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# Neural network analysis of construction safety management systems: a case study in Singapore

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A neural network analysis was conducted on a quantitative occupational safety and health management system (OSHMS) audit with accident data obtained from the Singapore construction industry. The analysis is meant to investigate, through a case study, how neural network methodology can be used to understand the relationship between OSHMS elements and safety performance, and identify the critical OSHMS elements that have significant influence on the occurrence and severity of accidents in Singapore. Based on the analysis, the model may be used to predict the severity of accidents with adequate accuracy. More importantly, it was identified that the three most significant OSHMS elements in the case study are: incident investigation and analysis, emergency preparedness, and group meetings. The findings imply that learning from incidents, having well-prepared consequence mitigation strategies and open communication can reduce the severity and likelihood of accidents on construction worksites in Singapore. It was also demonstrated that a neural network approach is feasible for analysing empirical OSHMS data to derive meaningful insights on how to improve safety performance.

*Keywords:* Accident, audit, management system, neural network, occupational safety.

## Introduction

Construction worksites are one of the most dangerous workplaces in the world. In 2008, the construction industry in Singapore had 6.9 fatalities per 100 000 persons employed as compared to 2.8 fatalities per 100 000 persons employed for all industries in the country (Ministry of Manpower, 2008). Similar statistics illustrating the poor safety performance of the industry can be observed in Taiwan (Cheng *et al.*, 2010), the UK (Meliá *et al.*, 2008), the US and Spain (Camino López *et al.*, 2008). Over the years, regulators, the architectural, engineering and construction (AEC) industry and companies have devised various approaches to improve the safety of construction worksites, of which one of the common interventions is the implementation of an occupational safety and health management system (OSHMS). An OSHMS is usually designed and implemented in accordance with standards such as CP79:1999 (Singapore Productivity and Standards Board, 1999) and International Labor Organization (ILO) guidelines on occupational safety and health management systems (International Labor Organization, 2001).

Although the OSHMS is ubiquitous, there is no clear consensus on its effectiveness. Fernandez-Muniz *et al.* (2009) showed that an OSHMS is beneficial to a company's overall performance. On the other hand, Gardner's (2000) research showed that the failure rate of quality management systems ranged between 67% and 93% and Robson *et al.* (2007) expected the failure rate of the OSHMS to be at least as high. Quinlan and Mayhew (2000) also expressed doubts about the effectiveness of the OSHMS due to the changing work context. Gunningham and Sinclair (2009) found that an OSHMS will only be effective if the formal system is supported by informal variables such as trust and commitment. It is interesting to note that Robson *et al.* (2007) concluded that there is insufficient evidence for them to make recommendations either in favour of or against the OSHMS. Nevertheless they identified five papers that suggested a level

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of correlation between selected elements of an OSH-MS and injury rates. The approach herein adopts a similar fundamental assumption that the OSHMS is a high level construct and that an examination of its effectiveness should be done at the element level.

Hallowell and Gambatese (2009) quantified the impact of different OSHMS elements on accident severity and frequency using the Delphi method. They calculated occupational safety and health (OSH) risk reduction based on the multiplication of expert-assigned frequency and severity of accidents. From their study, they found that the most critical elements are upper management support and commitment and strategic subcontractor selection and management and the least effective elements are recordkeeping and accident analyses and emergency response planning. However, their study adopted a linear approach in assessing the relationship between OSHMS elements and OSH risk and did not consider the possible interactions between different OSHMS elements. Furthermore, Hallowell and Gambatese (2009) made use of subjective expert data, which may be problematic due to the highly uncertain nature of frequency and severity of accidents. Fernandez-Muniz *et al.* (2007) modelled the complexity of the OSHMS construct using a hierarchical and multi-dimensional model. Nevertheless, as in most real-world systems, the interactions between OSHMS elements and safety performance are expected to be highly non-linear and complex (Samarasinghe, 2007).

The use of neural network analysis to better understand the non-linear relationship between OSHMS elements and safety performance is proposed. The relationship sought is between OSHMS elements defined in CP79:1999 (Singapore Productivity and Standards Board, 1999) and the safety performance of Singapore construction projects in terms of the occurrence and severity of accidents.

