Dynamic Human Reliability Assessment enhanced with Bayesian Networks; a Comparison with Classical Approaches

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Abstract: The reliability study of a production system allows to obtain important information to determine its performance and understand how to prevent failures and dangerous situations. Similarly, the assessment of the Human Reliability Assessment (HRA) is crucial in assessing production performance, but its estimation is complex, often more complex than the equipment reliability. Complexity lies in the very nature of the human being, who reacts in an articulated way to different environmental stress, to changes in company policy and to psychological personal situations. In this study, a new methodology to assess human reliability is developed, then a comparison with another one method is drawn to observe how they behave in an ever-changing situation. This is innovative, especially considering how input data for the method have been achieved. In the present case, the comparison was carried out by means of a case study, under uncertain conditions, in a company producing machines for the recovery, recycling and recharging of refrigerant gas in automotive air conditioning equipment. The new methodology is based on Bayesian Network (BN) while the compared one is SLIM Method. In both cases, the PIFs (Performance Influence Factors) were evaluated as starting points, identified and evaluated by means of expert opinions and theory of belief functions (Dempster-Shafer Theory - DST). By taking Human Error Probability (HEP) values for each task of the process, it was possible to have an overall picture of the impact of the human factor at the process stages and a demonstration of which method is best suited to changing information.

Keywords: HEP, Bayesian Networks, SLIM Method, Dempster-Shafer Theory, model uncertainty.

1. Introduction:

Direct impact of human role on system reliability gained an increasing attention. Human error is considered as a part of everyday functioning and it is expected that people will make errors, they are some of the most undesirable aspects of daily life (A. Noorozi, 2013). Based on literature human reliability can be defined as the probability that a person correctly performs his task (Kirwan 1998, Kirwan 1998). There are a lot of factors that can influence a person and, for this reason, affect human reliability. Despite human being complexity the possible causes for human error are needed to be evaluated. Human Reliability Assessment (HRA) defines the impact of human error and error recovery on a system.

A wide range of researches devoted to optimum the techniques of human reliability assessment (Kirwan 1992, Hollnagel 2005, Islam, Khan et al. 2018, Liu, Li et al. 2018). As a result, several novel methods has been proposed. A good literature review is provided in (Kirwan 1998, Kirwan 1998) in which Five broad classifications have been used to show the techniques' general orientation or form as presented in Table 1. Not only SLIM but also dozens of applied HRA techniques are suffer from two limitations; first, inconsistency and uncertainty of expert judgment, second, independence between human factors. This paper focused on reducing the uncertainty and also accounting dependency between human factors.

Based on these literature (Kirwan 1992, Kirwan 1992, Hollnagel 2005) there are three major components to an error:

- External Error Mode (EEM): the external manifestation of the error (e.g. closed wrong valve).
- Performance Shaping Factors (PSF) which influence the likelihood of the error occurring (e.g. quality of the operator interface, time pressure, training, etc.)
- Psychological Error Mechanism (PEM) the "internal" manifestation of error (how the operator failed, in psychologically meaningful terms, e.g. memory failure, pattern recognition failure, etc.).

EEM is easy to identify, while the other two components (that can be put together as Performance Influence Factors - PIF) need more effort to be recognized. Here, three categories are made to divide all the possible PIFs: environmental stress, psychological personal situation and company policy.

Table 1: Some of HRA techniques to determine HEP, divided in their five categories. SLIM method has a strong link with PIFs

Taxonomies	Psychological based tools	Cognitive modelling tools	Cognitive simulations	Realiability-oriented tools
SLIM	SHERPA	HEART	CES	HAZOP
SPAR-H		CREAM		FMEA

