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DOI
10.3850/978-981-11-2724-3_0248-cd

Publication date
2019

Document Version
Final published version

Published in
Proceedings of the 29th European Safety and Reliability Conference, ESREL 2019

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Success Likelihood Index Model (SLIM) is one of the widely-used methods in human reliability assessment especially when data is insufficient. However, this method suffers from uncertainty as it heavily relies on expert judgment for determining the model parameters such as the rates and weights of the performance shaping factors.

The present study is aimed at using Bayesian Network (BN) for improving the performance of SLIM in handling the uncertainty arising from experts opinion and lack of data. To this end, SLIM is combined with BN to form the so-called BN-SLIM technique. We applied both SLIM and BN-SLIM models to a hypothetical example and compared the results. It is shown that BN-SLIM is able to provide a better estimation of human error probability by considering dependencies. The probability updating feature of BN-SLIM in particular makes it possible to use new information to update the prior beliefs about the rates of the performance shaping factors, thus updating the resultant human error probabilities.

Keywords: Human error probability; Uncertainty; Bayesian network; Success likelihood index model

1. Introduction

Studies in different industries illustrate that human factor is the main cause of industrial accidents that leads to the damaging environment and costing billions of dollars. Human factor contributes to 60 to 90% of the disasters in different industries such as nuclear power plant, aerospace systems, marine industry, oil and gas facilities (Reason, 1990). Therefore, identifying potential human error and estimating their occurrence probability in the operation of complex systems and processes are crucial.

Human Reliability Analysis (HRA) is a systematic approach to analyze and identify the causes and consequences of human errors in different human-machine systems (Mkrtchyan et al., 2015). An integral part of HRA is assessing the Performance Shaping Factors (PSFs), i.e., the factors influencing Human Error Probability (HEP). In other words, PSFs are environmental, personal or task-oriented factors having positive or negative effects on human performance in different contexts (Griffith and Mahadevan, 2011).

During the last decades, a lot of research has been conducted to improve HRA methods, resulting in two main generations of HRA. In the first generation methods, such as Technique for Human Error Rate Prediction (THERP) (Swain and Guttmann, 1983), Human Cognition Reliability (HRC) (Hannaman et al., 1985), and Human Error Assessment and Reduction Technique (HEART) (Williams, 1992), human is considered as a mechanical or electrical (depending on the context) component who inherently has deficiencies (Pasquale et al, 2013).

These methods focus on the characteristics of tasks much more than the effects of the context and the environment in estimating the HEP. The second generation methods were developed to improve the application of the first generation.

Cognitive Reliability and Error analysis methods (CREAM) (Hollnagel, 1998), Standardized Plant Analysis Risk Human Reliability Analysis (SPAR-H) (Gertman et al., 2005) and Information, Decision and Action in Crew context (IDAC) (Chang and Mosleh, 2007) are some famous methods in which the operator cognition and context are considered as the major factors modifying the HEP.

However, both generations have some limitations such as being highly subjective, lacking a causal mechanism to link PSFs to the operator performance (Ekanem et al, 2016), and not being easily compatible with other

Proceedings of the 29th European Safety and Reliability Conference.
Edited by Michael Beer and Enrico Zio

Published by Research Publishing, Singapore.
ISBN: 978-981-11-2724-3; doi:10.3850/978-981-11-2724-3_0248-cd

probabilistic safety assessment models (Groth and Swiler, 2013).

Among the HRA methods, Success Likelihood Index Model (SLIM), proposed by Embrey (1984), is one of the most flexible and commonly used techniques for estimating HEP. This method can estimate HEP under the combined effects of a small set of PSFs. DiMattia et al. (2005) used SLIM to calculate HEP during offshore platform muster; similarly, Musharraf et al. (2013) compared the results of BN and SLIM for the same case study. Noroozi et al. (2013) and Islam et al. (2017) employed SLIM to estimate HEP in maintenance procedures.

SLIM suffers from the foregoing drawbacks of the 1st and 2nd generations of HRA techniques. More importantly, in case of data scarcity, the parameters of SLIM such as the rates and weights of PSFs are determined by experts, exposing the assessment of HEP to degrees of epistemic uncertainty.

To alleviate the limitations and to improve the performance of SLIM, we used Bayesian Network (BN) as a probabilistic graphical model to handle the uncertainty and consider causal probabilistic relationships (Pearl, 1986). BN can help decrease the uncertainties when the updated beliefs in each simulation are substituted for prior beliefs in the previous simulations, converging a priori subjective estimates to a posteriori objective results (Khakzad et al., 2011).

