Songklanakarin J. Sci. Technol.
43 (2), 596-602, Mar. - Apr. 2021

http://www.sjst.psu.ac.th

Original Article

Non-linear modelling of construction workers' behaviors for accident prediction

Nart Sooksil[1] and Vacharapoom Benjaoran[2*]

[1] *Department of Civil Engineering, Faculty of Engineering, Nakhon Phanom University, Mueang, Nakhon Phanom, 48000 Thailand*

[2] *School of Civil Engineering, Institute of Engineering, Suranaree University of Technology, Mueang, Nakhon Ratchasima, 30000 Thailand*

Received: 8 April 2019; Revised: 22 March 2020; Accepted: 16 April 2020

Abstract

The cognitive engineering principle suggests that the unsafe behaviors of construction workers are associated with numerous attributes, and 23 task demands and 12 capability attributes have been proposed in the construction worker's behavior model (CWBM). Two models utilizing Logistic Regression (LR) and Artificial Neural Networks (ANN) were developed as accident prediction models, and the forecasting efficiencies of these two models were investigated. Robustness of these models was proven by verification. The results provide a basis for designing an in-depth study on the cognitive attributes influencing workers' behaviors and expanding the choice of analysis techniques.

Keywords: artificial neural network, capability, cognitive engineering, construction safety, logistic regression, task demand, workers' behaviors

1. Introduction

Statistics shows that one in every six fatal accidents at work, and nearly 60,000 fatal accidents per annum occur at construction sites all over the world (ILO, 2005). The construction industry in the United States was ranked the second highest in number of fatal work injuries (BLS, 2015). The average fatal accident rate for Indian construction industries was estimated as 15.8 incidents/1,000 employees/ year (Patel & Jha, 2015). In 2008, the construction industry in Singapore had 6.9 fatalities per 100,000 employees which is higher than the average 2.8 across all industries (MOM, 2008). The record of occupational injuries in the year 2015 by the Thailand Social Security Office (SSO, 2015) showed that the construction trade occupied the third place in work-related fatalities with 87 fatal injuries from a total of 590. The trend in these figures from both developed and developing countries is the same. Despite great improvements achieved via new interventions or solutions in the construction industry, this industry remains one of the top contributors of workplace fatalities across the world.

Haslam *et al*. (2005) revealed that the main causal factors of construction accidents were the workers' work behaviors. Health and Safety Executives (2002) also concluded that worker behavior was the main contributing factor in approximately 80% of the accidents. Kaila (2011) found that 80-95% of all accidents were due to unsafe behaviors and actions. These unsafe behaviors are more difficult to identify and prevent than unsafe conditions. Moreover, workers tend to overestimate their ability to control or prevent an accident, and this leads to an under-estimation of the risk and to intentionally adopting risky behaviors. Hence, the construction industry clearly needs to shift safety management effort towards the elimination of unsafe behaviors.

It is usual for workers to adjust their behaviors because of the production pressure for a faster work pace while they try to reduce the effort made (Rasmussen, 1997). This concept is based on cognitive perspective, which is related to the characteristics of the work system that influences decisions, behaviors, and the possibility of errors and failures (Fuller,

*Corresponding author
Email address: vacharapoom@sut.ac.th

2005). Nevertheless, previous research has provided quite limited explanations regarding how the characteristics of tasks and workers' capabilities influence the possibility of errors and accidents. Mitropuolos and Cupido (2009) proposed the Task Demand-Capability model, which pointed out that the root cause of construction accidents is shaped by workers' behaviors, a dynamic interaction between the workers' capabilities and task demands. Later, Sooksil and Benjaoran (2017) determined 23 task demand and 12 capability attributes and their relative weights for Thai construction settings. These factors influence workers' behaviors and create as consequence unsafe actions, and the possibility of accidents, because they are based on the cognition process. Hence, a niche is addressed as the link between these 35 attributes and an accident has not been provided yet. Furthermore, providing an accident prediction model from these attributes would be of great significance to construction safety studies, and would fill in this research gap.

