2008-5435/14/63-1-8
INTERNATIONAL JOURNAL OF OCCUPATIONAL HYGIENE

IJOH 236-249, 2018

ORIGINAL ARTICLE

Predicting Occupational Struck-by Incident Probability in Oil and Gas Industries: a Bayesian Network Model

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Received November 11, 2018; Revised December 06, 2018; Accepted December 16, 2018

This paper is available on-line at *http://ijoh.tums.ac.ir*

ABSTRACT

Risk of injury or death due to occupational incidents in the oil and gas industries is higher than that of major incidents such as fire or explosion. In 2017, the largest proportion (36%) of fatalities and greatest number of incidents (24%) in the oil and gas industries were categorized as Struck-by. This study was aimed to develop a Bayesian network (BN) model for predicting occupational struck-by incident probability. Nineteen struck-by causal factors were extracted from the literature. Expert knowledge in addition to Dempster-Shafer theory was used to construct a BN. A questionnaire was developed to measure conditional probabilities of causal factors among participants. Struck-by probabilities of different states of causal factors were also estimated. The prior probability of struck-by incident was 3.09% (approximately 31 per 1000 operational workers per year). Belief updating predicted that preventing workers from being in improper position (in line of fire) would decrease the struck-by incidents by 37%. In contrary, failure of hazard warning (true state) and violation of procedures increased the struck-by probability by 4.08% (an increase of 32%) and 3.96% (an increase of 28%), respectively. The proposed BN model predicted that preventing workers from being in improper position (in line of fire) would decrease the struck-by occupational incidents by 37%. This approach was a step toward quantification of risks associated with occupational incidents. It had advantages including graphical representation of causal factors relationships, easily customizing model, and simply introducing of new evidence (belief updating).

Keywords: *Bayesian Network, Incident Prediction, Oil Industry, Struck-by Incident*

INTRODUCTION

Risk of injury or death due to occupational incidents in the oil and gas industries is higher than that of major incidents such as explosion or fire [1]. International Association of Oil and Gas Producers (IOGP) annually publish fatal incident reports based on data obtained from some oil and gas industries throughout the world [2]. Three major incidents that resulted in five workforce fatalities compared to 27 workforce fatalities due to occupational incidents in 2017 emphasizes this situation [2].

"Incidents or events where injury results from being hit by moving equipment and machinery or by flying or falling objects" were categorized as struck-by [2]. Fifty-seven cases of 184 fatal incidents

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reported from 2013 to 2017 were related to struck-by. Also, the largest proportion (36%) of fatalities and greatest number of incidents (24%) reported in 2017 were categorized as Struck-by [2]

Although contributing factors of occupational incidents have been identified at least to some extent [3-4-5-6], their analysis is not as rigorous as the major accidents [1] and relationships among these factors have not been explored enough for better prevention [6].

Influencing factors of occupational struck-by incident have been explored by a few studies. Hinze et al. [8] reviewed 743 accident reports in construction industry. The most frequent human factors involved in struck-by accidents were misjudgment of hazardous situation, malfunction of procedure for securing operation or warning of hazardous situation, inappropriate procedure for handling materials, and inappropriate operational position for task [8]. Esmaeili and Hallowell [9] reviewed 300 injury reports from National databases to identify risk factors attributed to struck-by incident. The highest risk values were associated with working under or near lifted loads (15.6%), working with heavy equipment (17.1%), and workers on foot and moving equipment (13.5%).

Based on the accident models, occupational incident was considered to be a consequence of contributing factors interaction among several levels of organization. Baksh et al [10] compared some features of available accident models including Domino theory [11], Swiss cheese model [12], Logic model [13], Kujath's model [14], and SHIPP methodology [15] with Bayesian network (BN) model. They concluded that BN has the advantages of model validation, updating mechanism, and integrating human and management barriers.

Bayesian networks: A Bayes net is composed of a set of nodes, which represents variables of interest connected by directed links. If there is a link from variable A to variable B, it indicates that B (to some extent) depends on A. The quantitative part of a BN utilizes conditional probability formula (Equation 1). As represented in Figure 1, each variable has a conditional probability table (CPT) that depends on probability of parent nodes [16].