Although the performance of some HRA methods such as CREAM and SPAR-H have been improved using BN (Kim et al., 1986; Groth and Swiler, 2013), no attempts have been made with regard to SLIM. In this study, SLIM is mapped into BN to form a so-called BN-SLIM technique. we apply BN-SLIM to a hypothetical example to show how the proposed model outperforms SLIM by handling dependencies and performing belief updating.

The outline of this paper is as follow. Section 2 provides an overview of SLIM and BN techniques. The development steps of BN-SLIM are described in Section 3. In Section 4, the results of applying the developed model to a case study are presented and compared with SLIM. Conclusions are given in Section 5.

2. Background

2.1 Success Likelihood Index Model (SLIM)

SLIM (Embrey, 1984) is one of the flexible methods in HRA. This method is based on calculating the likelihood of human error occurrence under the combined effects of PSFs. In this method, weights and rates of PSFs define how each PSF contribute to the success likelihood index of a task. A rate shows to what extent a corresponding PSF is desirable for a task. A weight shows the relative importance of the PSF to the task. Once the rates and weights are determined, Eq. (1) can be employed to calculate the Success Likelihood Index (SLI) (Kirwan, 1994):

$$SLI = \sum_{i=1}^{n} W_i R_i \qquad (1)$$

where Ri and Wi are the rate and the normalized weight, respectively, of i-th PSF. Ri is an integer between 1 to 9 with 1 for the worst and 9 for the best conditions of PSFi. Considering that several PSFs contribute to the SLI in a certain task, the largest weight is assigned to the most important PSF, and so on. To estimate HEP, the logarithmic relationship in Eq. (2) can be used (Kirwan, 1994):

$$Log(HEP) = a\,SLI + b \qquad (2)$$

where parameters a and b can be determined by two tasks for which the HEPs and the corresponding SLIs are known.

2.2 Bayesian Network (BN)

BN is a probabilistic graphical model for reasoning under uncertainty. The qualitative part of BN is a directed acyclic graph composed of nodes and arcs. The nodes display random variables with various states, and the arcs represent the causal relationships between the nodes (Pearl, 1986).

Conditional Probability Tables (CPTs) are the quantitative part of BN which make it a powerful reasoning tool. CPTs quantify the conditional dependency of a child node given all possible combinations of the states of its parent nodes; instead of CPT, marginal probabilities are assigned to root nodes (i.e., nodes with no parent). Regarding the chain rule, the joint probability distribution of nodes P(U) is calculated as:

$$P(U) = \prod_{i=1}^{n} P(A_i|Pa(A_i)) \qquad (3)$$

where Pa(Ai) is the parent set of Ai, and P(U) reflects the properties of BN with n variables (Fenton and Neil, 2012).

Using Bayes' theorem, it is possible to update the prior probability of events by observing new evidence E as an exclusive feature of BN (Kjaerulff and Madsen, 2008):

$$P(U|E) = \frac{P(E|U)P(U)}{P(E)} = \frac{P(U,E)}{\sum_U P(U,E)} \qquad (4)$$

3. BN-SLIM

To estimate the HEP in SLIM, the rates and the weights of the PSFs must be determined. In the absence of relevant data, which is usually the case, subjective measuring of rates and weights by experts can increase the uncertainty of SLIM outcomes. To alleviate this drawback, we map SLIM into an equivalent BN to develop an innovative technique, BN-SLIM. The benefit of doing so, is twofold:

(i) The developed technique enables experts to express their uncertainty in the form of probability distributions of rates instead of deterministic point estimates; given new evidence about HEP, the probability distribution of the rates can thus be updated, which in turn can help decrease the uncertainties.

(ii) An operation may include a number of tasks to be fulfilled in parallel or series. Since tasks may share common PSFs, there would be dependencies among the SLIs of the tasks. Such dependencies, if not taken into account (as is the case in SLIM), can lead to an overestimation or underestimation of the total HEP. The developed technique, thanks to the capability of BN in considering dependencies, is expected to address this drawback of SLIM.

Moreover, BN as an effective technique for data fusion and aggregation can be used to aggregate multiple experts opinions about the parameters of SLIM.

3.1. Model development

A simplified structure of BN-SLIM only for one task is depicted in Fig. 1 in three levels. The first level includes PSFs identified for a specific task. Each PSF is modelled as a node with several states indicating the rates. The number of the states can thus be equal to the number of rates ($1 \le R_i \le 9$).

