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A practical guideline for human error assessment: A causal model

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Abstract. To meet the availability target and reduce system downtime, effective maintenance have a great importance. However, maintenance performance is greatly affected in complex ways by human factors. Hence, to have an effective maintenance operation, these factors needs to be assessed and quantified. To avoid the inadequacies of traditional human error assessment (HEA) approaches, the application of Bayesian Networks (BN) is gaining popularity. The main purpose of this paper is to propose a HEA framework based on the BN for maintenance operation. The proposed framework aids for assessing the effects of human performance influencing factors on the likelihood of human error during maintenance activities. Further, the paper investigates how operational issues must be considered in system failure-rate analysis, maintenance planning, and prediction of human error in pre- and post-maintenance operations. The goal is to assess how performance monitoring and evaluation of human factors can effect better operation and maintenance.

1. Introduction

To meet the availability target and reduce system downtime, effective maintenance operation have a great importance. Maintenance performance is greatly affected in complex ways by human factors, since these factors play an important role in the pre- and post-maintenance operations [1, 2]. Further, there are several factors, which influences human error, such as internal (psychological and physiological) or external (technological and social) human performance shaping factors [2-4]. Therefore, in order to have an effective maintenance operation, these factors needs to be assessed and quantified. Further, all factors affecting human performance must be recognized and quantified throughout the various phases of the maintenance operation. The evaluations of these factors can help to have an effective maintenance operation with high level of safety.

Human factors analysis is rooted in the concept that the frequency and consequences of human errors are related to the maintenance work environment, culture, and maintenance procedures. This can be accounted for in the design of equipment, structures, maintenance processes and procedures. In general, the human error analysis concentrates on the effects of human performance on the maintenance operation, recognising that pre- and post-maintenance operations are influenced by human actions. To



evaluate the risk of human error during maintenance activities, several studies have been carried out; see e.g. Apostolakis, et al. [5], Noroozi, et al. [1], Deacon, et al. [6], Noroozi, et al. [7], and Khan, et al. [8]. For instance, Noroozi, et al. [1] proposed a risk-based methodology for pre- and post-maintenance and, illustrated how to calculate the human error probabilities (HEP) for both maintenance activity. Apostolakis, et al. [5] critically reviewed the human cognitive reliability (HCR) and the success likelihood index methodology–multiattribute utility decomposition (SLIM-MAUD) model.

For a long time, traditional HEA strategies have been preoccupied with estimating the frequency of an undesirable event and its magnitude to give an overall measure of human error or risk. This type of human error or risk measure is quite useful for prioritising risks (the larger the number, the greater the risk); however, it is normally impractical and can be irrational when applied blindly [9]. One immediate problem with expressing the risk as a product of frequency and consequence is that, usually, one cannot directly obtain the numbers needed to calculate the risk without complete knowledge of the relation between the causes and effects of risk of events [10]. Hence, to avoid the inadequacies of traditional human error assessment approaches and to provide solutions to the problems mentioned above, the application of BN is gaining popularity and has been discussed in several pieces of the literature; see e.g. Fenton and Neil [9], Røed, et al. [10], Ayele, et al. [11] and Lee and Lee [12]. BNs are particularly useful in the HEA of maintenance activities, as they allow us to understand the causal relationship as well as combine any historical data that is available with qualitative data and subjective judgements about the risk of events.

Most of the conventional BN based risk assessment approaches are, however, broad, holistic, practical guides or roadmaps, developed for off-the-shelf nuclear systems, for non-maintenance operations. Moreover, current issues regarding the traditional HEA methodologies are lack of an explicit causal model linking observed behaviour to personal and situational factors–theoretical & empirical basis; lack of consistency or reproducibility; lack of traceability/ transparency; and variability in results [2]. Furthermore, there is a lack of causal methodology to quantify the HEPs of maintenance activities. A BN model offers a way to use both limited data and expert judgment to estimate HEPs. Data can be used to inform both the BN structure and the BN quantification.

