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Application of Framework for Risk Assessment in Ultrasonic Testing (UT) of Critical Parts – A Case Study

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This paper presents the application of a framework for identifying risks in the Ultrasonic Testing of critical parts. This topic is significant because failing to inspect critical parts with UT in the industry correctly may lead to operational failure. Catastrophic accidents can happen if risks are not identified and responses are not provided. In the European Congress for Reliability and Safety held in 2022 in Dublin, a framework proposal was presented based on the Analytic Hierarchy Process (AHP) and Bayesian Belief Network (BBN). This study complements the proposal presented in ESREL 2022, focusing on applying the framework. As a methodological approach, a survey was prepared to elicit experts' probabilities. These were uploaded into BBN software to combine the risk factors contributing to an inspection failure. AHP was used to define to prioritize the impact of risk categories. The combination of probability and impact identified the most significant risk categories. As a result, the method revealed the most significant risk factors in UT. The conclusion is that the model proved adequate to reduce the risk of hardware failure significantly. As a contribution, the proposed method is an invaluable source of information for safety engineers and decision-makers in companies. It can be generalized to other industries and fields of work that wear UT.

Keywords: Risk assessment, Bayesian belief network, Analytic hierarchy process, Critical parts, Ultrasonic Testing.

1. Introduction

Non-Destructive Testing (NDT) is essential for evaluating the integrity of products and equipment in various sectors such as oil, petrochemical, steel, aerospace, and naval. Applying NDT techniques, detecting and measuring discontinuities present on the surface and inside a material without changing its properties is possible. The tests can be ultrasonic, eddy currents, radiography, thermography, magnetic particle, penetrant liquid, acoustic emission, and visual.

The choice of a particular test depends on characteristics such as the nature of the material, its dimensions, type of material surface (smooth or rough), probable type of defect, defect position (superficial or internal), among others (França, 2015).

Ultrasonic Testing has the main objective in the industry: to detect internal discontinuities existing in materials in different shapes. (Stein, 2017). According to Stein (2017), discontinuities are generated in the material manufacturing process, for example, by porosity, slag, inclusions, lamination folds, and micro-cracks in laminated materials.

Like any non-destructive testing, UT aims to guarantee quality and reduce uncertainty in the use of materials for industrial applications. The ultrasound test has been widely used in the industrial area for various materials, such as steel, aluminum, wood, concrete, etc. The inspection process aims to analyze whether the damage is caused to industrial equipment's internal structures that store or transport substances of the most diverse types. These inspection tests aim to analyze whether there are cracks, breaks, leaks, and material losses.

According to França (2015), several factors can influence the correct assessment of discontinuities. Momentary variations in equipment calibration, material properties, geometry, and defect orientation are factors that can lead to an erroneous interpretation of results.

Human error is also a parameter that interferes with the reliability of the test. The inspector's assessment under stress after working hours in a noisy environment is not similar to that in the opposite situation. These factors contribute to inspection uncertainties and allow for a probabilistic characterization of inspection capability.

This study aims to present the application of a framework for identifying risks in the Ultrasonic Testing (UT) of critical parts based on the Analytic Hierarchy Process (AHP) and Bayesian Belief Network (BBN). This topic is significant because failing to inspect critical parts with UT in the industry correctly may lead to operational failure. If risks are not identified, and responses are not provided, catastrophic accidents can happen. The correct selection and use of an acceptable method are essential for the success of the inspection.

No previous work has addressed which operational risks interfere in the effective execution of the ultrasonic test, much less to list which risks these are and the subsequent prioritization of these risks.

A case study was conducted in an aero-engine repair station facility to identify gaps and opportunities to improve UT risk management, safety, and quality. The study aims to respond to the following research questions:

Research Question 1: What risk factors are present in the UT of critical parts?

Research Question 2: How to categorize the risk factors in Levels (L) and Sublevels (SL) to allow the application of Bayesian Belief Networks (BBN) and Analytical Hierarchy Process (AHP)?

Research Question 3: What are the most impactful risks when combining probability and impact?

The study is structured as follows: Section 2 covers Literature Review, presenting previous studies on Risk Assessment in Ultrasonic Inspection, BBN (Bayesian Belief Networks), and Analytic Hierarchy Process (AHP. Section 3 addresses Methodology. Section 4 shows the results. Section 5 discusses results, and section 6 the conclusion.