Dealing with the mental actions of human thinking is complicated. Nonlinear modelling can be utilized in these situations. Thus, Logistic Regression (LR) and Artificial Neural Network (ANN) techniques are tested in the current study. The objectives of this research, therefore, are to develop accident prediction models by using LR and ANN techniques, and to evaluate the prediction efficiency of these two approaches.

2. Literature

2.1 Workers' behaviors

Many construction accident investigations have pointed out that most causal factors are unsafe behaviors of workers. Abdelhamid and Everett (2000) studied the perspective of workers' risk perception and found three root causes, namely unsafe conditions, worker responses to unsafe conditions, and worker unsafe acts. The findings from 500 accident reports by Suraji, Duff, and Peckitt (2001) revealed that inappropriate operative actions and inappropriate construction operations were the two main causes of accidents at construction sites, and both of these were directly linked to the workers' unsafe behaviors. Toole (2002) defined eight root causes of accidents, one of which is isolated deviations from prescribed behavior. Haslam *et al*. (2005) found that 70% of accidents were initiated by worker and work team factors, and 49% stemmed from workers' unsafe behaviors.

A cognitive perspective can elucidate the mechanisms of human error and how unsafe behaviors are produced (Fang, Zhao, & Zhang, 2016). The cognitive approach accounts for not only the individual's behaviors but also the impact factors from outside environment as well. This reflects the real situations that construction crews confront on a daily basis.

2.2 Cognitive perspective

Rasmussen (1997) proposed a descriptive model of work behavior, which explains how workers' behaviors tend to migrate closer to the boundary of functionally acceptable performance. These behaviors are caused by two primary pressures: the management pressures for increased efficiency of production, and the tendency for less effort in response to an increased workload. The result is likely a systematic migration towards the boundary of functionally acceptable performance, and if crossing the boundary is irreversible, an error or an accident may occur (Rasmussen, 1997). Fuller (2005) proposed the Task Demand-Capability Interface (TCI) model, which provides a new conceptualization of the process by which collisions occur. At the heart of the TCI model is the relationship between the task demand and the capability applied to achieve a safe outcome while driving a vehicle. When the task demand is less than the capability, the driver is in control of the situation. When the task demand is greater than the applied capability, then the driver loses control. This situation may or may not result in a crash depending on compensatory actions by others. Thus, to maintain control, it is necessary that the driver anticipates the task demand and matches it with suitable capabilities.

The TCI model is based on the cognitive perspective and is linked with the Rasmussen principle of the workers' behaviors. The task demand can be interpreted as the management pressures that the worker tries to satisfy under limited resources. Capability can be interpreted as the tendency for less effort, which is derived from workers' effort gradient, and it depends on physical and mental attributes.

Mitropoulos, Cupido, and Namboodiri (2009) have synthesized a cognitive model for construction safety, and the model was developed with three key propositions: (1) a construction task is conceptualized as a dynamic interaction between workers (capabilities) and work situations (task demands); (2) construction accidents are a result of loss of control when task demands surpasses capabilities; and (3) the work practices and team processes of work crew form the work situation (between task demand and capability) and finally the likelihood of accidents.

Based on previous studies of the cognitive perspective, this research aims to develop a construction worker behavior model (CWBM) for predicting a construction accident.

2.3 Non-linear modelling

Logistic regression (LR) is a form of regression analysis used when the dependent variable is a dichotomy (binary variable) and the independent variables are of any type (Field, 2009). LR technique is recommended for modelling and analyzing epidemiological data to calculate the probability of disease outcome, which is a dichotomous variable (Kleinbaum, Klein, & Pryor, 2002). LR has been applied to predict the likelihood of contract disputes in construction projects (Diekmann, Girard, & Abdul-Hadi, 1994). Wong (2004) developed an LR model for predicting contractor performance from 31 clients' tender evaluation criteria. Thus, LR is adopted in this study to model the occurrence of construction accidents using the task demand and worker capability attributes.