Human error influence has been primarily inspected for off-shore application, nuclear plant, maintenance application etc. (Abaei, Arzaghi et al. , Lin, Wang et al. 2014, Toroody, Abaiee et al. 2016, Bell and Williams 2017, Islam, Khan et al. 2018, Islam and Yu 2018). Recently, advanced statistical approaches are also applied to reduce the inherent uncertainty comes in HRA (Lin, Wang et al. 2014, Aju Kumar, Gandhi et al. 2015, Mkrtchyan, Podofillini et al. 2015, Su, Mahadevan et al. 2015). In this regard, BN as a parametric and non-parametric probabilistic method has been widely used (Smith, Veitch et al. 2017, Zwirglmaier, Straub et al. 2017, Deng and Jiang 2018, Leva and Hansen 2018, Ung 2018). (Zwirglmaier, Straub et al. 2017) adopted a framework for building traceable BNs for HRA, based on cognitive causal paths in which Node reduction algorithms are used for making the BN structure quantifiable. BN quantified through expert estimates and observed data (Bayesian updating) however, an approach accounted for modelling the related uncertainty with expert judgments is not applied. In another work, (Islam, Khan et al. 2017) calculated the human error probability in a maintenance activity of a marine operation using probability theory applied to Bayesian network. The model is tested using the data received through the developed questionnaire survey of >200 experienced seafarers with >5 years of experience.

The objective of the paper is to develop a comprehensive methodology to estimate the HEPs and modelling its uncertainty. To this end, an integration of BN and classical HRA techniques are made in order to estimate the final HEP of a considered engineering process. The DST application is used to control the uncertainty associated with expert judgements. A case study of an automotive equipment manufacturing company is determined to examine the methodology. The final result of proposed methodology on case study then will be compared with a SLIM result to observe how the new method fit better to uncertainty and achieve information about effective of human factor for each task inside the process.

The structure of remaining part of the paper are as follow: section 2 is devoted to materials and methods. In section 3 proposed methodology is verified by an application of case study while in section 4 and 5, discussion and conclusion are made.

2. materials and methods

The framework of developed methodology is illustrated in Figure. 1 . It can be split in two main parts; qualitative (grey part) and quantitative analysis (red part). First part is started by process selection and followed by PIFs assignment. DST, BN and SLIM are three steps which contributing HEP calculation. DST and SLIM Method theories improve the BN creating a brand-new methodology to determine HEP. Based on dynamic feature of BN, the final HEP value can be updated in the light of new evidence. Next, each step of proposed method is sketched out.

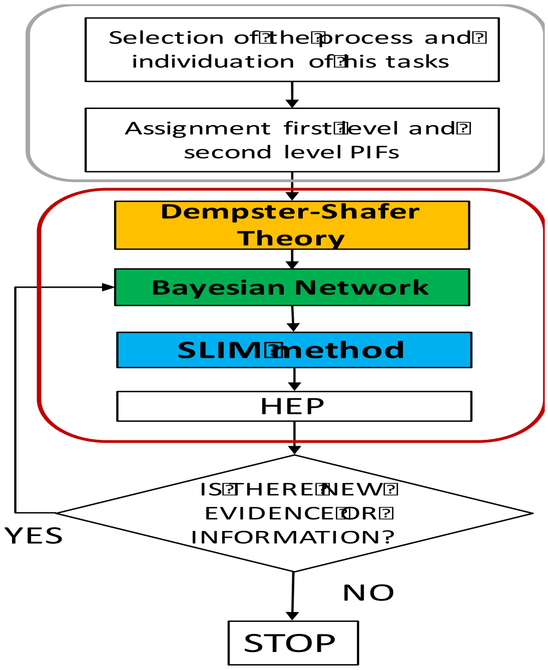

Figure. 1: Framework of developed methodology on HRA in engineering process

2.1 qualitative analysis

Processes can be divided up in different "major" tasks, e.g., Design and Development, Purchasing, Production, etc. PIFs is defined as basic human error tendencies and the possible creator of error-likely situations. PIFs help to describe the likelihood of error or ineffective due to human performance, so there is a direct correlation between the PIFs and performance, meaning that if PIFs are optimal, performance will be optimal and consequently the likelihood of error will be minimized. As (Noroozi, Khakzad et al. 2013) stated that, the list of PIFs can be identified according to the problem areas by which the error potential increased. In the process of incident investigations, PIFs are also studied to establish the underlying causes of error for each activity. Literatures established up to 12 PIFs in calculation of HEP, however in present method, in order to reduce the uncertainty associated with qualitative modelling, 18 PIFs are taken into account. Some factors have a primary influence on the considered task, while other PIFs can influence the task and a direct correlation with the previous factors. So in this study, PIFs are divided into two level.