2. Literature Review

2.1.*Risk Assessment in Ultrasonic Inspection*

UT has been practiced for several decades. One of the several possibilities of applying this test is determining the thickness of industrial parts to make the data collection more manageable and better (NDT Resource Center, 2011). the techniques derived from ultrasound are used in several areas, highlighting applications in the health area and non-destructive Testing (Oliveira, 2008). According to Silva (2012), the ultrasonic test is characterized by a non-destructive method that aims to detect defects or internal discontinuities in the most varied types or forms of ferrous or non-ferrous materials. Such defects are characterized by the manufacturing process of the part or components to be examined, such as gas bubbles in castings, double lamination in laminates, micro-cracks in forgings, slag in welded joints, and many others.

According to Udell et al. (2019), the ultrasonic inspection devices present in the market have not changed much compared to today's mobile devices, such as smartphones and tablets. They remain challenging to learn, and their resources are limited, featuring small screens and multiple buttons on outdated hardware. As a result, it was demonstrated how mobile and digital technologies would beneficially revolutionize the traditional way of performing inspections and managing the lifecycle of inspection data. Results show a significant improvement of the ultrasonic test over traditional inspection techniques regarding sensitivity and determination for this specific type of defect. Masayoshi, Hideharu, and Hiroshige (2019) demonstrated the effects of the capability improvement of UT examiners on the reduction of piping failure risk in nuclear power plants and compared the results to evaluate relationships between the capability improvement of the examiners and the piping failure risks. The results showed that the capability improvement of examiners affects the reduction of piping failure risk (Masayoshi; Hideharu; Hiroshige, 2019).

For Bertovic et al. (2013), the difficulty of dealing with human factors in non-destructive Testing (NDT) stems from their variety and complexity – no single human or structural factor is accountable for the entire fluctuations in the NDT performance. The standard approach to lessening the variability in the inspection results has been found in substituting manual NDT with automated methods.

However, although some human faults can be avoided by systematizing the process, new risks can arise from its use and need further examination.

An analysis of potential risks in using mechanized inspection methods for spent fuel canisters has shown potential for human error in acquiring and evaluating the collected results. Assessed causes of those faults lay in the inspector and the organization and shortcomings of the inspection procedure (Bertovic et al., 2013).

2.2.*Analytical Hierarchy Process (AHP)*

Multicriteria programming by the Analytic Hierarchy Process is an organized technique for decision-making in complex situations in which several variables or criteria are considered for prioritizing and selecting alternatives. AHP was developed in the 1970s by Thomas L. Saaty and has been studied extensively since then. It is currently applied for decision-making in several complex scenarios (Vargas, 2010). The use of AHP begins by decomposing the problem into a hierarchy of criteria that are more easily analyzed and independently comparable. From the moment this logical hierarchy is built, decision-makers systematically evaluate alternatives by comparing, two by two, within each criteria. This comparison can use concrete data from alternatives or human judgments as underlying information (Saaty, 2008). According to Vargas (2010), AHP transforms comparisons, often empirical, into numerical values processed and compared. The weight of each factor allows the estimation of each of the elements within the defined hierarchy. This ability to convert empirical data into mathematical models is the main differentiator of AHP concerning other comparative techniques. Once all comparisons have been made, and the relative weights between the criteria to be evaluated have been established, the probability of each of the alternatives was calculated. This probability determines the alternative's probability of meeting the established goal. The higher the probability, the more that alternative contributes to the ultimate goal. The first step of the AHP is to build a pairwise comparison matrix. Each element aij (i, j = 1, 2, ..., n) represents the relative importance of elements i and j. A higher value denotes a stronger preference of element i over element j (Pereira; Almeida, 2021).

2.3.*Bayesian Belief Networks (BBNs)*

According to Hammond and O'Brien (2001), Bayesian Networks constitute a graphical model that represents the probabilistic relationships between the variables of a system. A set of vertices and a set of edges always represent such networks. Each vertex represents a particular random variable, and each variable must have a finite number of mutually exclusive states, such as True and False. Each edge represents a causal relationship between the variables, and the edge is directed from cause to effect with the symbol of an arrow. Bayesian modeling allows the inclusion of subjective data from experts in case of insufficiency of past information. In addition, such modeling allows the systematic measurement of risk factors that can lead to low-frequency and high-severity events. As a result, such models measure operational risk, identify the influence of risk factors, calculate sensitivity in loss events and simulate the distribution of losses and excessive loss scenarios (Marques; Dutra, 2008).