LR is a mathematical modelling approach which describes the non-occurrence or occurrence of an event. The dichotomous outcome is labelled by 0 or 1. In this study, 0 is for indicating "no accident" while 1 indicates "accident". The LR model is shown in Equation (1), where P is the probability of accident, and X_i is the cognitive attribute that affects the accident occurrence.

$$ln\left(\frac{P}{1-P}\right) = B_o X_0 + B_1 X_1 + B_2 X_2 + \cdots + B_k X_k = \sum B_i X_i \quad (1)$$

Artificial neural network (ANN) is an artificial intelligence technique initially inspired by biological nervous systems as a simplified model of how the brain works (Rumelhart, Widrow, & Lehr, 1994). ANN models usually include an input layer, one or more hidden layers, and an output layer, each of which can have a number of various nodes. Each node in the hidden layer(s) will receive one or more inputs and the inputs will be multiplied by their weights and summed together and with the bias (threshold). The weight and bias values will be initially selected at random and will be adjusted during the training (or learning) process, to give best fit to the training data. A learning algorithm is applied to shape the weights of the connections between the nodes so that the network is able to minimize prediction errors (Goh & Sa'adon, 2015).

ANN has been successfully applied in a wide spectrum of real-world problems, including accident analysis (Chiou, 2006; Wei & Lee, 2007), construction industry (Tam, Leung, & Liu, 2002), and construction safety (Goh & Chua, 2013; Goh & Sa'adon, 2015; Patel & Jha, 2015, 2016). However, there is a lack of application of ANN on the analysis of construction workers' behaviors, which are expected to be complex and highly non-linear.

A binary threshold unit as a computational model for an artificial neuron/node is displayed in Figure 1 This mathematical model calculates a weighted sum of its n input signals X_i = 1, 2,..., n and creates an output of 1 or 0. Each neuron applies an activation function (transfer function) to the incoming signal to identify its output signal. Each neuron j sums its weighted input as Equation (2):

$$net_j = \sum_{i=0}^{n} w_j x_i \quad (2)$$

The output of a neuron, y is a function of its weighted input or net_j. The back-propagation is a type of supervised learning strategy, where in each learning cycle (or epoch) the neural network produces an output that is compared with the target or actual output. The error or the difference between output and target is used to adjust the connections weights between neurons to minimize the root mean square error (RMSE) (Goh & Chua, 2013). RMSE is expressed as Equation (3):

$$RMSE = \sqrt{\frac{1}{n}\sum(D_i - P_i)^2} \quad (3)$$

where D_i is the actual output or target for the i^{th} input dataset, P_i is the predicted output for the i^{th} input dataset, and n is the number of datasets presented to the network. For 10-fold cross-validation (Witten, 2011) the training set is randomly partitioned into 10 subsets and each subset in turn serves as 10% of the original training set assigned for testing (removed from the training process). This process was repeated 10 times (once for each test set), and the average of RMSE from the 10 test sets was assessed. This technique reduces bias in the selection of training and testing sets, and is helpful for small datasets (Witten, 2011; Goh & Chua, 2013; Goh & Sa'adon, 2015).

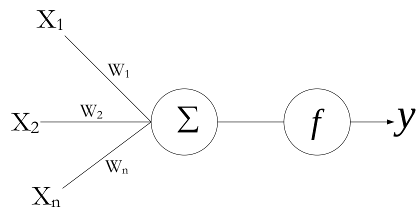

Figure 1. McCulloch–Pitts model of a neuron

From a cognitive perspective, errors are not simply human failures but a symptom of a problem in the work system (Dekker, 2014). Rasmussen's definition indicates that errors are to be expected, and that they are part of a natural or normal learning and explorative cognitive process (Le Coze, 2015). Thus, to understand human errors, we need to capture the systematic connections between human perception and human actions. So, this study employs empirical data to continue the CWBM development

3. Data Collection

A questionnaire survey was selected as an instrument for the data collection. Its successes have been proven in many psychological investigations of safety-related behaviors (e.g., Goh & Sa'adon, 2015; Ross *et al*., 2011; Sniehotta, 2009). The questionnaire was designed based on the results from Sooksil and Benjaoran (2017) which discovered 23 TD- and 12 C-factors of the CWBM. The respondents were 120 workers at various high-rise building construction projects, and each of them represented one incident case. A total of 120 cases were categorized into two groups: accident, and no-accident cases (excluding fatal accident). The accident cases must occur within 3 months prior to the interview session. For the no-accident cases, the task on the day before the interview is asked.