2.2 HEP quantification process

2.2.1 Dempster-Shafer Theory to determine root nodes value

The theory of belief functions, also referred to as evidence theory or Dempster–Shafer theory (DST), is a general framework for reasoning with uncertainty, with understood connections to other frameworks such as probability, possibility and imprecise probability theories (Shafer 1976, Beynon, Curry et al. 2000). The theory allows to combine evidence from different sources and arrive at a degree of belief (represented by a mathematical object called belief function) that considers all the available evidence. Using expert judgment, the Basic Probability Assignment (BPA) (or belief mass) for each second level PIFs from the two experts (one operator and one process engineer) are collected.

BPA is characterized by the following equations (Musharraf, Hassan et al. 2013):

$$m(p_i) \rightarrow [0;1];\ m(\varphi) = 0;\ \sum_{p_i \subseteq P} m(p_i) = 1 \tag{1}$$

A DST combination rule is then employed to aggregate the different knowledge sourced according to their individual degree of belief. If there are n different knowledge sources that are integrated, the orthogonal sum combination rule is (Musharraf, Hassan et al. 2013):

$$m_{1-n} = m_1 \oplus m_2 \oplus \dots \oplus m_n \tag{2}$$

The DST combination rule applies a normalizing factor (1-k) to achieve an agreement among the different knowledge sources and denies all conflicting evidence through normalization. Given that knowledge sources are independent; this integration rule applies AND-type operators (product). As an illustration, if the $m_1(p_a)$ and $m_2(p_b)$ are two sets of information for the same event collected from two independent sources, the DST combination rule establishes equation.3 to combine the evidence (Musharraf, Hassan et al. 2013):

$$[m_1 \oplus m_2](p_i) \begin{cases} 0 & for\ p_i = \varphi \\ \dfrac{\sum_{p_a \cap p_b = p_i} m_1(p_a) m_2(p_b)}{1-k} & for\ p_i \neq \varphi \end{cases} \tag{3}$$

That is the combined knowledge of two experts for an event, and k measures the degree of conflict between the two experts, which is determined by the factor (Musharraf, Hassan et al. 2013):

$$k = \sum_{p_a \cap p_b = \emptyset} m_1(p_a) m_2(p_b) \tag{4}$$

2.2.2 *Bayesian Network: a different approach for human reliability.*

An comprehensive review including a verity of engineering application is provided by (Kjaerulff and Madsen 2008), (Neapolitan 2004) and (Barber 2012). Bayesian Network, also called Bayesian Belief Network (BBN), is a graphical method, known as a directed acyclic graph (DAG). The random variables are denoted by nodes and the directed arcs represent the conditional dependencies among the nodes. Each node has a probability value for each state associated with it. The arc arises from a parent node to a child node. An example of BN is shown in Figure. 2 The entire BN can be represented using joint probability as given by:

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P\left(X_i | Pa(X_i)\right) \tag{5}$$

While nodes and links together define the qualitative part of the network, the conditional probabilities associated with the variables define the quantitative part. As (Musharraf, Hassan et al. 2013) said, the probabilities of root nodes are usually given or previously calculated, however, in this study, it is made using DST. In case new evidence becomes available for chance nodes, BN is able to update the joint probability based on Bayes' theorem:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{6}$$