The probabilistic models are presented as alternatives to circumvent the problems typically found in measuring operational risks since it is common to have insufficient data. When they exist, they are usually historical data. BBNs can be used to make decisions based on probabilities, decide what additional evidence should be observed to obtain helpful information from the system, and analyze the system to search for the aspects of the model that have the most significant impact on the query variables. (Marques; Dutra, 2008).

In relation to other available probabilistic models, Bayesian Networks have advantages because they are easily understood, given that the relationships between variables are primarily intuitive. Another advantage is that this model provides information on the effect of possible interventions on the network variables and requires less computational time for a solution since normally, Bayesian Network algorithms are less complex than other probabilistic models (Hammond; O'Brien, 2001).

3. Methodology

3.1.*Selecting the Population and Sample*

The study adopted the approach of building theory from Case Study Research (Eisenhardt, 1989; Hancock, Algozzine, and Lim,2021).

It combined data from archives, interviews, and observations and was carried out in an aero-engine repair station (population) with approximately 2.000 employees. This repair station is big and performs overhauls on about 500 engines a year, having customers worldwide and being considered a reference in its segment. The sample for the study was the Ultrasonic Inspection Area within this repair station. The number of site stakeholders participating in the study is listed in Table 1. These stakeholders were selected based on their expertise in a specific domain. The sample size is appropriate and significant since all the studied areas are covered.

Table 1 - Stakeholders participating in the study

Area	Function	Number of participants	Experience (years)
Engineering	Manufacturing Engineer	1	6
Quality	Quality Engineer	1	35
Operation	Inspector Level III	1	5
Operation	Engineering Intern	1	5
Operation	Inspector Level II	1	5

3.2. *Using Instruments and Tools*

A detailed process map of Ultrasonic Inspection for two methods (contact and immersion) was prepared to understand the process variables. The list of risk factors was prepared by combining data from archives, observations of the processes, and interviews with employees directly involved.

3.3. *Data Collection*

Scientific data was obtained from in-depth literature research addressing Risk assessment - Bayesian belief network - Analytic hierarchy process - Critical parts – Ultrasonic Testing. The field study collected operational data from documents, observations, and interviews with stakeholders in the studied company.

Information obtained from the literature research and operational areas in the aero-engine repair station were combined and displayed in the process maps and Tables.

3.4. *Data Analysis & Actions*

An in-depth literature review on Ultrasonic Testing was conducted to identify risk factors. An affinity Diagram was used to categorize the risk factors. Bayesian Network is used to combine the risk factors that contributed to an inspection failure, and AHP is used to prioritize the impact of risk categories. The combination of probability and impact identifies the most significant risk categories.

4. Results

The process maps in Figures 1 and 2 present two different UT inspection processes: immersion (coupling agent is water) and by contact (coupling agent is a Special Fluid). The study team analyzed the flow charts and the researched literature to list the risk factors shown in Table 2.

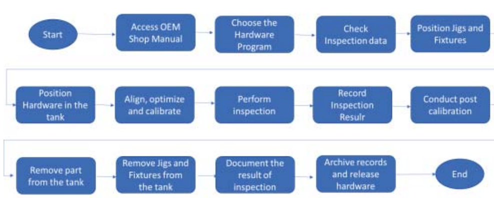

Figure 1 – Immersion Process

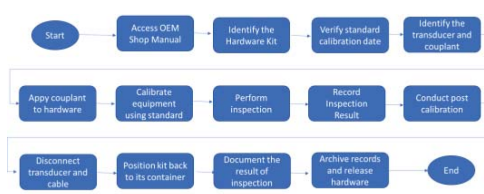

Figure 2 – Contact Process

Table 2 lists the risk factors identified by reviewing the process maps of figures 1 and 2 and the researched literature.