The probabilities assigned to states of PSF node can be elicited from the probability distribution of the rates identified, for instance, via sampling or by experts. The number of nodes in this level depends on the number of PSFs contributing to HEP.

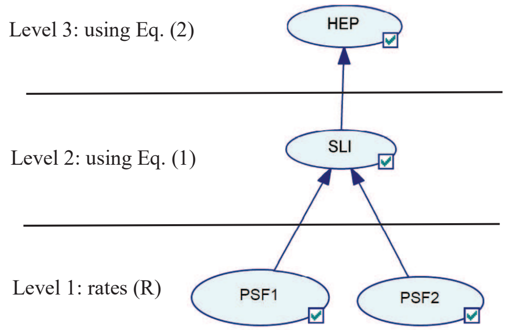

Fig. 1. The structure of BN-SLIM

3.2. Model quantification

After the structure of the BN-SLIM is completed, the conditional probabilities of variables should be identified. The CPT of a PSF node encodes the probability distribution of its rates. This probability distribution can be developed using empirical data or expert opinion. The CPT of the SLI node is an identity square matrix the number of cells of which equal to the multiplication of the number of states (rates) of its parent nodes, i.e., PSFs.

Since the HEP node has just one parent (SLI), the size of its CPT is equal to the number of states of SLI nodes. The CPT can be populated according to the Eq. (2) for each value of the SLI node.

4. An example

Assume a procedure consisting of two sequential tasks: Task 1 and Task 2. The task nodes have states 1 and 2 referring to error occurrence and no error occurrence, respectively. Experience (Exp) and Training (Tr) are considered as the main PSFs influencing the success likelihood in performing the tasks. According to the explanation in Section 3, the structure of corresponding BN-SLIM can be developed as in Fig.2(a) using GeNIe software.

To determine the network parameters, three rates are considered for each PSF (Table 1). The rates can be equal to one (the worst condition) if the operator has no experience or has not attended any training course; equal to 5 if the operator has at least 5 years of experience or has attended half of the required training course, equal to 9 if the operator has more than ten years of experience or has attended all required training courses. The probability distributions of the rates have been presented in Table 2. The weights of the PSFs are defined in Table 3.

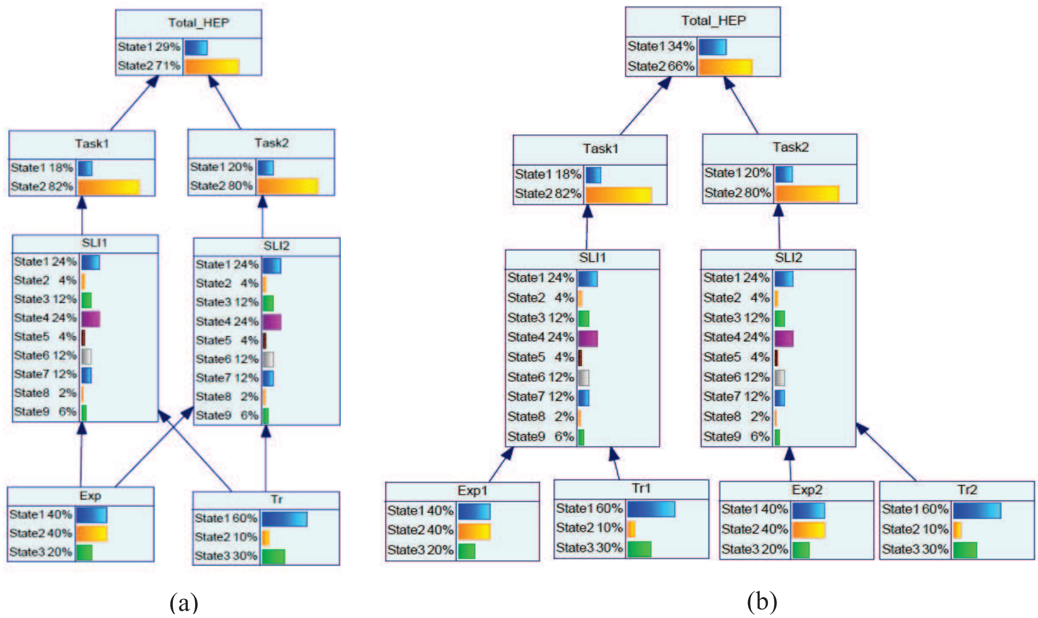

Fig. 2. Developed BN-SLIM. (a) The structure where dependencies between HEP1 and HEP2 are considered. (b) The structure where dependencies are ignored, equivalent to SLIM. States are defined in Table 1.