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i \mid Parents(X_i)) \qquad (1)$$

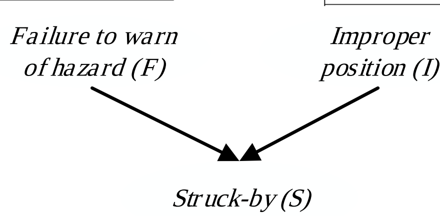
Here is a basic BN that illustrates these concepts. If a worker is in improper position and also failure of hazard warning, what is the probability of struck-by incident? Given the probability of variables in Figure 1, the answer is 0.75.

$$\mathrm{P(S = True|F = True,\ I = True)} = \frac{\mathrm{P(F = T, I = T, S = T)}}{\sum_{X\in\{T,F\}} \mathrm{P(F = T)\,P(I = T)}} \qquad (2)$$

$$= \frac{0.2 \times 0.3 \times 0.75}{0.2 \times 0.3 \times 0.75 + 0.2 \times 0.3 \times 0.25} = 0.75$$

Failure to warn of hazard (F)	True	False
Probability	0.2	0.8

Improper position (I)	True	False
Probability	0.3	0.7



Improper Position (I)	Failure to warn of hazard (F)	True	False
F	F	0.1	0.9
F	T	0.45	0.55
T	F	0.4	0.6
T	T	0.75	0.25

Fig. 1. Example of a basic BN structure and conditional probability table (CPT)

Published online: December 24, 2018

Similarly, probability of struck-by incident could be predicted in other scenarios using Equation 2.

Study aims: This study is part of a research program with the aim of predicting occupational incidents probability in the oil and gas industries. BN was used for this purpose. This is a significant step toward quantification of risks associated with occupational incidents.

The present study was designed to achieve following objectives: 1) causal modeling of factors associated with occupational struck-by incidents; 2) predicting struck-by incident probability in various states of contributing factors for improving prevention strategies.

MATERIALS AND METHODS

To predict struck-by incident probability in oil industry, the study was performed in following steps (Figure 2).

Struck-by risk factors: The only available source for obtaining struck-by accident contributing factors in the oil and gas industries was safety performance report of IOGP [2]. Extracted causal factors (n = 34) from IOGP reports were listed in Table 1. These causal factors were selected as the basic probable struck-by incident contributing factors.

Customizing struck-by contributing factors:

Five senior safety experts from different oil refinery companies with more than five years of experience in safety departments were selected as members of expert panel. They had background of accident investigation.

They were asked to verify which factors are credible for assessing the risk of struck-by in oil refineries. They were requested to point out how a factor (e.g., organizational climate) is significant based on a 5-point scale (not significant, slightly significant, moderately significant, significant, or very significant). Factors that 4/5 of experts assigned not significant / slightly significant were excluded from struck-by causal factors list. Nguyen et al. used similar method for customizing risk factors of working at height [7]. Also, they were requested to add more contributing factors, if they were not present in the list. Considering 4/5 of expert's agreement criterion, inadequate resource, failed to correct known problems, and poor environment conditions were three added factors (Table 3).