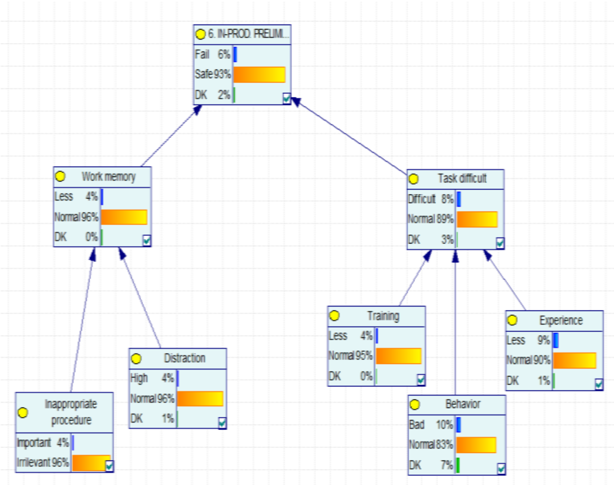

Figure. 2: Example of Bayesian Network which shows the likelihood of every states that nodes can assume

2.2.3 *SLIM*

SLIM Method represent one of the HRA technique to calculate Human Error Probability. It is a method for probabilistic reliability analysis in which the preference for a set of options is quantified based on an expert judgment. In this study, SLIM theory is applied to connect the information provided by top event and the Human Error Probability (see equation (7)).

$$LOG(HEP) = a * SLI + b \tag{7}$$

Table 2: task analysis for production process and the application of expert judgment to assign first and second level PIFs to each task

Task	PIFs involved	
	1st level	2nd level
1) Component collection	Deal with circumstances	Work overload
		Clarity of written
	Behavior	Routine
		Work memory
2) Mechanical interior assembly	Physical capability and condition	Work overload
		Time pressure
	Task difficult	Experience
		Clarity of instruction
		Training
3) Electronic/	Physical	Work overload

panel assembly	capability and condition	Experience
		Routine
	Task difficult	Time pressure
		Training
4) Internal wiring /electronic connection	Training	-
	Work memory	Distraction
		Stress
	Task difficult	Clarity of instruction
		System interface
5) Software download/ transducer calibration	Task difficult	Training
		Experience
	Inappropriate procedure	Work memory
		Distraction
6) In production preliminary tests/product completing	Task difficult	Training
		Experience
		Behavior
	Work memory	Distraction
		Inappropriate procedure
7) Final test	Task difficult	Training
		Experience
	Deal with circumstances	Distraction
		Time available
8) Final inspection	Work memory	Time pressure
		Experience
	Competence to Deal with circumstances	Communication
		Clarity of signals
9) Packaging /warehousing	Work memory	Time pressure
		Distraction
		Fatigue
	Deal with circumstances	Stress
		Communication

The methodology can be repeated if any new evidences or new information is being available. BN in fact has the flexibility to update the probability of the nodes when the state of some variable in a network are known due to new evidence or information emerging (Musharraf, Hassan et al. 2013).

3. Results

3.1 Case study

The developed methodology has been applied to the production process of a manufacturing company for workshop equipment machines (Oksys s.r.l.). The company produce machines for the recovery, recycling, recharging refrigerant into A/C system of passengers' cars and trucks. The main sections of a Oksys machine are internal compressor, vacuum pump, internal tank, solenoid valve and electronic board. The internal compressor and a distiller recovers and recycles the refrigerant. The vacuum pump dehydrates A/C system and internal tank are provided for refrigerant storage. Meanwhile, the solenoid valve and electronic board operates all devices and opens pneumatic circuit. The production average is about 1.500 machines per year.

3.2 Application of the methodology

Inside production process 9 tasks is determined as the whole process reported in Table 2. Using experts' judgment, the first and second level PIFs for each task is assigned, then for each second level PIFs the experts assign a probability of occurrence. Two different experts inside the company are considered as sources of data, (in our case study the experts judgements is made based on the information given by the chief of production process and the CEO of the company).