The samples represented 13 high-rise building construction projects. Three of them were private, and the rest were public. The questionnaire consisted of four parts. The first part comprises personal information, including gender, age, nationality, job position and work experience. The respondents were carpenters, masons, steelworkers, electricians, welders and laborers, and their average age was 41.27 years old (the youngest was 15 and the oldest was 60). Their work experiences ranged from 3 months to 30 years. The second part details incident/accident conditions, including job title, time, month and day of week, task/activity, tools, materials, machines/equipment, environment (conditions of light, noise, temperature etc.), site location, the injured body parts, and lost hours from the accident. The third and fourth parts consist with 23 TD- and 12 C-factors. For both parts, the response to each item is measured on a five-point Likert scale. The Likert scale is a psychometric response scale primarily used in questionnaires to obtain participant's preferences or degree of agreement with a statement or set of statements. The linguistic terms, very low, low, moderate, high, and very high were assigned to the values 1, 2, 3, 4, and 5, respectively. Among a total of 120 empirical cases, 100 cases of accidents/incidents were used to develop the CWBM, and the remaining 20 cases were employed in verification.

4. Application of LR and ANN Techniques

CWBM will work as an accident prediction model, which can forecast the incident, accident or no-accident, as shown in Figure 2. On using LR and ANN techniques to crate the prediction models, all 35 attributes were set as independent variables; the dependent variable indicated accident or no-accident.

The LR analyses were conducted using IBM SPSS statistics version 21 (2012). The analysis process started with finding statistically significant independent variables to be added into the model stepwise. Cox & Snell R^2 and Nagelkerke R^2 summarize the proportion of variance in the dependent variable associated with the independent variables, with larger R^2 values indicating that a larger part of the variation is explained by the model. The B coefficient indicates the factor by which the odds of an accident occurring will increase or decrease with a unit change in the independent variable. The significance of each variable in the LR equation was evaluated by the Wald statistic, which has a chi-square distribution (Mohamed, Ali, & Tam, 2009).

For ANN modelling, the type of network was a multilayer perceptron trained with back-propagation. The sigmoid function was selected as the nonlinear activation function in Waikato Environment for Knowledge Analysis: WEKA version 3.8.0 (2016) program. A total of 100 data records were used to train the neural network. The learning rate parameter n was set to 0.3, and the momentum factor to $\alpha = 0.2$, as default values of the program. The maximum number of training iterations was 1,000 epochs. The model was equipped with one single hidden layer, as suggested by Haykin (1994), and 10-fold cross-validation was utilized to examine the network performance in new data, not used in the training.

In this research, a trial-and-error process was adopted to optimize the number of nodes in the hidden layer. A rule of thumb suggests that the number of hidden layer neurons should be less than half of neurons in the input layer, meaning less than 17. Therefore, five networks were implemented with different numbers of neurons in the hidden layer, from 16 to 20 neurons. An example of "35-17-2" ANN model is displayed in Figure 3, the label meaning that the network consists of 35, 17, and 2 neurons in the input, hidden, and output layers, respectively.