## OSHMS and audit

Standards Australia and Standards New Zealand (2001, p. 4) defines OSHMS as, 'That part of the overall management system which includes organizational structure, planning activities, responsibilities, practices, procedures, processes and resources for developing, implementing, achieving, reviewing and maintaining the OSH policy, and so managing the risks associated with the business of the organization.' In addition, the International Labor Organization (2001, p. 19) defines OSHMS as 'a set of interrelated or interacting elements to establish OSH policy and objectives, and to achieve those objectives'. As can be seen, an OSHMS has a range of distinguishable elements and these elements, through their interactions, are designed to reduce OSH risks.

Unlike most OSHMS standards, CP79:1999 (Singapore Productivity and Standards Board, 1999) is written specifically for the construction industry in Singapore. Since 1994 construction worksites in Singapore with a contract sum of SG$30 million or more are legally required to implement an OSHMS. The OSHMS has to be audited by approved independent auditors based on CP79:1999 once every six months. The 14 elements of the CP79:1999 are summarized in Table 1. The focus of the analysis was on occupational accidents so that element 14, 'Occupational health programme', was not included.

Toohey *et al.* (2005) define an OSHMS audit as a regular check on the OSHMS to determine its compliance with relevant standards and legislation. For the OSHMS audit to be thorough and useful, it has to be carefully planned and structured (Waring, 1996). Accordingly a wide range of quantitative and qualitative safety auditing protocols has been developed to ensure systematic and consistent auditing. These audit protocols are frequently quantitative, generating significant empirical data for OSH research.

## Neural network

### *Overview*

A neural network is an information-processing paradigm inspired by the way the densely interconnected, parallel structure of the human brain processes information (Samarasinghe, 2007). A neural network is a collection of mathematical models that imitate some of the observed properties of biological nervous systems and draw on the analogies of adaptive biological learning. While the basic concept of a neural network is relatively straightforward, a neural network is capable of solving a wide spectrum of real-world problems in a wide range of fields including plant ecosystems, disease diagnosis, land use modelling, forecasting of inflows into rivers and lakes (Samarasinghe, 2007) and traffic analysis (Chiou, 2006; Pande and Abdel-Aty, 2006; Wei and Lee, 2007; Mohammadipour and Alavi, 2009).

The neural network approach has also been successfully applied in different aspects of the construction industry (e.g. Chua *et al.*, 1997; Cheng *et al.*, 2009; Jha and Chockalingam, 2011). However, there is insufficient interest in the application of neural network and other soft computing techniques in the analysis of OSH issues (Ciarapica and Giacchetta, 2009). Even though Ciarapica and Giacchetta (2009) used a neural network to analyse occupational injury data, their work did not study the relationship between OSHMS and safety performance in the construction industry. Thus the neural network

**Table 1** Elements of CP79:1999

| No. | Elements of CP79:1999 |
|---|---|
| 1 | Safety policy |
| 2 | Safe work practices |
| 3 | Safety training |
| 4 | Group meetings |
| 5 | Incident investigation and analysis |
| 6 | In-house safety rules and regulations |
| 7 | Safety promotion |
| 8 | Evaluation, selection and control of subcontractors |
| 9 | Safety inspections |
| 10 | Maintenance regime for all machinery and equipment |
| 11 | Hazard analysis |
| 12 | The control of movement and use of hazardous substances and chemicals |
| 13 | Emergency preparedness |
| 14 | Occupational health programme |

Source: Singapore Productivity and Standards Board, 1999.

approach has been adopted in the present study to determine the relationship between the OSHMS elements and the occurrence and severity of construction accidents.

*Learning and sensitivity analysis*

The neural network approach adopted utilizes the back-propagation learning strategy, which is a very commonly applied approach (e.g. Chua *et al.*, 1997; Chang, 2005; Delen *et al.*, 2006). The back-propagation learning strategy is a type of supervised learning strategy, where each learning cycle (also known as an epoch) involves a forward pass where an example is presented as an input to the network. The neural network produces an output that is compared with the target or actual output that came with the example. The error, as defined by the difference between output and target, facilitates a backward pass through the network to adjust the weights of the connections between neurons to minimize the error. Each set of forward and backward passes is a training cycle or epoch. The back-propagation strategy is a kind of gradient descent technique (Samarasinghe, 2007), where the adjustments of interconnection weights are dependent on the error gradient of each weight. As a whole the network is adjusted in the direction of the steepest descent on the error surface. The training examples are presented to the network until the output error is minimized or below a specified acceptable limit. In this way, the neural network would then be expected to have learned the non-linear patterns within the examples and can be used to produce predicted outcomes based on new inputs. In addition, a sensitivity analysis (Delen *et al.*, 2006) can be conducted to determine the importance of different inputs in relation to the output. This is done by dithering the inputs one at a time (e.g. increase the input by 5%) to determine the percentage change in the output. Accordingly, the input variables that result in significant changes in the output can be identified.