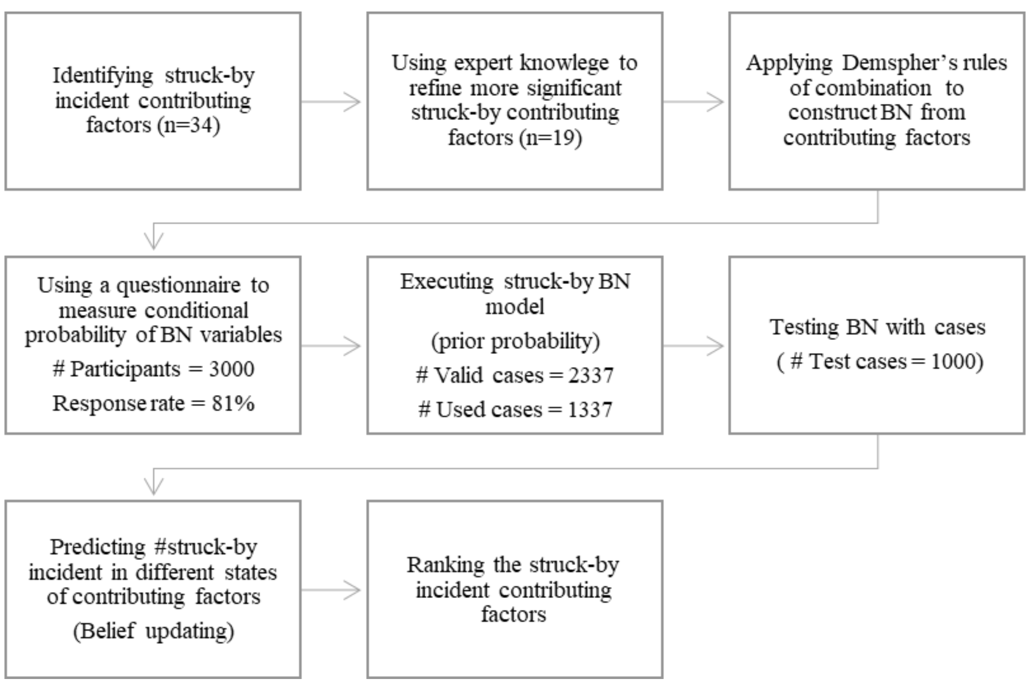


Fig.2. study steps for predicting struck-by incident probability

Table 1. IOGP struck-by causal factors frequency

Causal Factors	Freq.
Organizational	**93**
Inadequate supervision	23
Inadequate hazard identification or risk assessment	22
Inadequate training/competence	15
Inadequate work standards/procedures	12
Poor leadership/organizational culture	10
Inadequate communication	8
Failure to report/learn from events	3
Following Procedures	**43**
Improper position (in the line of fire)	21
Unintentional violation (by individual or group)	10
Work or motion at improper speed	4
Intentional violation (by individual or group)	3
Improper lifting or loading	3
Overexertion or improper position/posture for task	2
Inattention/Lack of Awareness	**31**
Improper decision making or lack of judgment	19
Lack of attention/distracted by other concerns/stress	9
Use of drugs or alcohol	1
Fatigue	1
Acts of violence	1
Tools, Equipment, Materials & Products	**24**
Inadequate/defective tools/equipment/materials/products	9
Inadequate maintenance/inspection/testing	9
Inadequate design/specification/management of change	6
Use of Protective Methods	**19**
Equipment or materials not secured	7
Failure to warn of hazard	7
Inadequate use of safety systems	3
Personal Protective Equipment not used or improperly used	1
Disabled or removed guards, warning systems or safety devices	1
Use of Tools, Equipment, Materials and Products	**16**
Improper use/position of tools/equipment/materials/products	13
Servicing of energized equipment/inadequate energy isolation	3
Protective Systems	**10**
Inadequate security provisions or systems	4
Inadequate/defective warning systems/safety devices	3
Inadequate/defective guards or protective barriers	3
Work Place Hazards	**3**
Inadequate surfaces, floors, walkways or roads	2
Storms or acts of nature	1

Constructing Bayesian network: Based on Reason's theory [12] causal factors were categorized in 4 layers (organizational, supervisory, preconditions, and unsafe acts), as described in Table 3. In Reason's model, each layer affects the next layer.

To construct the structure (causal relationship among variables) of BN, expert's knowledge was used. There were three possible relationships between two variables A and B. Variable B depends on A (A→B), variable A depend on B (A←B), and variable A and B are independent (A↑B). Each expert was requested to assign a probability of each possible relationship, given that sum of the probabilities is equal to one (Table 2).

Dempster-Shafer theory was applied to integrate expert's opinions (Equation 3). It is a suitable technique to resolve inconsistencies originated from independent multiple sources. Equation 3 was applied for calculating mass probability of possible relationships between each pair of casual factors [17].

$$m(A) = \frac{1}{1-k} \sum_{A_1 \cap A_2 \ldots \cap A_n = A} m_1(A_1).m_2(A_2)\ldots m_n(A_n) \qquad (3)$$

$$K = \sum_{A_1 \cap A_2 \ldots \cap A_n = \emptyset} m_1(A_1).m_2(A_2)\ldots m_n(A_n) \qquad (4)$$

Where; m (A) is the calculated mass probability of each relationship, mn (An) is the probability that expert "n" specified to a relationship, K is a measure of the amount of conflict between the two mass sets. Relationship with maximum value of mass probability was selected to represent relationship between two variables.