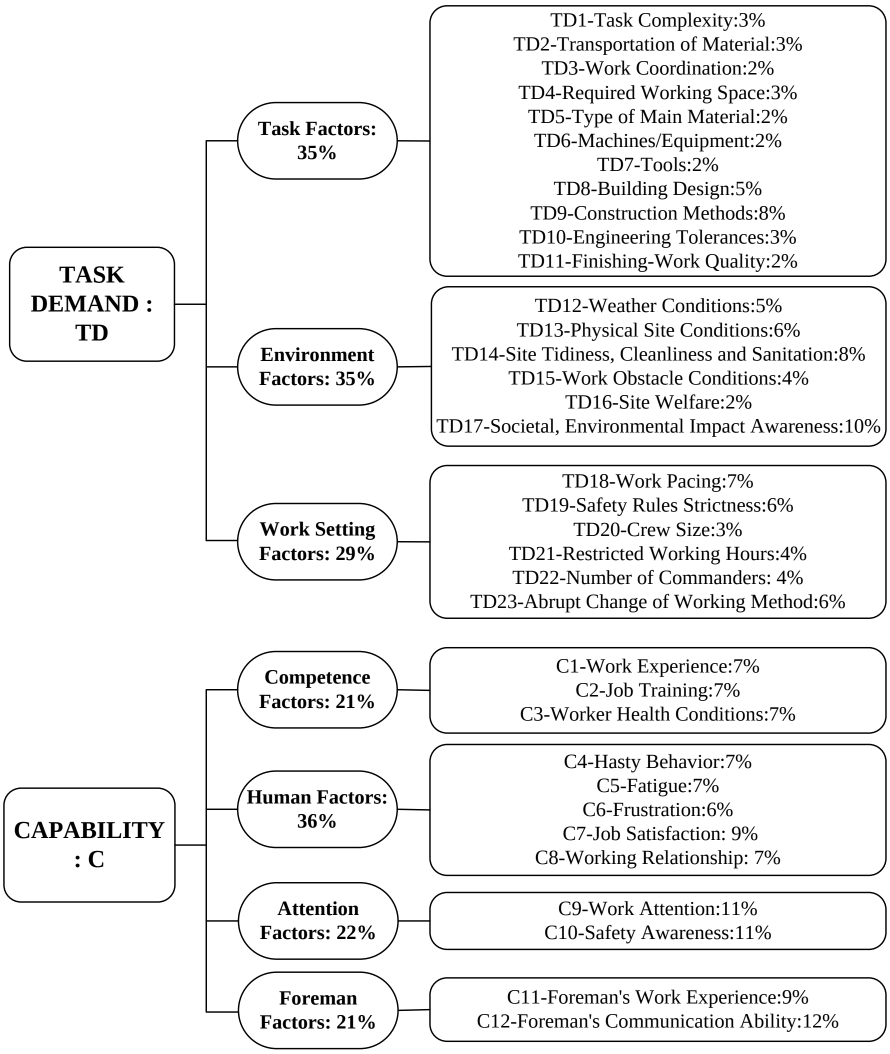

Figure 2. Attributes of task demand and capability and their relative weights

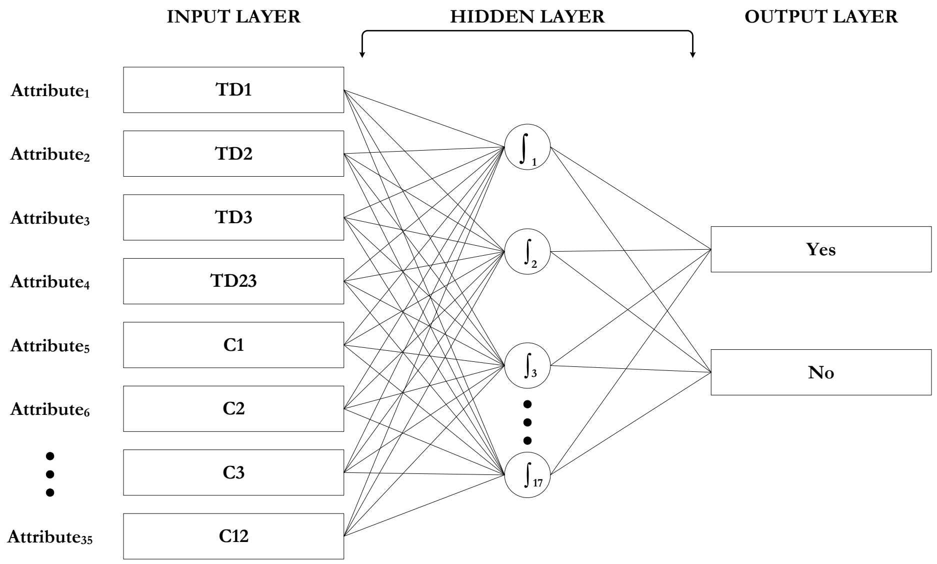

Figure 3. Example ANN model (35-17-2) structure used in this research.