The main purpose of this paper is thus to propose a BN based HEA (BNB-HEA) framework for maintenance operation. The proposed framework can help to assess the effects of human performance influencing factors (PIFs) on the likelihood of human error during maintenance activities. Further, this paper investigate how operational issues must be considered in system failure-rate analysis, maintenance planning, as well as prediction of human error in pre- and post-maintenance operations. The goal is to assess how performance monitoring and evaluation of human factors can effect better operation and maintenance.

The rest of the paper is organised as follows. The basic concepts of static BN are described in Section 2. Thereafter, the proposed BNB-HEA framework for maintenance activities is presented in Section 3. Finally, some concluding remarks are presented in Section 4.

In this paper, human error (HE) is taken to mean the failure to implement a definite task (or performance of a not allowed action) that could result in disruption of planned tasks or damage to equipment and property. The human error with which this paper is concerned are all in some way related to 'maintenance activity'. They are the actual or potential threat of adverse effect of inadequate training and skill, poor maintenance instructions and operating procedures, poor work layout, poor equipment design and improper work tools [13]. Further, risk is roughly considered as a function of the probability of particular occurrences and, the expected losses (lives lost, persons injured, damage to property, and disruption of economic activity) caused by a particular phenomenon [14, 15].

2. Bayesian network – a bird's eye view

Static BN are a probabilistic graphical model consists of a qualitative part, an acyclic directed graph (DAG), where the nodes represent random variables and a quantitative part, a set of conditional probability functions [16]. The nodes can be discrete or continuous, and may or may not be observable and the arcs (from parent to child) represent the conditional dependencies or the cause-effect

relationships among the variables [16]. Parent nodes are nodes with links pointing towards the child nodes. Nodes that are not connected represent variables, which are conditionally independent of each other. Further, when BN contain discrete and continuous variables (nodes) generally it is called a Hybrid BN.

The quantitative part of a BN structure can be represented as a product of conditional distribution of each node N_i given its parents nodes $parents(N_i)$. Each node is described by the conditional probability function of that variable. Then, the joint probability distributions, considering discrete variable, can be expressed as:

$$\Pr(N_1, N_2, \dots, N_M) = \prod_i^M \Pr(N_i | parents(N_i)) \quad (1)$$

where: $\Pr(N_i | parents(N_i))$ is the conditional distribution mass function of node, N_i .

Moreover, to understand the complex interaction between PIFs and estimate the consequence of human error, a causal approach can be used. Figure 1 illustrates the causal relationships between a human error and other main events.

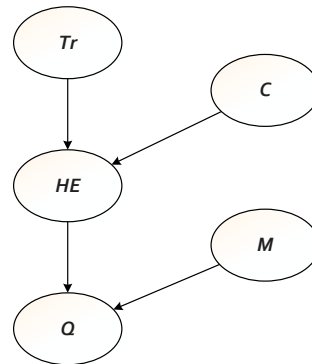


Figure 1. Causal relationships between a human error and other main events.

Tr denotes a set of any initiating (trigger) events, which are the performance influencing factors and **C** denotes the control measure, such as barriers. **HE** denotes the main risk event – human error, which shows that the cause of the trigger **Tr** produces the effect **HE**. **Q** denotes the consequence of the human error. **M** denotes the mitigating event that prevents any cause of **Q**, such as any response that avoids or reduces the consequence event.

In the causal relationships, a human error, which is an event can be characterised by causal chain involving [9]:

- The event itself (i.e. the error),
- At least one consequence event that characterizes the impact,
- One or more initiating (trigger) events,
- One or more control events, which can stop the trigger event, and
- One or more mitigating events, which avoid or reduce the consequence event.

3. Proposed BNB-HEA framework

The proposed BNB-HEA framework consists of two parts: qualitative and quantitative. The main aim of qualitative part is to investigate the interaction of the predominant PIFs and their negative synergy effect on the maintenance activities. On the other hand, the focus of quantitative part is to estimate the posterior probabilities of the human error and, quantify the risk by employing causal analysis, i.e. BN.