For instance, suppose two experts were asked to assign a probability for each possible relationship between supervisory (A) and safety culture (B) and $A \rightarrow B$, $A \leftarrow B$ and $A \uparrow B$ are a, b, and c, respectively.

Table 2. Example of combination of evidence in Dempster-Shafer theory [17]

Expert 2	Expert 1		
	$m_1(a) = 0.6$	$m_1(b) = 0.3$	$m_1(c) = 0.1$
m2(a) = 0.1	$m_1(a).\ m_2(a) = 0.06$	$m_1(b).\ m_2(a) = 0.03$	$m_1(c).\ m_2(a) = 0.01$
$m_2(b) = 0.7$	$m_1(a).\ m_2(b) = 0.42$	$m_1(b).\ m_2(b) = 0.21$	$m_1(c).\ m_2(b) = 0.07$
$m_2(c) = 0.2$	$m_1(a).\ m_2(c) = 0.12$	$m_1(b).\ m_2(c) = 0.06$	$m_1(c).\ m_2(c) = 0.02$

K=0.42×0.12+0.03+0.06+0.01+0.07=0.71
m_(1-2) (a)=0.06⁄0.29=0.21
m_(1-2) (b)=0.21⁄0.29=0.72
m_(1-2) (c)=0.02⁄0.29=0.07

Therefore, among three possible relationships, safety culture → supervisory was applied in BN structure. More details of this phase have been determined by Mohammadfam et al [18].

Conditional probability of BN variables: A five Likert scale questionnaire was designed to measure the probability of struck-by causal factors (Table 3). The questionnaire was developed using several already existed questionnaires in the fields of safety culture, safety climate [19-20-21], safety behavior [18], and job stress [22].

Judgments of ten experts were used for content validation of the questionnaire. According to Lawshe (1975)[23], questions with validity ratio lower than 0.62 were excluded (Table 3).

The study was conducted in four oil refineries. A total of 7722 persons were working as blue collar. All participants were male with age ranged between 21 and 65 years. Required sample size was determined based on Morgan and Krejcie table. Considering unknown response-rate as well as 1000 cases for testing the model, 3000 participants were selected randomly based on personnel number.

The response-rate of the participants was approximately 81 percent. Ninety-three questionnaires were excluded because of incompleteness (1337 questionnaires remained for analysis and 1000 cases for model testing).

Confirmatory factor analysis (CFA) was conducted to test how well the measured variables (questions) represent the influencing factors. The questions with the factor loading lower than 0.3 were excluded (Table 3).

To determine the (true or false) states of each contributing factor, sum score of each factor assigned by a responder was divided by number of questions of the factor. Scores less than half of the maximum were considered as “true” state for the factor and more than half of it as “false” state. “true” state means the contributing factor (e.g. PPE not used) is true for that responder and “false” state means the contributing factor (e.g. PPE not used) is false for that responder. Positivity and negativity of questionnaire’s items were considered carefully for calculating factor score.

The probabilities of each contributing factor in BN were estimated based on acquired data from questionnaires (Table 4). The CPT for any factor has the number of cells equal to the product number of variable’s state and the number of its parent’s states [16].

Prior probability of struck-by BN model: Netica software package (version 5.18) was used for developing struck-by BN. Causal graphical model was implemented and CPT of causal factors were filled based on probabilities database (questionnaires). When there are latent variables and missing data, it is recommended to use a process, called as parameter estimation to complete CPT. Expectation-Maximization (EM) learning is more robust than other types of learning algorithms. First, it uses regular BN inference with the existing Bayes net to compute the expected value of all the missing data. Then, the maximization step finds the maximum likelihood of BN [16].

The database was prepared by 1337 cases. Next, to estimate prior probability of struck-by causal factors, the BN was compiled (performing parameter estimation). It demonstrates current probabilities of struck-by contributing factors in understudy workplaces.

Testing model performance: The subsequent step was to test how well the predictions of the model match the actual cases. Confusion matrix is the most common statistic for testing model performance. It compares true value of selected node in test cases with the beliefs generated by model. The result was demonstrated as Error Rate (%). It means the percent of cases that model has predicted the wrong value. Another index for testing model performance is spherical payoff (Equation 5). It ranges between 0 and 1, with 1 being the best [24].

$$\text{Spherical payoff} = \text{MOAC}\ [\text{Pc} / \text{sqrt}\ (\text{sum}\ [\text{j} = 1 \text{ to n}]\ (\text{Pj} \wedge 2))] \qquad (5)$$

Where Pc is the probability predicted for the correct state, Pj is the probability predicted for state j, n is the number of states and MOAC stands for the mean (average) over all cases (i.e. all cases for which the case file provides a value for the variable in question).