## Materials and methods

### Data sources

One of the key data sources is the quantitative audit data of an OSHMS audit firm specializing in the Singapore construction industry. The company is one of the largest OSHMS audit firms in Singapore with a sizable audit database. The company developed its audit protocol in the 1990s and has progressively improved the protocol over the years. The protocol has a hierarchical structure modelled after the elements in CP79:1999 (see Table 1). Each element is broken down into sub-elements and selected sub-elements are split into lower level elements. As the tool is proprietary, the details of the protocol cannot be discussed herein. The scoring system and the corresponding weights were carefully designed and adjusted over the years by the company, which has safety auditors with more than 20 years of experience in the industry. The auditors usually work in pairs and were frequently rotated to ensure consistency in the audits. As indicated earlier, element 14 of CP79:1999, 'Occupational health programme' (hearing conservation programme and respiration protection programme), was not included in the analysis because it does not relate directly to accidents. The audit scores of the other 13 elements were used as inputs for the neural network analysis.

The audit data were matched with accident cases obtained from the Ministry of Manpower (MOM) and Land Transport Authority (LTA). The accident cases are categorized based on severity of the injury:

(1) an A case involves a temporary disablement injury with more than three days' medical leave or more than 24 hours of hospitalization;
(2) a B case involves a permanent disablement injury where the injured is unable to undertake any type of work or it results in a reduction of earning capacity; and
(3) a C case involves at least one fatality.

The classification of injury severity is based on the classification used by the Ministry of Manpower and it is widely adopted in the industry. It is important for the classification to be aligned with industry norm to enable the findings of the study to be readily understood and adopted.

The rules for the matching of audit data and accident cases are illustrated in the hypothetical timescale of Figure 1. As discussed earlier, in Singapore a site that has contract sum of SG$30 million and above is required to be audited every six months. Thus if an accident, say Accident X in Figure 1, occurs within the two-month period after an audit, Audit 1, the audit score of Audit 1 is deemed to be reflective of the quality of the OSHMS that contributed to the occurrence and severity of Accident X. Similarly, Accident Z in Figure 1 is matched to Audit 2 because it occurred within the two-month period before the audit. In the case of Accident Y, which occurs in between Audit 1 and Audit 2 (i.e. three to four months after Audit 1 and three to four months before Audit 2), the average score of Audit 1 and Audit 2 was used. In addition, audits that did not have any accident occurring within the four months before and after the audit are classified as 'no accident' audits. The above classification rules are based on the assumption that OSHMS models in medium to large projects are relatively stable and the audit score is representative of the status of the OSHMS in the short run. The assumption is generally valid because most medium to large sites have tight resource and time constraints such that there are no significant changes in the short run.

To ensure that the neural network is not trained in favour of any possible output categories, the study had to ensure that there were uniform numbers of examples across the four output categories (Hashemi *et al.*, 1995): no accident, A case, B case and C case. Since B cases had the lowest frequency at 40, a total of 160 examples were randomly selected to ensure that there were 40 examples within each output category. To facilitate the neural network analysis, three intermediate output categories: between B and C, between A and B, and between no accident and A were included. The intermediate classifications were created to allow better assessment of accuracy of classification. As the neural network is trained to predict the accident severity as a continuous variable, the classification thresholds were determined for each accident severity category (see Table 2) by distributing an equal range for each category. Furthermore, a class value is determined based on the average of the range for each category. The error in prediction is determined from the difference between actual and predicted class values. For illustration, if a set of inputs (OSHMS element scores) yields a predicted output (accident severity) of 0.45, the output would be classified as an accident with severity between 'A' and 'B' (refer to Table 2). Note that the accident severity categories used in this study are similar to the output categories used by Delen *et al.* (2006).