3.1. Qualitative assessment

Figure 2 illustrates specific steps that should be followed to construct the BN for maintenance operations and, to estimate the main query – the posterior probability of the human error.

Step 1.1 – Define the problem and perform evaluation of human PIFs: The purpose the initial stage of the proposed framework is to study and investigate the effect of the predominant PIFs on the pro- and

post-maintenance activities. Further, the interaction of the PIFs, the dependability of these factors on various variables, their negative synergy effect on the human performance needs to be assessed and specified. During this process, the consultation of all relevant stakeholders should be corroborated.

Step 1.2 – Perform classification of the maintenance task: In the next step, the assessment of the main repair or maintenance tasks during system failure should be carried out. For instance, the repair or maintenance tasks during gearbox failure are as follows:

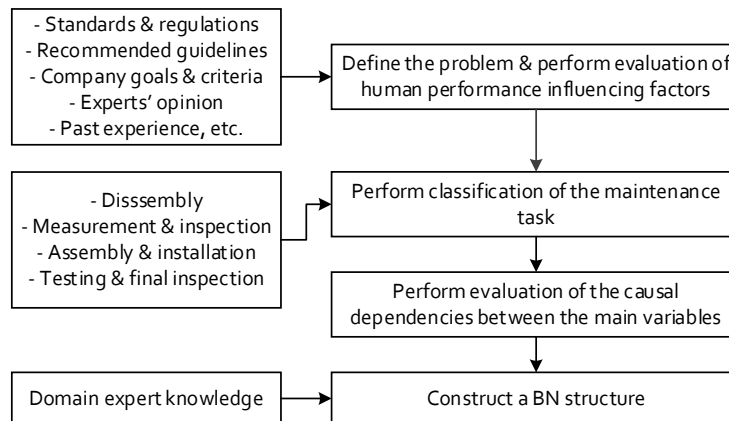


Figure 2. Qualitative part of the proposed BNB-HEA

- Disassembly of gear box;
- Measurement and inspection;
- Corrective maintenance;
- Assembly and installation; and
- Testing and final inspection.

Step 1.3 – Perform evaluation of the causal dependencies between the main variables: In the next stage, the interactions or causal dependencies between the main variables, i.e. the PIFs, maintenance operation, and the human error, needs to be understood and then the structure of the BN has to be decided. In general, BNs can be used for three kinds of reasoning [17]: *i*) causal reasoning – from known causes to unknown effects, *ii*) diagnostic reasoning – from known effects to unknown causes, and *iii*) a combination of casual and diagnostic reasoning.

Step 1.4 – Construct a BN structure: The final stage in the qualitative evaluation is to construct the BN. Intrinsically, the static BN is a solution for estimating the potential human error probabilities with maintenance operations. The main aim of this step is thus to build the Bayesian structure that captures the main variables, which comprises both discrete and continuous variables. During this stage, the key is to focus on the causal relationships between the main variables.

3.2. Quantitative assessment

Figure 3 describes the quantitative part of the proposed BNB-HEA framework and, illustrates the specific steps that should be followed to determine the posterior probability of the human error.

Step 2.1 – Define the state of the discrete nodes: The first step in the quantitative assessment is to define the state of each discrete node. A discrete node (variable) is one with a well-defined finite set of possible values, called states [18]. The state can take binary values (such as true or false) or ordered values (such as low, medium, or high) [19].

Step 2.2 – Assign MPT for each root discrete node and CPT for other discrete nodes: After specifying the states of discrete nodes, then the next step is to quantify the relationships between the connected nodes (variables). In this step, marginal probabilities of each root nodes should be assigned. For other discrete node (other than the root nodes), conditional probability tables (CPT's) needs to be

defined. For each particular discrete node, all possible combinations of values of those parent nodes needs to be observed; and such combination is called instantiation of the parent [19]. For a Boolean network, for instance, a variable with n parents requires a CPT with 2^{n+1} probabilities [19]. These probabilities can be estimated or assigned using direct elicitation and/ or machine-learning techniques [19].