Predicting struck-by incident probability: In this step, the state of each causal factor (n = 19) was changed to “true” and “false” and corresponding variation in struck-by incident probability was computed by BN model (belief updating). Thereby struck-by probability was estimated for different scenarios.

Ranking struck-by risk factors: The next step was to rank struck-by contributing factors. Ranking was implemented based on the relative variation in probability of struck-by incident corresponded to each causal factor states (Table 5).

Table 3. Questionnaire for measuring probability of contributing factors

#	Factors	Questions (factor loading)
Organizational		
1.	Poor organizational culture	
		1. Management operates decisively to correct safety problems (0.70).
		2. Workers can refuse work assigned to them because of safety concerns (0.87).
		3. Following safety rules and procedures are appreciated by the management (0.70).
		4. The purpose of accident investigation is not to establish blame against someone (0.61).
		5. My safe behavior is appreciated by co-workers (0.69)
2.	Inadequate risk assessment	
		1. How safety department handle the unsafe condition satisfies me (0.58)
		2. My workplace is a safer place to work than other companies I have worked for (0.71)
		3. The safety concerns at this workplace is decreasing (0.47)
3.	Inadequate procedures	
		1. Some safety rules and procedures are not practical (0.72)
		2. Safety procedures are always available for me (0.75)
		3. I have easy access to safety procedures of my tasks (0.79)
		4. lack of safety procedure is one the reasons that put employees at risk (0.65)
4.	Inadequate resource	
		1. Tools and equipment necessary to do my job safely are always available for me (0.64)
		2. My PPEs are appropriate for the job and have a good quality (0.53).
		3. To do the job safely, always enough workforce is available (0.72)
		4. Sometime I receive an assignment without adequate resources and materials to execute it (0.59)
5.	Inadequate training	
		1. The quality of safety training courses held by the company are satisfying (0.53)
		2. I am aware of safety requirements of my tasks (0.73)
		3. I am aware of the specific hazards of my job (0.62)
		4. Safety training is appropriate for my job (0.49)
Supervisory		
6.	Failure to correct known problem	
		1. Management/supervisor acts quickly to correct safety problems (0.74)
		2. There are some safety concerns in my workplace that have not been resolved for a long time (0.42)
		3. The safety department will try to fix reported unsafe conditions immediately (0.53)
7.	Inadequate supervision	
		1. Safety information is always brought to my attention by my line manager/supervisor (0.65)
		2. Supervisors inform employees about how to perform a work in a safe manner (0.63)
		3. If there are safety concerns, the work may be stopped by supervisor (0.84)
8.	Inadequate planning	
		1. Operational targets often conflict with safety measures (0.71)
		2. Work planning in term of workload and schedule satisfy me (0.65)
		3. Work planning often conflict with safety concerns (0.55)
Preconditions		
9.	Inadequate/defective guards	
		1. I'm in struck-by risk because of inadequate/defective guards in my work area (0.65)
		2. Equipment, machines, and operation zone have adequate guards in my work area (0.74)
		3. Defective guards are fixed as soon as possible (0.72)
10.	Lack of attention/ distracted by other concerns/stress	
		1. My co-workers say that I am a careless person (0.65)
		2. I am under stress because of out-of-work problems (0.74)
		3. I usually have trouble keeping my mind on what I am doing (0.59)
11.	Inadequate competence	
		1. I have adequate experience to do the job safety (0.71)

2. My co-workers have enough competency to do their job safely (0.65)
3. Managers ensure the competence of all people in safety matters (0.83)

12. Inadequate/defective PPE
1. I cannot always get the PPE I need to do the job safely (0.71)
2. The quality and comfort of PPEs satisfy me (0.52)
3. I always check my PPE before use (0.65)

13. Poor environmental conditions
1. I'm exposed to noise loud enough that I would raise my voices to keep a conversation during work (0.69)
2. The level of lighting in the area(s) in which I work is usually poor (0.58)
3. The temperature of my work area(s) during the summer is usually comfortable (0.65)
4. The humidity in my work area(s) is usually either too high or too low (0.69)

14. Work or motion at improper speed
1. My job requires me to work very fast (0.71).
2. My job leaves me with little time to get things done (0.66).
3. Usually I have to move fast to do my task (0.53).