Table 2 – Risk Factors by Category

Type	Event	Risk Factors
ManPower	Man1	Operators not trained and lack of knowledge
	Man2	Operator lack of attention
	Man3	Operator distraction
	Man4	On the job training not performed
	Man5	Training material poor
	Man6	Horizontal comunication poor
	Man7	Preventive Maintenance operator error
	Man8	Operator skill and experience
	Man9	Operator Fatigue
	Man10	Visual acuity, color vision
	Man11	Inspectors attitude and motivation
	Man12	Eyewear
Material & Hardware	Mat1	Incorrect Couplant
	Mat2	Surface condition of part
	Mat3	Complexity of part
	Mat4	Defect type
	Mat5	Defect dimensions
Method	Met1	Part cleaning procedure not defined
	Met2	Part cleaning procedure wrongly defined
	Met3	Inspection kit not defined
	Met4	Inspection kit wrongly defined
	Met5	Couplant not defined
	Met6	Couplant wrongly defined
	Met7	Calibration procedure not defined
	Met8	Calibration procedure wrongly defined
	Met9	Set up process wrongly defined
	Met10	Set up process not defined
	Met11	Acceptance criteria wrongly defined
	Met12	Acceptance criteria not defined
Machine & Instruments	Mac1	Transducer not functioning properly
	Mac2	Cable not functioning properly
	Mac3	Standard not calibrated
	Mac4	Standard calibrated umproperly
	Mac5	Inspection software not functioning properly
	Mac6	Jigs and Fixtures in bad condition
	Mac7	Error in equipment calibration
	Mac8	Calibration not performed
	Mac9	Equipment missing
	Mac10	Unserviceable equipment used

Continuation of table 2 – Risk Factors by Category

Type	Event	Risk Factors
Control & Environment	Env1	Couplant performance not monitored
	Env2	Inadequate control of standards, cables and transd.
	Env3	Environment temperature not monitored
	Env4	Perceived pressure or haste
	Env5	Space restrictions, ilumination
	Env6	Unproper production planning
	Env7	Time constraint
	Env8	Unrealistic targets
	Env9	Ergonomics - Man/machine interface
	Env10	Inspection variables (lighting) and inspection env.
Organizational	Org1	Quality system ineffective
	Org2	Preventive maintenance program innefective
	Org3	Lack of management oversight, control e monit.
	Org4	Training program poor
	Org5	Imcompatible goals
	Org6	Poor production planning
	Org7	Lack of materials
	Org8	Inadequate safety culture
	Org9	Inexistence of employee recognition program
	Org10	Lack of adequate equipment
	Org11	Inadequare headcount
	Org12	Lack of proper facilities

An affinity Diagram was used to classify the risk factors in risk sub-levels. The selected factors identified by experts were copied on insight cards to build an explicit picture of the main points raised. The insight cards were grouped by affinity and similarity into the respective risk sub-levels. The team identified six Risk Levels: operator failure, inappropriate material, uncorrected method, defective equipment, unfavorable environment, and negative organization factors. They also identified three Risk Sub-Levels related to each Risk Level and the potential associated risk factors presented in Table 3. The risk factors were classified into pertinent risk sublevels so that the causes and consequences of each risk could be assessed. Table 3 shows the levels, sublevels, and associated risk factors.

Table 3 – Risk Factors and Levels /Sublevels

Risk Levels		Risk Sub-Levels		Associated Risk Factor
L1	Manpower poorly prepared	SL1	Inadequate Training	Man1, Man4, Man5, Man7, Man8
		SL2	Negative Atitude	Man2, Man3, Man6, Man11
		SL3	Lack of Skills	Man9, Man10, Man12
L2	Improper Material & Hardware	SL4	Wrong choice of materials	Mat1
		SL5	Incompatibility of defect to inspe	Mat4, Mat5
		SL6	Improper hardware condition	Mat2, Mat3
L3	Uncorrected method	SL7	Operational Procedure not availab	Met1, Met3, Met5, Met7, Met10, Met12
		SL8	Operational Procedure not used	x
		SL9	Operational Procedure Wrong	Met2, Met4, Met6, Met8, Met9, Met11
L4	Equipment/Instrument Failure	SL10	Processing equipment failure	Mac1, Mac2, Mac5, Mac6, Mac10
		SL11	Calibration failure	Mac4, Mac7, Mac8
		SL12	Equipment Missing	Mac3, Mac9
L5	Unfavourable Control & Environ	SL13	Material control failure	Env1
		SL14	Equipment/instrument control failu	Env2
		SL15	Environment control failure	Env3, Env4, Env5, Env6, Env7, Env8, Env9
L6	Negative Organization Factors	SL16	Monitoring and control ineffective	Org3, Org5, Org6
		SL17	Quality & safety Management inef	Org1, Org2, Org4, Org8, Org9
		SL18	Lack of adequate resources	Org7, Org10, Org11, Org12