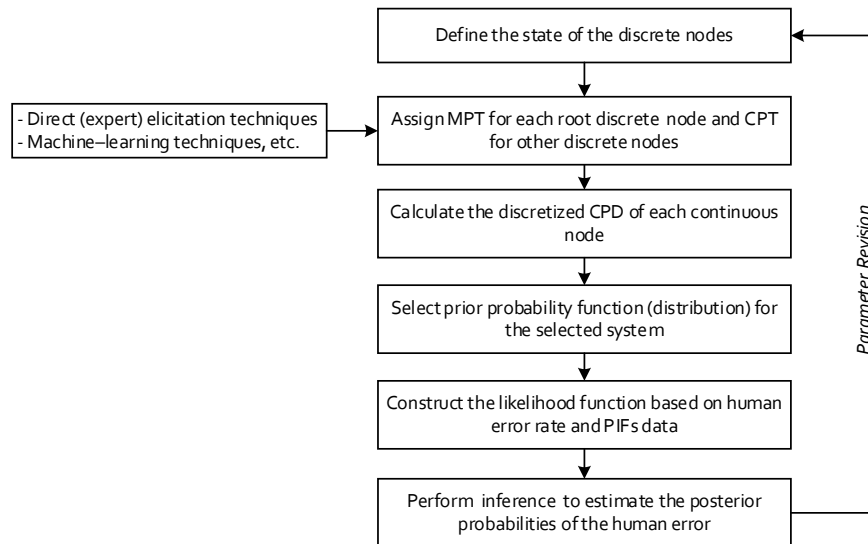


Figure 3. Quantitative part of the proposed BNB-HEA

Step 2.3 – Calculate the discretized CPD of each continuous node: The next stage is defining the conditional probability distributions (CPD's) for each continuous variable. A continuous variable (node) is one which can take on a value between any other two values [18]. Typically, there are two approaches to handle the continuous variable: static and dynamic discretization. Both approaches try to specify the states of the continuous nodes. Basically, a static discretization requires the breakup of the total range of the continuous variable into a number of intervals [18]. However, this process is cumbersome and error prone, and where a model contains numerical nodes having a potentially large range, results are necessarily only crude approximations [16]. To overcome this problem, the dynamic discretization has been developed, by Neil, et al. [20].

Step 2.4 – Select prior probability function (distribution) for the selected system: In this stage, a prior probability function or distribution needs to be asserted, for the defined system or component. This function is the representation of the failure rate of the system or component; and failure rate is the measure of frequency of system or component failure. The prior function describes the probability of n or fewer failures during a time interval of $(0, t)$, when all PIFs are equal to zero or absent (i.e. “ideal” operating environment), during maintenance operations. For instance, by assuming that the components fail according to a Poisson process, the probability of n or fewer failures, can be estimated by the following equation [20]:

$$P(S_f) = \sum_{i=0}^n \frac{(\lambda t)^i}{i!} e^{-\lambda t} \quad (2)$$

where $P(S_f)$ is the probability of n or fewer failures and λ is a failure rate of the system/ component.

Step 2.5 – Construct the likelihood function based on human error rate and PIFs data: After defining the prior probability function and observing the PIFs data, then the likelihood function has to be constructed. Likelihood function generally is the joint probability function and, it can be expressed as a product of conditional probabilities [21]. Hence, by considering discrete PIFs, the likelihood function of the system failure, based on Glickman and van Dyk [21] approach, can be expressed as follows:

$$L(S_f|Tr) = p(Tr_1, Tr_2, \dots, Tr_{r-1}, Tr_r | S_f) \quad (3)$$

where $Tr_1, Tr_2, \dots, Tr_{r-1}, Tr_r$ is a set of PIFs or triggers.