Unsafe acts

15. Improper position (in the line of fire)
1. Usually I have to work near moving equipment (0.45)
2. There are moving equipment without safeguards in my work area (0.61)
3. There are enough safeguards in my work area to protect me from struck-by moving objects (0.59)

16. Failure to warn of hazard
1. I am aware of the specific hazards posed by the tasks I am performing (0.67)
2. Usually my co-workers or supervisor warn me hazards while doing my tasks (0.61)
3. Before starting the tasks, toolbox meeting is conducted to warn specific hazards (0.48)

17. Procedures violation
1. Sometimes it is necessary to depart from safety requirements for production's sake (0.75)
2. Some safety rules and procedures do not need to be followed to get the job done safely (0.71)
3. I have to bend or break a rule in order to carry out an assignment (0.65)
4. Managers and supervisors express concern if safety procedures are not adhered to (0.55)
5. Carefully following safety rules and procedures are of my great importance (0.61)

18. PPE not used
1. I am well aware of how to use PPEs (0.58)
2. I always prefer to use PPEs and follow safe work practices (0.49)
3. Managers and supervisors express concern if PPE are not used by workers (0.72)

19. Equipment or material not secured
1. Equipment or materials are secured properly in my work area (0.55).
2. I am at risk of struck-by unsecure equipment or material while doing my tasks (0.69).
3. My direct supervisor pays high attention to housekeeping in my work area (0.47).

20. Struck-by event: During the past 12 months, have you had any on the job struck-by accident? (Yes/No).

Table 4. Example of CPT for "PPE not used" factor

Inadequate Competence	Poor Environmental Conditions	Inadequate /Defective PPE	True	False
True	True	True	0.29	0.71
True	False	True	0.30	0.70
True	True	False	0.52	0.48
True	False	False	0.53	0.47
False	True	True	0.82	0.18
False	False	True	0.49	0.51
False	True	False	0.25	0.75
False	False	False	0.23	0.77

RESULTS

Prior probability of struck-by contributing factors: Nineteen causal factors as well as directed links among them were elicited by applying Demspher's rules of combination. This part resulted in graphical network of struck-by incident factors (Figure 3). The prior probabilities of contributing factors have been shown in Figure 3. It demonstrates current situation of understudy workplaces in terms of struck-by causal factors. The model implied that nearly 31 cases of struck-by incidents occurred per 1000 operational workers in past 12 months. More than 83% of workers believed that organizational culture is poor. Poor supervision was believed to be affected by almost all organizational factors and in turn affects all factors of preconditions layer. Approximately 67% of workers were not satisfied with supervisory situation. Nearly 55% of employees pointed out those poor environmental conditions (noisy, hot & humid, and inadequate lighting) are the case in their work area.

Predicted probability of struck-by incident: To predict the probability of struck-by incidents at different states of influencing factors, the state of each factor was changed to "true" and "false". Table 5 represents the predicted probabilities of struck-by incident. In compare with prior probability of struck-by incident (3.09%), preventing workers from being in improper position (false state) decreased the probability to 1.94% (a reduction of 37%). In contrary, being in improper position (true state) increased the probability to 4.71% (an increase of 34%). It showed that direct influencing factors (unsafe acts layer) as well as inadequate competence (from preconditions layer) had the highest effect on struck-by incident probability.

Testing model performance: To test model performance, 1000 cases different from those applied for prior probability estimation were used. Error rate values for negative true and negative false were 15.3% and 1.2% respectively (Table 6). Another model performance index was spherical payoff. It ranges between 0 and 1, with 1 being the best. The value of this index was 0.8147.

Sensitivity analysis: Sensitivity analysis describes the degree of sensitivity of one variable to another. The mutual information (MI) is a measure of the mutual dependence between two variables (Equation 6) [16]. It demonstrated that in the layer of unsafe acts, improper position and failure of hazard warning were two factors that struck-by incident probability highly depends on them.

$$MI = \sum_{xy} p(x,y) log \frac{p(x,y)}{p(x).p(y)} \qquad (6)$$

Where; $p(x,y)$ is joint distribution of variables x and y, (x), and $p(y)$ are the marginal distribution of x and y. The measure of MI for struck-by influencing factors has been shown in Table 7.