Each PIF has three values related to its likelihood to take part of the human error (YES, NO, DK): YES – the PIFs has a negative influence on the operator doing the considered task; NO – the PIFs doesn't occur in a negative way for that task; DK – we don't have any information about his influence on the operator. The final value of probability for each PIF are computed by DST.

Table 3: Expert judgment using two experts for second level PIFs of task N°1 (Component Collection)

TASK	**1.Component collection**											
PIF 1st level	Behavior						Deal with circumstances					
PIF 2nd level	work memory			routine			work overload			clarity of signs		
	YES	NO	DK	YES	NO	DK	YES	NO	DK	YES	NO	DK
Expert N.1 (%)	12	72	16	21	73	6	11	66	23	15	78	7
Expert N.2 (%)	19	64	17	15	80	5	7	83	10	17	78	5

Table 4: Calculation of probability of each state for each PIFs using DST combination rule

1) Component collection											
Work memory			routine			Work overload			Clarity of signs		
YES	NO	DK	YES	NO	DK	YES	NO	DK	YES	NO	DK

0. 09 36	0. 87 18	0. 03 45	0. 07 06	0. 92 53	0. 0 0 4	0. 04 03	0. 9 3 3	0 . 0 3	0. 0 6	0 . 9 4	0. 0 0 5

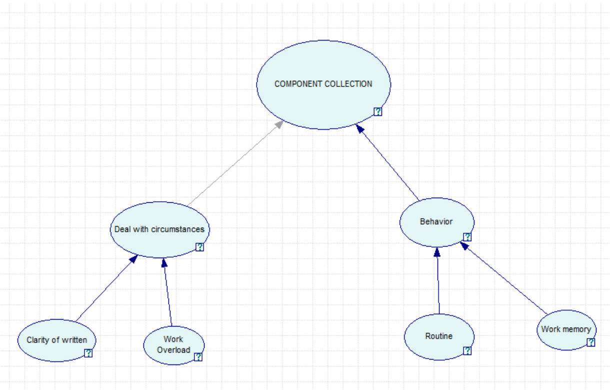

Figure. 3: Drawn Bayesian Network built for task N°1

Meanwhile Bayesian Network for each task is built, initializing the root nodes with the probabilities calculated by DST and filling the Conditional Probabilities Table for the first level PIF and the entire task. HEP is calculated given the correlation with SLI by equation (7). Given:

$$\begin{cases} HEP = 0{,}9 \; for \; SLI = 1 \\ HEP = 1E^{-5} \; for \; SLI = 0 \end{cases}$$

The values of the 2 variables are given as:
$a = 0{,}45424, b = 0{,}5$, so the HEP is calculated as:

$$HEP = 10^{(SLI*0{,}45424)-0{,}5} \tag{8}$$

4. Discussion: comparison with SLIM Method

The new methodology can be compared with a direct application of SLIM method from the provided set of data. The basic principle of SLIM is that the likelihood of a particular error occurring in a specific situation is associated with the combined effect of a relatively number of PIFs (Noroozi, Khakzad et al. 2013).

The Success Likelihood Index (SLI) of a considered activity/task is calculated given by equation (9) as the summation of products between rate and weight of each PIF. Weight are assigned with expert judgments and rate is considered equal to the "failure probability" of each second level PIF (that means the probability of YES).

$$SLI_j = \sum R_{ij} w_i \tag{9}$$

When the two methodologies are applied to a certain situation, the results are approximatively the same (see Table 5 and Figure 4) and there is no real advantage preferring one method to the other one.