Taking into account the rates of the PSFs, nine SLI values for each task can be calculated using Eq. (1):

$$SLI1 = \{0.7 \times R_{Exp}\} + \{0.3 \times R_{TR}\} = \{0.7 \times 1, 0.7 \times 5, 0.7 \times 9\} + \{0.3 \times 1, 0.3 \times 5, 0.3 \times 9\} = \{1.0, 2.2, 3.4, 3.8, 5.0, 6.2, 6.6, 7.8, 9.0\} \quad (5)$$

$$SLI2 = \{0.4 \times R_{Exp}\} + \{0.6 \times R_{TR}\} = \{0.4 \times 1, 0.4 \times 5, 0.4 \times 9\} + \{0.6 \times 1, 0.6 \times 5, 0.6 \times 9\} = \{1.0, 3.4, 5.8, 2.6, 5.0, 7.4, 4.2, 6.6, 9.0\} \quad (6)$$

Table 1. State of the variable in the BN in Fig. 2(a)

State	Exp	Tr	SLI1	SLI2	Task1	Task2
1	1	1	1.0	1.0	Error	Error
2	5	5	2.2	3.4	No error	No error
3	9	9	3.4	5.8		
4			3.8	2.6		
5			5.0	5.0		
6			6.2	7.4		
7			6.6	4.3		
8			7.8	6.6		
9			9.0	9.0		

Table 2. Specified rates of PSFs and their probabilities

PSF	Exp			Tr		
Rate	1	5	9	1	5	9
P(rate)	0.4	0.4	0.2	0.6	0.1	0.3

Table 3. Weights of the PSFs for each task

	Exp	Tr
Task1	0.7	0.3
Task2	0.4	0.6

The nine values of SLI1 and SLI2 are corresponding to States1 to 9 in Table 1. Table 4 presents the CPT of nodes SLI1 and SLI2 which is an identity matrix with ones in the main diagonal making a relationship between a SLI value and its corresponding rates combination. For example, the one in the second row of this matrix illustrates that the SLI1 value 2.2 (State2) was calculated using rate 1 (State1) of Exp node and rate 5 (State2) of Tr node.

It is worth noting that the model can be refined so that the rates of PSF nodes could vary from 1 to 9 (i.e., 9 states for each PSF node). Such modification, however, may significantly increase the size of the CPTs of SLI nodes.

Table 4. CPT of SLI1 and SLI2 nodes with two parents, Exp and Tr.

Exp	1			2			3		
Tr	1	2	3	1	2	3	1	2	3
1	1	0	0	0	0	0	0	0	0
2	0	1	0	0	0	0	0	0	0
3	0	0	1	0	0	0	0	0	0
4	0	0	0	1	0	0	0	0	0
5	0	0	0	0	1	0	0	0	0
6	0	0	0	0	0	1	0	0	0
7	0	0	0	0	0	0	1	0	0
8	0	0	0	0	0	0	0	1	0
9	0	0	0	0	0	0	0	0	1

To compute the error probability of tasks in the third level of the network, the CPTs of Task1 and Task2 were populated using HEPs calculated based on SLI values (Eq. (2)) where $a = -3.48$ and $b = 0.128$ were calculated with the lowest and highest HEPs of 10-3 and 0.6 and the corresponding SLIs of 9 and 1, respectively. The conditional probabilities of HEP nodes are presented in Tables 5 and 6.

In Table 5, for instance, $P(Task1 = State1|SLI1 = State1) = 10^{-3.48\times1+0.128} = 0.6$. Since the tasks should be performed sequentially (in series), OR gate can be used to calculate the total HEP of the tasks.

As can be seen from Fig.2(a), the HEPs of Tasks 1 and 2 have been calculated as 0.18 and 0.20, respectively, while the total HEP has been estimated as 0.29.

Table 5. CPT of Task1 given SLI 1

SLI1→	1	2	3	4	5	6	7	8	9
1	0.60	0.23	0.09	0.06	0.02	0.01	0.01	0.003	0.001
2	0.40	0.77	0.91	0.94	0.98	0.99	0.99	0.997	0.999

Table 6. CPT of Task2 given SLI2

SLI2→	1	2	3	4	5	6	7	8	9
1	0.60	0.09	0.01	0.17	0.02	0.004	0.05	0.01	0.001
2	0.40	0.91	0.99	0.83	0.98	0.996	0.95	0.99	0.999

4.1. Belief updating

One of the main abilities of BN-SLIM is probability updating given new information. In other words, if we know the procedure is failed because of human error, BN-SLIM can determine which PSF rate is likely to present, while the conventional SLIM is not able to do so. Figs. 3 and 4 depict the updated probability distributions of the rates of experience and training, respectively, given the evidence of the failed procedure.