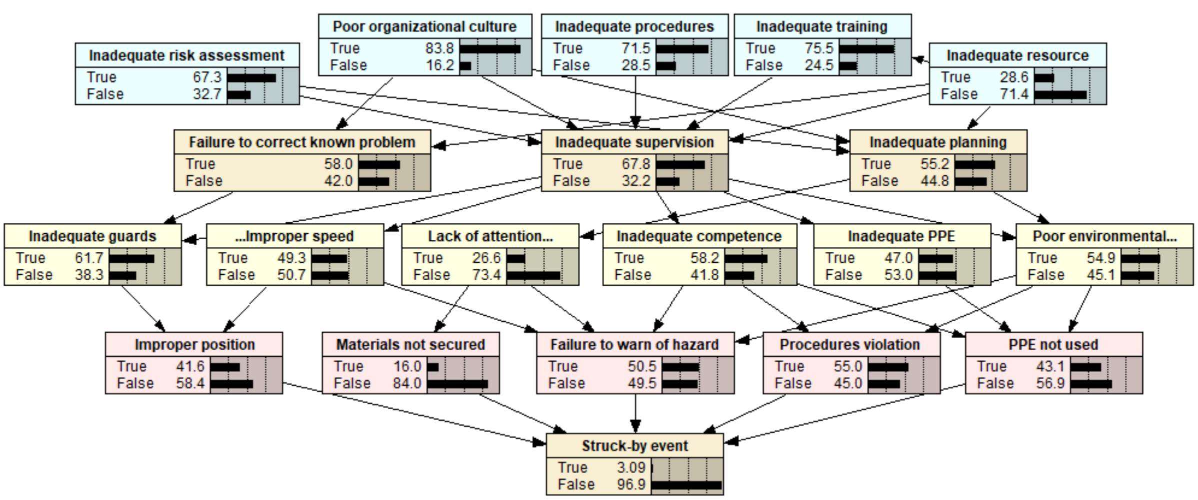


Fig. 3. Struck-by incident model: prior probability of influencing factors

Table 5. Predicted struck-by incident probability (%) corresponded to other variable states

Contributing factor (variable)	State		Range	Rank
	True	False		
Improper position (in line of fire)	4.71	1.94	2.77	1
Failure of hazard warning	4.08	2.07	2.01	2
Procedures violation	3.96	2.02	1.94	3
Inadequate competence	3.65	2.31	1.34	4
Inadequate guards	3.41	2.58	0.83	5
PPE not used	3.62	2.68	0.94	6
Materials not secured	3.91	2.93	0.98	7
Work or move in improper speed	3.31	2.87	0.44	8
Lack of attention	3.40	2.98	0.42	9
Inadequate supervision	3.18	2.89	0.29	10
Failure to correct known problem	3.18	2.96	0.22	11
Poor environmental condition	3.17	2.99	0.18	12
Inadequate planning	3.15	3.01	0.14	13
Poor organizational culture	3.11	2.96	0.15	14
Inadequate PPE	3.11	3.01	0.1	15
Inadequate training	3.11	3.03	0.08	16
Inadequate resource	3.12	3.07	0.05	17
Inadequate risk assessment	3.10	3.06	0.04	18

Table 6. Testing model using cases (Confusion Matrix)

Predicted		Actual	Error rate
True	False		
22	4	True	15.3%
12	962	False	1.2%

Published online: December 24, 2018

Table 7. Sensitivity of 'Struck-by event' to a finding at another nodes

Variable	**Mutual Information**	**% Entropy Reduction**
Improper position (in line of fire)	0.0492	2.52
Failure of hazard warning	0.0290	1.49
Procedures violation	0.0280	1.43
Inadequate competence	0.0129	0.661
Inadequate guards	0.0045	0.231
PPE not used	0.0042	0.213
Materials not secured	0.0029	0.149
Work or move in improper speed	0.0013	0.0644
Lack of attention	0.0009	0.0485
Inadequate supervision	0.0006	0.0292
Failure to correct known problem	0.0003	0.0168
Poor environmental condition	0.0002	0.0088
Inadequate planning	0.0001	0.00615
Poor organizational culture	0.0001	0.00487
Inadequate PPE	0.0001	0.00269
Inadequate training	0.0000	0.00145
Inadequate resource	0.0000	0.00086

DISCUSSION

Even with significant relationship that has been found between safety performance (incident frequency) and leading indices such as safety climate [23-24], number of incident was more expressive for managers. Predicting occupational incident probability by category of event, not only measures the safety performance directly, but also has the advantages of proactive indicators.