The risk factors and sublevels were combined in BBNs for each risk level. A risk factor probability was given by UT process experts. These data are BBN inputs, which consequently generate the probability of occurrence of each process level. BBN was applied to obtain the probability of occurrence of each process level from the occurrence data of each risk factor on the shop floor.BBN's were developed for all Levels, Sub-levels, and associated risk factors, as shown in Figure 3.

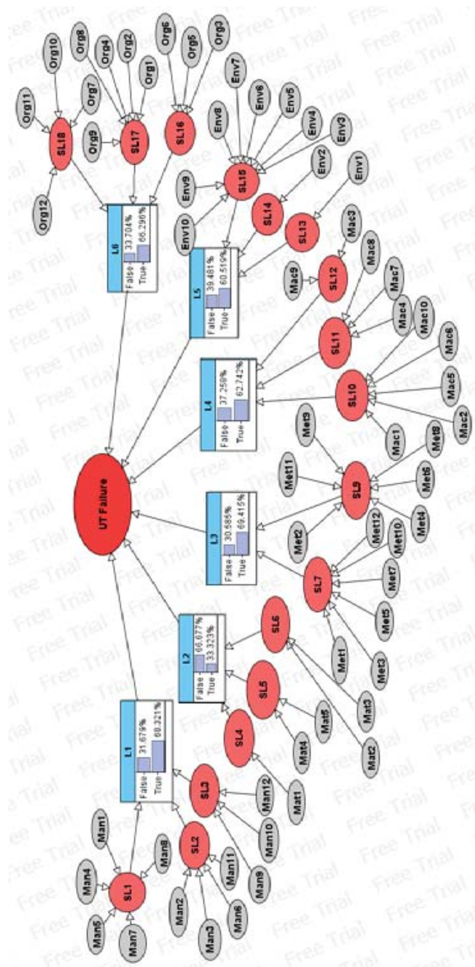

Figure 3 – BBN combining Levels and Sublevels

As shown in the figure, the BBN resulted in the probabilities of the nodes representing the risk levels that were: Manpower poorly prepared(L1) = 68.321%, Improper Material & Hardware(L2)= 33,323%, Uncorrected method (L3) = 69,415%, Equipment/Instrument Failure (L4) = 62.742%, Unfavourable Control & Environment (L5) = 60.519, Negative Organization Factors(L6)= 66.296%.

In order to analyze the risk impact by AHP, pairwise comparison matrices are developed based on the six risk Levels. The Pairwise Comparison Matrix will be computed by expert opinion using Google Forms, and different experts will do the pairwise comparison and the mean will be obtained at the end. The study team needs to work together to complete the relative importance matrix in Table 4, considering the failure of UT.

Table 4 - Pairwise Comparison Matrix- AHP Results

Risk Level	Criteria Comparison Matrix: Manpower poorly prepared (L1)	Improper Material & Hardware (L2)	Uncorrected method (L3)	Equipament/Instrument Failure (L4)	Unfavorable Control & Enviroment (L5)	Negative Organization Factors(L6)	Normalized Matrix						Weights
Manpower poorly prepared (L1)	1	5	5	5	5	5	0.50	0.68	0.51	0.31	0.31	0.36	0.45
Improper Material & Hardware (L2)	1/5	1	3	3	3	3	0.10	0.14	0.31	0.19	0.19	0.21	0.19
Uncorrected method (L3)	1/5	1/3	1	5	5	3	0.10	0.05	0.10	0.31	0.31	0.21	0.18
Equipament/Instrument Failure (L4)	1/5	1/3	1/5	1	1	1	0.10	0.05	0.02	0.06	0.06	0.07	0.06
Unfavorable Control & Enviroment (L5)	1/5	1/3	1/5	1	1	1	0.10	0.05	0.02	0.06	0.06	0.07	0.06
Negative Organization Factors(L6)	1/5	1/3	1/3	1	1	1	0.10	0.05	0.03	0.06	0.06	0.07	0.06
TOTAL	2,00	7,33	9,73	16,00	16,00	14,00							

Once the probabilities are obtained from BBN and the impact from AHP for the different Levels, Table 5 was completed considering the scores for probability and impact shown in Tables 6 and 7.