As shown in Fig.3, for node Exp, the updated probability of rate 1 (State1) is 0.78 and the updated probability of rate 5 (State2) is 0.2, implying a higher contribution of inexperienced operators to the error than moderately experienced operators.

Fig.4 also illustrates that the updated probabilities of rate 9 (State3) and rate 5 (State2) of node Tr have the same contribution although rate 9 was deemed more likely according to its prior belief. This ability of BN-SLIM can help HRA analysts determine the most probable root causes of the error.

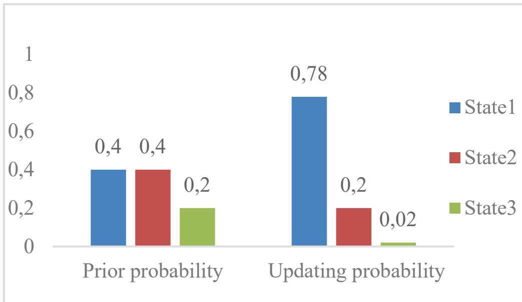

Fig. 3. Prior and updating probability distribution of experience rates

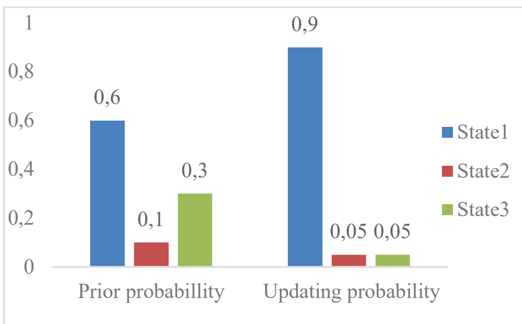

Fig. 4. Prior and updating probability distribution of training rates

4.2. Dependency analysis

As previously mentioned, there could be possible dependencies among the SLIs of the tasks due to the common PSFs. Our proposed model can consider these dependencies thanks to BN.

To make the discussion more concrete, the BN structure in Fig.2(b) is used to calculate the Total_HEP in which the dependencies between Task 1 and Task 2 due to common Exp and Tr nodes are not taken into account.

Fig.2(b) is similar to a SLIM model where common PSFs and conditional dependencies between tasks cannot be considered, whereas Fig. 2(a) allows such dependencies to be taken into account.

In the BN of Fig.2(b), the probability of Total_HEP is calculated as 0.34, whereas in the other case it is calculated as 0.29. These outcomes show that ignoring dependencies for this example results in an overestimation of total HEP in the procedure.

4.3. Comparison with SLIM

The BN-SLIM in Fig.2(a) can be applied to predict HEP even when the rates of the PSFs are given deterministically, as is the case in conventional SLIM. To compare the results of BN-SLIM and SLIM, we applied the evidence $R_{Exp} = 1$ to node Exp (State1) and $R_{Tr} = 9$ to node Tr (State3). Results in Table 7 illustrate that the models have the same outcomes in this case. So, in the absence of probability distributions of the rates, the BN-SLIM model can still provide a quick estimation of HEP if the all steps of conventional SLIM are considered in the model.

Table 7. Comparison of the HEPs calculated by BN-SLIM and SLIM.

BN-SLIM		SLIM	
$P(Task1 \mid Exp = State1, Tr = State3)$	$P(Task2 \mid Exp = State1, Tr = State3)$	P(Task1)	P(Task2)
0.09	0.01	0.09	0.01

5. Conclusions

This paper has presented a new approach, BN-SLIM, for improving the performance of SLIM methodology using Bayesian network. To show the outperformance of the BN-SLIM over conventional SLIM, we applied the model to a hypothetical example.

The results showed that the developed model is able to provide a better estimation of HEPs by considering conditional dependencies. Moreover, BN-SLIM is better able to handle uncertainty by considering probabilistic rates rather than deterministic ones.

Updating the prior information about PSFs is a particular feature of this method which could help HRA analysts reason about the rate of PSFs given new evidence about human performance, and specify these parameters more accurately.

Updating the prior rates could also be an efficient way to reduce the uncertainty of expert judgment, especially when the experts with high knowledge are not available, or judgment elicitation is time-consuming due to a large number of tasks or relevant PSFs.

Acknowledgment

This work was sponsored by the EU-H2020 NARSIS project under grant No. 755439.

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