5. Results

The results in Table 1 show the selected input variables from the first to the fourth step. The four significant variables were: C10-Safety Awareness, TD10-Engineering Tolerances, TD17-Societal and Environmental Impact Awareness, and C2-Job Training. At the first step, the input variable with the highest chi-square score (81.994) that meets the p value condition (significant at 5% level) was selected in the model. The Cox & Snell R^2 and Nagelkerke R^2 values in the first step indicated that the model accounted for 56.0%–74.6% of the variance. After adding three more input variables, the model in the fourth step attained 67.1%–89.5% of the variance, and had been significantly improved. When the entire process was over, the final LR model had four input variables. The final model had 96% accuracy in classifying the accident occurrence.

Table 2 displays the results of the estimated coefficients and related statistics of the binary LR model. By using the statistically significance level 5%, all four input variables could predict the probability of an accident. Given these coefficients, the LR model can be written as Equation (4):

$$Y = -4.377 - 72.144\, C_{10} + 80.461 TD_{10} + 41.487 TD_{17} + 27.366 C_2 \quad (4)$$

The results of the ANN models are tabulated in Table 3. Once the network had been trained, root mean square error (RMSE) was used to evaluate the performance of the developed model. All five networks achieved very good similar results, with 92% precision. The 35-17-2 network was selected for use.

After the models have been developed, model verification process is carried out to check for creditability and robustness.

The LR-based and ANN-based models were verified over 20 data records, including 10 accident cases and 10 no-accident cases. The results in Table 4 demonstrate that the developed model ANN model gave a wrong prediction only for 2 cases out of the 20. The two wrongly predicted cases were accident cases, but the model predicted them as no-accident ones. The LR-based model gave five wrong answers. Two of these five cases were predicted as no-accident cases instead of accident ones and the rest 3 cases were predicted as accident in place of no-accident. The results indicate that the ANN-based model had a better performance than the LR-based model, at 90% and 75% accuracies, respectively.

6. Conclusions

CWBM was proposed following principles of cognitive perspectives. The unsafe actions of frontline workforces are shaped by 23 TD- and 12 C- factors, and they lead to likelihood of accidents. The LR and ANN techniques were compared for prediction efficiencies, and the 35-17-2 ANN-based model achieved 90% precision and should thus be the preferred accident predictor of CWBM. Unlike the LR-based model that accounted for only four attributes, the ANN-based model incorporated the entire 35 candidate input attributes. This result is consistent with the findings of Goh and Sa'adon (2015), suggesting that the ANN approach should be highly recommended, especially for research dealing with construction workers' behaviors. Nonetheless, both modelling approaches were useful for understanding cognitive attributes of safety-related behaviors.

Utilizing CWBM, practitioners can forecast each individual accident of construction workers before starting their task. By assessing the 23 TD- and 12 C-attributes in 5-point rating scale through an assessment form, the model will indicate a prediction result that identifies the outlier workers who are not ready for their assigned task, and to avoid accidents they should be replaced with more suited workers instead. This research is expected to continue with a more in-depth study on cognitive attributes influencing construction workers' unsafe behaviors. Finally, this report provided the foundation for selecting non-linear modelling techniques in future research.

The limitations and future work are summarized as follows: (1) The data used in this research are from construction projects in Thailand only, and confined to high-rise building

Table 1. Stepwise logistic regression statistics

Step	Variable	Chi-sq.	df	Sig.[a]	-2 Log likelihood	Cox & Snell R^2	Nagelkerke R^2	Class %
1	IN: C10	81.994	1	.000	56.635	.560	.746	90.0
2	IN: TD10	95.496	2	.000	43.134	.615	.820	94.0
3	IN: TD17	104.364	3	.000	34.265	.648	.864	93.0
4	IN: C2	111.189	4	.000	27.441	.671	.895	96.0

[a] Statistically significant at 5% level

Table 2. Coefficients in the logistic regression fit

Variable	B	S.E.	Wald	df	Sig.[a]	Exp(B)
Constant	-4.377	4.432	.975	1	.323	.013
C10	-72.144	18.128	15.838	1	.000	.000
TD10	80.461	26.569	9.171	1	.002	8.79E+34
TD17	41.487	13.856	8.965	1	.003	1.04E+18
C2	27.336	12.159	5.054	1	.025	7.45E+11