Previously, Mohammadfam et al. [18] used BN for predicting unsafe behavior and Nguyen et al. [7] applied it for predicting safety risk of fall from height in construction industry. A BN using expert knowledge and a questionnaire for data gathering was constructed to predict struck-by incident probability among oil refinery workers. The model had relatively acceptable performance.

Errors and violations are two broad categories of unsafe act. Mearns et al. suggested that unsafe behavior is the best predictor of accidents or near misses measured by self-report data [21]. In proposed model, errors included failure of hazard warning and improper position (in line of fire). Violations included PPE not used, procedure violation, and unsecured materials.

The sensitivity analysis demonstrated that, among unsafe acts, improper position (in line of fire) and failure of hazard warning as well as procedure violation have the highest effect on struck-by incident probability. These three causal factors have been reported as significant risk factors of struck-by incident in construction industry [8].

Inadequate guards and work or motion in improper speed had negative effect on being in improper position (Figure 3). Belief updating predicted that preventing workers from being in improper position decreased struck-by incidents by 37%. Sammarco et al. [27] successfully used visual warning system, as a safety intervention for reducing struck-by accidents involving continuous mining machines.

Failure of hazard warning was another factor that had significant effect on struck-by incident probability. It could occur due to lack of warning signs, inadequate competence or lack of attention/distraction [28]. Body control and awareness have been reported as an important barrier for contact with moving parts of machines [27].

The impact of poor environmental conditions (noise, heat stress, etc.) on risk of occupational incident has been demonstrated by García-Herrero et al [27]. Dzhambov and Dimitrova [30], in a meta-analysis study concluded that exposure to occupational noise above 90 dBA will increase the risk ratio of work-related incident to 2.16 compared to the least exposed group. However, improving environmental condition node (changing poor environmental condition state to false) in the struck-by model predicted a reduction of 3.2% in struck-by incident probability. It implies that impact of environmental conditions on occupational incident probability is not the same in different industries for different types of incidents.

The established model determines that preconditions of unsafe acts (such as inadequate competence, lack of attention/distracted by other concerns/stress, and work or motion in improper speed) are affected by inadequate supervision. Zohar and Polachek [26] revealed that supervisory intervention make significant changes to safety behavior and safety performance [31].

Per 1000 operational workers in a year, the prior probability was 30.9 struck-by incidents. It was relatively higher than recorded number of struck-by accident in understudy oil refineries. Considering lack of recording near misses and under-reported occupational incident, it was expected. It has been Probst et al. [32] found that companies with a poor safety climate did not report more than 80% of eligible injuries as well as near misses.

Study limitations: Causal factors of the struck-by incident model were extracted from IOGP fatal incident reports. These factors were reviewed by expert panel in this study. However, the process of incident investigation that resulted in these causal factors is unknown. Therefore, comprehensiveness and validity of these causal factors should be proved using a systematic method.

Participant recall bias regarding struck-by event experience can cause under-estimated incident probability. However, considering relatively large sample size as well as 12-month period of time, it seems recall bias did not have significant impact on the event probability. Comprehensive incident reporting and recording system could resolve this type of bias.

CONCLUSIONS

In this study, the proposed BN model was predicted that preventing workers from being in improper position (in line of fire) would decrease 37% of struck-by occupational incidents. BN is a promising tool for predicting probability of occupational incident by category (such as struck-by). This approach was a step toward quantification of risks associated with occupational incidents. It had the advantages, including graphical representation of causal factors relationships, easily customizing model, and simply introducing new evidence (belief updating). Sensitivity analysis feature of BNs enabled us to rank contributing factors based on their influences.

Declarations of interest

The authors certify that they have NO conflict of interest in the subject matter or materials discussed in this manuscript.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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