurement method for reducing engine vibration, maximizing bearing life and identifying piece part irregularities. To meet this challenge, a Stack Prediction System is normally used. This instrument enables the operator to inspect individual compressor engine components and predict the stack alignment of its parts to achieve a final tolerance. alignment of its parts to achieve a final tolerance.

The paper classifies the risk factors into three categories: Operation, Design and Maintenance factors. The risk factors were combined to build the BBN's. The BBN's were used to estimate the probability of risk occurrence. The impact of risks was quantified using AHP. risks was quantified using AHP.

 $T_{\rm eff}$  factors into the risk factors into the risk factors into the risk factors into the categories:

The risk assessment in the manufacturing of jet engines allows leaders and decision makers to allocate resources for critical activities that can affect the reliability of the safety system. Currently, the diversity of models, for the structuring problem solving and risk assessment, ranges from a simple and conventional Fault Tree Analysis to more sophisticated methods such as Bayesian Networks. This paper proposes the utilization of Bayesian Networks and Analytic Hierarchy Process (AHP). Process (AHP).  $\mathcal{F}_{\mathcal{F}}$  is organized as follows: Section 1 presents the presents the section 1 presents the section

The paper is organized as follows: Section 1 presents the introduction. Section 2 is devoted to the description of Risk probability estimation with BBN, Section 3 addresses risk impact analysis with analytic hierarchy process (AHP), Section 4 shows an application of risk analysis method using Section 4 shows an application of risk analysis method using

BBN and AHP in the assembly of jet engines rotors and Section 5 presents the conclusion.

### 2. RISK PROBABILITY ESTIMATION WITH BBN (BAYESIAN BELIEF NETWORK)

#### 2.1 Risk Assessment using BBN (Bayesian Belief Network)

Bayesian Networks (BNs, also called Bayesian Belief Networks (BBN's) provides a causal structure that allows probability risk analysis practitioners to gain deeper insight into risk drivers and into specific interventions that reduce risk (Rechenthin, 2004, Mosleh 1992). There has been an increasing trend in the application of Bayesian networks in fields related to reliability, safety and maintenance (Mahadevan et al, 2001). Bayesian approaches to aggregate expert judgments on probabilities have been extensively investigated in risk and reliability analysis (Podofillini, Dang, 2013, Mosleh, 1986, Droguett et al. 2004). BN's provide a framework for addressing many of the shortcomings of human reliability analysis from a researcher perspective and from a practitioner perspective (Groth, Swiler, 2013, Boring et al. 2010). External human performance factors depend on company, society and technology (Calixto, 2013).

The Bayesian Network methodology was developed to make predictions easier. It can be defined as graphic frameworks, which represents arguments in uncertain domain. Such frameworks are unicycle Graphs, since they cannot make up closed cycles and have only one direction. The nodes represent random variables and arcs represent direct dependency between variables. The arcs direction represents cause and effect relation between variables. Fig. 1 represents the Bayesian Network, being node H consequence from causes T and P. In Fig. 1, nodes T and P are fathers of H and are called ancestral of H.



Fig.1 Bayesian Network

Considering Human Reliability analysis, for example, the nodes T and P represents performance human factors and node H represents human error probability conditioned to human performance factors T and P. In each node, there is a conditional probability table, which represent variables. The general equation (1) represents the probability of occurrence of variable H conditioned to the occurrence of nodes T and P.

$$
p(H) = \sum_{i=0}^{1} \sum_{j=0}^{1} p(H = 1/T = i, P = j) p(T = i) p(P = j)
$$
 (1)

For example, (2) shows the probability of variable H being true, conditioned to variables P and T being true or false.

$$
p(H = true) =
$$
  
\n
$$
p(H = true | T = true, P = true) p(T = true) p(P = true) +
$$
  
\n
$$
p(H = true | T = true, P = false) p(T = true) p(P = false) +
$$
  
\n
$$
p(H = true | T = false, P = true) p(T = false) p(P = true) +
$$
  
\n
$$
p(H = true | T = false, p = false) p(T = false) p(P = false)
$$
\n(2)

*2.2 Estimation of risks and construction of BBN in HPT Assembly Process*

In order to estimate the risks present in HPT Assembly Process, information about the risk and risk factors was gathered from experts. Risk in this case is the probability that a specific action or exposure will give rise to a HPT assembly process failure and risk factors are individual attributes or and organizational environment that increase the likelihood that a risk will occur. The sample of experts consisted of forty-five technicians, each with more than 5 years of experience in jetengine assembly. Each expert has been involved with the operational side of jet-engine manufacturing. In addition, each expert has academic training and has knowledge of different aspects of the subject. The risk and risk factors raised by experts were recorded in a specific protocol designed for this purpose. A list of risk factors was obtained from Pereira (2014b). Design thinking method was used to classify the risk factors identified in the different engine manufacturing processes. In the HPT Assembly process, the risks were classified into levels and sublevels. To obtain this classification, the risk factors were copied on insight cards, to build an explicit picture on the main points raised. By using an affinity diagram (a method that organizes a large number of ideas into their natural relationships), the insight cards were grouped by similarity into four categories : a) Software related malfunction, b) Hardware problem, c) Operation related problem and d) Maintenance related malfunction. Table 1 shows the risk categories and the codes for the associated risk factors. The risk factors codes listed in the third column of Table 1 were obtained from Table 2.

**Table 1**. **Risk Categories and the Associated Risk Factors**

<b>Risk Category</b>	<b>Risk Levels</b>		<b>Risk Factors (Table 2)</b>
	L1	Program Failure	Y3, Y4, Y5, Y14
Software related malfunction	L2	System functioning failure	Y6, Y7, Y8, Y12, Y15
	L <sub>3</sub>	Integration of Software & Hardware poor	Y11. Y15. Y13. Z10
	L4	Breakdown of system	Y2. Z3. Y1
Hardware related problem	L5	Speed of processing slow	Y2. Z4. Y1
	L <sub>6</sub>	System does not function properly	Y9. Y10. Y1
	L7	Operational sequence not followed	X1. X8
Operation related problem	L8	Incorrect interpretation of operational procedure	X2, X4, X5, X6, X7, X8
	L <sub>9</sub>	Ineffective production planning	X3. X9. X10
	L10	Hardware functioning improperly	Y2, Z2, Z5, Z6, Z7, Z8
Maintenance related malfunction	L11	Use of wrong software revision	Z11, Z12
	L12	Equipment not calibrated	Z1. Z9

The risk factors were classified into three categories, as shown in Table 2: operational factors, design factors and maintenance factors. The classification consisted of 10 operational factors (Events X1-X10), 15 design factors (Events Y1-Y15) and 11 maintenance factors (Events Z1- Z11). Table 1 shows the risk categories and the associated risk factors.

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