Table 5 - Probability, Impact, and Risk Scores

			Score		
Risks Levels	Probability	Impact	Probability	Impact	Risk
Manpower poorly prepared (L1)	0.68	0.45	4	5	20
Improper Material & Hardware (L2)	0.33	0.19	3	5	15
Uncorrected method (L3)	0.69	0.18	4	5	20
Equipament/Instrument Failure (L4)	0.63	0.06	4	2	8
Unfavorable Control & Enviroment (L5)	0.61	0.06	4	2	8
Negative Organization Factors(L6)	0.66	0.06	4	2	8

Table 6 and 7 – Scores for Probability and Impact

Impact Score	Probability Level	Probability	Impact Score	Impact level	Impact
5	Very Likely	More than 0.8	5	Very High	More than 0.16
4	Likely	0.5-0.8	4	High	0.12-0.16
3	Possible	0.31-0.50	3	Moderate	0.08-0.12
2	Unlikely	0.11-0.30	2	Low	0.04-0.08
1	Very Unlikely	Below 0.10	1	Very Low	Below 0.04

5. Discussion of Results

The proposed method revealed some interesting results that may help to overcome some of the above-described problems. It offers a set of evaluation parameters and makes the decision-makers more aware of the impact and probability of the high-scoring risks. The AHP provides the impact scores for the risks based on which meaningful inferences regarding risk significance could be drawn. BBN provides the probability for the occurrence of risk-taking into consideration the experience and knowledge of experts. Combining the impact and probability of the risks provides the final risk global score.

In the case study in question, it was possible to observe in the final score of risk levels that the most impactful risks are related to a poorly prepared workforce and an uncorrected UT operation method. These risks are classified in the risk matrix as intolerable, thus showing decision-makers what actions should be taken first.

The study also noted that the inappropriate material and hardware scored 15. The decision-makers must be alert so that this level of risk does not become intolerable.

There was a tie in the other three risk levels: Equipment/Instrument Failure, Unfavourable Control & Environment, and Negative Organization Factors, which are classified as tolerable.

The target of the study was to propose a model to prioritize the risks in UT used in an aero-engine repair station and provide responses to these risks that could affect operational safety and sustainability.

This paper aimed to fill this gap by proposing a model to apply BBN and AHP to prioritize risks in the UT Inspection in aero-engine repair station operation to optimize quality, safety, and sustainability. The implications are relevant since operational processes can be conducted more safely when adopting the proposed model. By using the model, operational failures and catastrophic accidents can be prevented.

6. Conclusion

The proposed method revealed some vital results and may help overcome some of the challenges operational leaders and other professionals looking for safety and quality through effective risk management. The study was conducted based on the experience and knowledge of inspectors and technicians on the subject.

The proposed method is essential for several reasons. First, risk assessment using AHP is gaining importance in the industry, and the adoption of multicriteria decision-making in jet UT has not been reported yet. Second, this study combines two approaches, the BBN and AHP, and considers the risk of UT failure as a decision-making criterion. Third, the paper shows that the risk factors identified in this study must be controlled to avoid critical parts failure. The probability and impact of risks associated with UT of critical parts are predicted quantitatively, and preventive actions can be planned to minimize the downtime of the assembly process, delay in production, and even engine failure.

In conclusion, this paper conceptualizes and demonstrates a new methodology illustrated with an application on the UT of critical parts. In responding to the first research question, “What are the risk factors in the UT of critical parts?” The risk factors identified in the literature review and the case study were listed by categories: Manpower, Material, Hardware, Method, Machine and Instrument, and Organizational. In response to the Second Research Question, “How to categorize the risk factors in Levels (L) and Sublevels (SL) to allow the application of Bayesian Belief Networks and AHP?” The risk factors were grouped in Levels (L) and Sublevels (SL) by using the Affinity Diagram that allows the application of BBN and AHP. In response to the Third Research Question, “What are the most impactful risks when combining probability and impact? The combination of BBN and AHP shows that the most impactful risks are related to manpower poorly prepared and uncorrected method UT operation. And the most sensitive categories to the UT process were Manpower and Method.

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