[a] Statistically significant at 5% level

Table 3. Performance of ANN model in accident prediction

Network	Correctly classified instances	Incorrectly classified instances	Total number of instances	Precision		Root mean square error
				No	Yes	
35-16-2	92.00%	8.00%	100	0.889	0.957	0.2663
35-17-2	92.00%	8.00%	100	0.889	0.957	0.2657
35-18-2	92.00%	8.00%	100	0.889	0.957	0.2664
35-19-2	92.00%	8.00%	100	0.889	0.957	0.2671
35-20-2	92.00%	8.00%	100	0.889	0.957	0.2669

Table 4. Comparing the precision of LG and ANN techniques in 20 test cases, not used in training

Case No.	Actual	Predicted		Case No.	Actual	Predicted	
		LR[a]	ANN[b]			LR[a]	ANN[b]
1	Y	Y	Y	11	N	N	N
2	N	Y	N	12	N	N	N
3	N	N	N	13	Y	Y	Y
4	Y	Y	N	14	N	N	N
5	Y	Y	Y	15	N	Y	N
6	Y	Y	Y	16	N	Y	N
7	Y	Y	Y	17	Y	Y	Y
8	N	N	N	18	Y	N	Y
9	N	N	N	19	Y	Y	N
10	N	N	N	20	Y	N	Y

[a] Five cases were wrongly classified by LR, therefore 75% (15/20) of 20 cases correctly classified.
[b] Two cases were wrongly classified by ANN, therefore 90% (18/20) of 20 cases correctly classified.

projects. The findings may therefore be more applicable to projects in the countries that share similar contextual conditions. (2) The study applied convenience sampling to ensure that there were enough data for meaningful analyses. Although the data were generally representative of the high-rise construction worker population in Thailand, the sampling method remains a threat to internal and external validity. (3) This research collected only snapshot data of cases, and a questionnaire approach may not reflect the phenomena in a dynamic decision environment. The development of information and communications technology (ICT) provides an opportunity to track construction workers and get information on a real-time basis.

Acknowledgements

This research is funded by Nakhon Phanom University, Thailand.

References

Abdelhamid, T. S., & Everett, J. G. (2000). Identifying root causes of construction accidents. *Journal of Construction Engineering and Management*, *126*(1), 52-60.

Bureau of Labor Statistics. (2015). *Census of fatal occupational injuries* (*CFOI*) – *Current and Revised Data*. Retrieved from https://www.bls.gov/iif/oshwc/cfoi/cfch0014.pdf

Chiou, Y. C. (2006). An artificial neural network-based expert system for the appraisal of two-car crash accidents. *Accident Analysis and Prevention*, *38*(4), 777-785.

Dekker, S. (2014). *The field guide to understanding human error*. Santa Clara, CA: Ashgate Publishing.

Diekmann, J., Girard, M., & Abdul-Hadi, N. (1994). *DPI-disputes potential index*: *A study into the predictability of contract disputes Source documents-101*. University of Texas at Austin, Austin, TX: Construction Industry Institute Publication.

Fang, D., Zhao, C., & Zhang, M. (2016). A cognitive model of construction workers' unsafe behaviors. *Journal of Construction Engineering and Management*, *142*(9), 04016039.

Field, A. (2009). *Discovering statistics using SPSS*, Thousand Oaks, CA: Sage publications.

Fuller, R. (2005). Towards a general theory of driver behavior. *Accident Analysis and Prevention*, *37*(3), 461-472.

Goh, Y. M., & Chua, D. (2013). Neural network analysis of construction safety management systems: A case study in Singapore. *Construction Management and Economics*, *31*(5), 460-470.

Goh, Y. M., & Sa'adon, N. F. B. (2015). Cognitive factors influencing safety behavior at height: A multimethod exploratory study. *Journal of Construction Engineering and Management*, *141*(6), 04015003.

Haslam, R. A., Hide, S. A., Gibb, A. G. F., Gyi, D. E., Pavitt, T., Atkinson, S., & Duff, A. R. (2005). Contributing factors in construction accidents. *Applied Ergonomics*, *36*(4), 401-415.

Haykin, S. (1994). *Neural networks*: *A comprehensive foundation*. New York, NY: Macmillan College Publishing.