Then, by grouping the PIFs into vectors of size R , (3), can be re-written as follows:

$$L(S_f|Tr) = \prod_{i=1}^M p(Tr_i | S_f) \quad (4)$$

where M is a vector of size.

By following the same approach, the likelihood function of the human error can be expressed as, by considering the discrete PIFs variables:

$$L(HE|Tr) = \prod_{i=1}^M p(Tr_i | HE) \quad (5)$$

where HE is representing the human error.

Step 2.6 – Perform inference to estimate the posterior probabilities of the human error: The final stage is to perform inference for estimating the posterior probabilities of the human error. Probabilistic inference is the task of computing the probability of each node in BN, according to the most recent PIFs to provide posterior probabilities. The posterior distribution combines prior PIFs information with actual observed data to predict the future potential human error probabilities. That means the current information about the PIFs will be used to continuously update the potential human error relating to maintenance activity. Simply, the distribution describes the probability that the error will occur, given the predominant PIFs has observed. The posterior distribution of the human error, considering discrete PIFs (variables), based on Glickman and van Dyk [21] approach, can be expressed as:

$$P(HE|Tr) = \frac{P(HE)P(HE|Tr)}{\int p(HE)p(Tr|HE)d_{HE}} \quad (6)$$

By substituting the likelihood function and applying Bayes' theorem, Equation (6) can be re-written as:

$$P(HE|Tr) = \frac{P(HE)L(HE|Tr)}{P(Tr)} \propto P(HE)L(HE|Tr) \quad (7)$$

To solve, Equation (6) and Equation (7), we can first multiply the prior distribution by the likelihood, and then determine the marginal constant that forces the expression to integrate to 1.

4. Concluding remarks

This work introduced a framework for a human error assessment of maintenance activities based on BN. The methodology consists of two parts: qualitative and quantitative. The qualitative analysis involves the following steps:

- (i) evaluation of the PIFs (to investigate the influence of the PIFs on the maintenance),
- (ii) performing maintenance task identification (to investigate the main repair or maintenance tasks),
- (iii) evaluating the causal dependencies between the main variables (to understand the interactions between the main variables), and
- (iv) constructing a BN structure.

The quantitative part illustrates the specific steps that should be followed to estimate the posterior probability of the human error and involves the following steps: (i) defining the state of each discrete node, (ii) assigning a MPT for root discrete nodes and a CPT for other discrete nodes, (iii) calculating the discretized CPD of each continuous node, (iv) selecting the prior probability distribution for the selected system, (v) constructing the likelihood function, based on the system failure rate data, (vi) computing the posterior distribution or probabilistic inference.

The findings are as follows:

- The proposed BNB-HEA framework is beneficial as it outlines a set of steps that assist the maintenance manager to estimate the probabilities of the human error due to the negative impact of performance influencing factors.
- By employing the proposed BNB-HEA framework, decision maker can analyse different maintenance strategies for operational costs, risk, flexibility, and resource constraints.

Nomenclature

BN	Bayesian networks
HE	Human error
HEA	Human error assessment
HEPs	Human error probabilities
HCR	Human cognitive reliability
SLIM-MAUD	Success likelihood index methodology–multiattribute utility decomposition
BNB-HEA	Bayesian networks based human error assessment
PIFs	Performance influencing factors
$\Pr(N_i parents(N_i))$	The conditional distribution mass function of node, N_i .
N_i	Conditional distribution of a node i
$P(S_f)$	The probability of n or fewer failures
λ	Failure rate of the system/ component.
$L(S_f Tr)$	Likelihood function of the system failure,
$Tr_1, Tr_2, \dots, Tr_{r-1}, Tr_r$	A set of PIFs.
$L(HE Tr)$	Likelihood function of the human error
$P(HE Tr)$	Posterior distribution of the human error

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