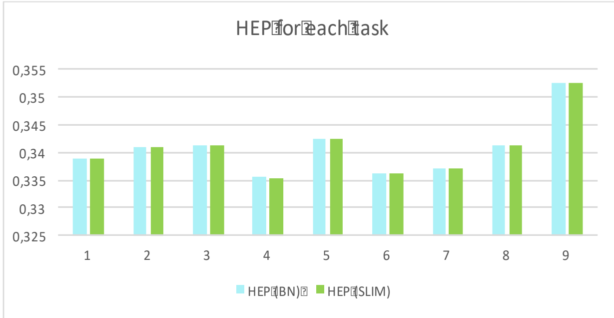

Figure 4: HEP values based on BN and SLIM methods

Table 5: SLI and HEP final results based on BN and SLIM methods for each task

Task N°	SLI(BN)	SLI(SLIM)	HEP(BN)	HEP(SLIM)
1	0.0661	0.0660	0.339	0.338
2	0.0721	0.0720	0.341	0.340
3	0.0728	0.0727	0.341	0.341
4	0.0566	0.0562	0.336	0.335
5	0.0757	0.0758	0.342	0.342
6	0.0584	0.0583	0.336	0.336
7	0.0608	0.0608	0.337	0.336
8	0.0727	0.0727	0.341	0.341
9	0.1037	0.1035	0.352	0.352

a "good" evidence for each task is targeted in order to observe the capabilities of each method in case new information becomes available. (for example "Distraction" is not present or "Work memory" is perfect). The results are presented in Figure 5 and Table 6 .

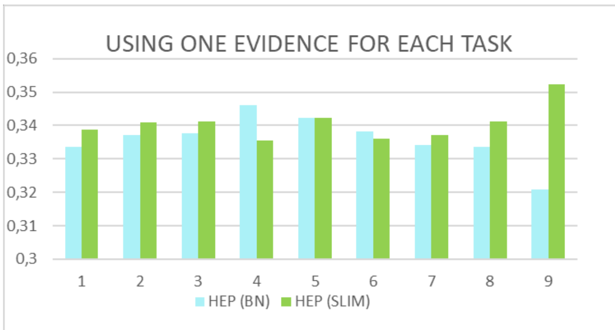

Figure 5: updated HEP values in the light of new evidence

Table 6: updated HEP and SLI summary based on BN and SLIM applications in the light of new evidence

Task N°	SLI(BN)	SLI(SLIM)	HEP(BN)	HEP(SLIM)
1	0.0511	0.0660	0.333	0.338
2	0.0611	0.0720	0.337	0.340

3	0.0629	0.0727	0.337	0.341
4	0.0860	0.0562	0.345	0.335
5	0.0759	0.0758	0.342	0.342
6	0.0639	0.0583	0.338	0.336
7	0.0526	0.0608	0.334	0.336
8	0.0507	0.0727	0.333	0.341
9	0.0139	0.1035	0.320	0.352

It can be seen easily that the new methodology is able to change accordingly with uncertainty, while SLIM method doesn't have the flexibility to take new evidence into account and consequently to be update. This capability can provide more reliable results, permit to find the most effective PIF to control human error and detect which is the most critical task toward human error: in particular, "Packaging/Warehousing" and "Software download/transducer calibration". SLIM looks as an easy method to calculate the impact of human error using PIFs, but it's not able to model uncertainty: when rate and weight are given by the experts, they aren't variable and can't adapt itself with new evidence or information. Not only SLIM but also dozens of applied HRA techniques are suffer from two limitations; first, inconsistency and uncertainty of expert judgment, second, independence between human factors. Proposed method focused on reducing the uncertainty and accounting dependency between human factors.

5. Conclusions

This analysis can represent a methodology to study ever-changing attitude of the human factor and its uncertainty, considering PIFs. Using BN, it is managed to consider interdependency among human factors and reinforce the study. The DST gives the opportunity to overcome the limitation about subjectivity of expert's opinion. The application of the method is illustrated in a novel situation, an automotive equipment company, that represent a brand-new area of application. This methodology could help a company to decide which kind of task improve and how to do it, or what process need a special attention toward human factor. Human reliability can assume the same importance that systems or machine reliability have inside an entire company, and this method can provide a complete knowledge about human aspects. Results are compared with SLIM Method but this method can be compared with every HRA technique that use PIFs. This method can be further improved, considering not only two experts but an entire pool.

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