Health and Safety Executive. (2002). *Strategies to promote safe behavior as part of a health and safety management system* (Contract Research Report 430/2002). Retrieved from http://www.hse.gov.uk/research/crr_pdf/2002/crr02430.pdf

International Business Machines Corporation. (2012). *IBM SPSS statistics for windows* [Computer software]. New York, NY: Armonk.

International Labor Organization. (2005). *Facts on safety work*. Retrieved from http://www.ilo.org/wcmsp5/groups/public/dgreports/dcomm/documents/publication/wcms_067574.pdf

Kaila, H. L. (2011). Organizational cases on behavior-based safety (BBS) in India. *The International Journal of Human Resource Management*, *22*(10), 2135-2146.

Kleinbaum, D. G., Klein, M., & Pryor, E. (2002). *Logistic regression*: *A self-learning text*. New York, NY: Springer.

Le Coze, JC. (2015). Reflecting on Jens Rasmussen's legacy. A strong program for a hard problem. *Safety Science*, *71*(0), 123-141.

Machine Learning Group at the University of Waikato. (2016). *WEKA* [Computer software]. Hamilton, New Zealand: The University of Waikato.

Mitropoulos, P., Cupido, G., & Namboodiri, M. (2009). Cognitive approach to construction safety: Task demand-capability model. *Journal of Construction Engineering and Management*, *135*(9), 881-889.

Mohamed, S., Ali, T. H., & Tam, W. (2009). National culture and safe work behavior of construction workers in Pakistan. *Safety Science*, *47*(1), 29-35.

Ministry of Manpower. (2008) *Reports and statistics*. Retrieved from http://www.mom.gov.sg/Home/Pages/reports_and_statistics. aspx

Patel, D. A., & Jha, K. N. (2016). Evaluation of construction projects based on the safe work behavior of co-employees through a neural network model. *Safety Science*, *89*, 240-248.

Patel, D. A., & Jha, K. N. (2015). Neural network approach for safety climate prediction. *Journal of Management in Engineering*, *31*(6), 05014027.

Rasmussen, J. (1997). Risk management in a dynamic society: A modelling problem. *Safety Science*, *27*(2), 183-213.

Ross, L. T., Ross, T. P., Farber, S., Davidson, C., Trevino, M., & Hawkins, A. (2011). The theory of planned behavior and helmet use among college students. *American Journal of Health Behavior*, *35*(5), 581-590.

Rumelhart, D. E., Widrow, B., & Lehr, M. A. (1994). The basic ideas in neural networks. *Communications of the ACM*, *37*(3), 87-93.

Sniehotta, F. (2009). An experimental test of the theory of planned behavior. *Applied Psychology*: *Health and Well-Being*, *1*(2), 257-270.

Sooksil, N., & Benjaoran, V. (2017). The relative factors shaping construction workers' Behaviors and leading to accidents. *Engineering Journal*, *21*(5), 257-271.

Social Security Office. (2015). *Record of occupational injuries classified by severity and type of firm on year 2015*. Retrieved from http://www.sso.go.th/wpr/uploads/uploadImages/file/AnnualReportBook2558.pdf

Suraji, A., Duff, A. R., & Peckitt, S. J. (2001). Development of causal model of construction accident causation. *Journal of Construction Engineering and Management*, *127*(4), 337-344.

Tam, C. M., Leung, A. W. T., & Liu, D. K. (2002). Nonlinear models for predicting hoisting times of tower cranes. *Journal of Computing in Civil Engineering*, *16*(1), 76-81.

Toole, T. M. (2002). Construction site safety roles. *Journal of Construction Engineering and Management*, *128*(3), 203-210.

Wei, C.-H., & Lee, Y. (2007). Sequential forecast of incident duration using artificial neural network models. *Accident Analysis and Prevention*, *39*(5), 944-954.

Witten, I. H. (2011). *Data Mining*: *Practical machine learning tools and techniques*. Burlington, MA: Morgan Kaufmann.

Wong, C. H. (2004). Contractor performance prediction model for the United Kingdom construction contractor: Study of logistic regression approach. *Journal of Construction Engineering and Management*, *130*(5), 691-698.