## Methods

*Initial model configuration*

Typical back-propagation networks have an input layer, an output layer and at least one hidden layer. In this study the initial neural network has 13 neurons in the input layer corresponding to the 13 CP79:1999 elements (elements 1 to 13 of Table 1) being analysed. The output layer consists of one neuron, representing accident severity, i.e. non-occurrence or severity of accident. There is no clear guideline on the best approach to determine the number of hidden layers and the number of neurons in each hidden layer (Flood and Kartam, 1994). Studies have shown that natural selection techniques such as genetic algorithms are potentially effective approaches to select optimal network configuration (Arena *et al.*, 1992; Blanco *et al.*, 2000). However, most researchers (e.g. Chua *et al.*, 1997; Onken and Feraric, 1997; Delen *et al.*, 2006) had adopted a trial-and-error approach to determine the 'optimal' configuration (or

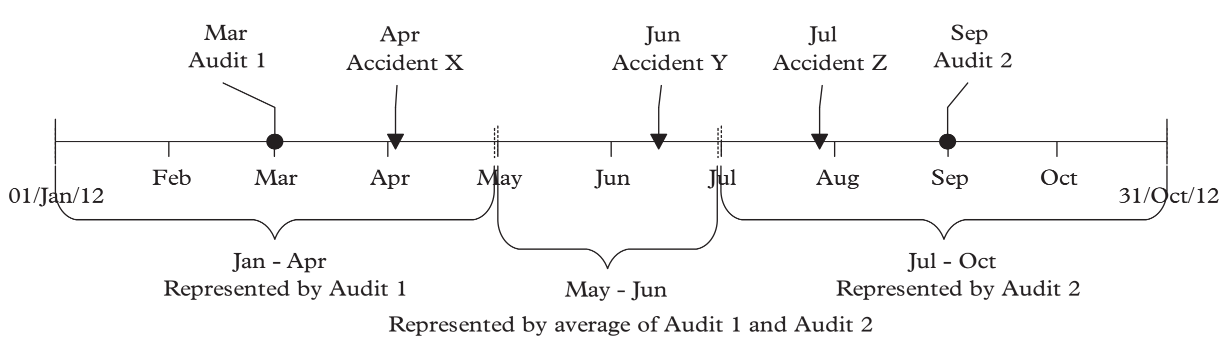


**Figure 1** Selection of representative audit score for accident case (hypothetical timescale)

**Table 2** Classification of accident severity

| Accident severity | Class value | Classification threshold for predicted performance (X) |
|---|---|---|
| Fatal (C cases) | 0.07 | $0.00 \leqslant X < 0.14$ |
| Between 'B' and 'C' | 0.21 | $0.14 \leqslant X < 0.29$ |
| Permanent disablement (B cases) | 0.36 | $0.29 \leqslant X < 0.43$ |
| Between 'A' and 'B' | 0.50 | $0.43 \leqslant X < 0.57$ |
| Temporary disablement (A cases) | 0.64 | $0.57 \leqslant X < 0.71$ |
| Between 'no accident' and 'A' | 0.79 | $0.71 \leqslant X < 0.86$ |
| No accident | 0.93 | $0.86 \leqslant X \leqslant 1.00$ |

'sub-optimal' as suggested by Delen *et al.* (2006) because not all possible combinations are evaluated). The trial-and-error process is typically guided by the root mean square (RMS) error of the network output, $\varepsilon$, defined in Equation 1 below:

$$\varepsilon = \sqrt{\frac{1}{n}\sum(D_i - P_i)^2} \tag{1}$$

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.

Another key variable in the network configuration is the type of activation function embedded in the neurons. Sigmoid functions, for example the hyperbolic and logistic functions, are frequently used as activation functions. Similar to the number of neurons, there is no standard rule for selecting the activation function for each neuron. In addition, input values should be scaled into a suitable range using a scaling function to ensure efficient computation (Ward Systems Group, 2008). Most networks scale input values into the range of 0 to 1 or –1 to +1 using linear, sine, hyperbolic and logistic functions, for example.

Initial experiments were conducted to decide on the basic configuration of the model. The trials used the leave-one-out cross-validation technique (Fu, 1994) which is illustrated in Table 3. Unlike the traditional approach of fixing the training set and testing set arbitrarily, in the leave-one-out cross-validation technique, the training process for each model was repeated $n$ times for $n$ number of datasets; each training cycle uses one dataset for testing and the rest for training. The leave-one-out technique has the advantage of reducing possible bias in the artificial selection of training and testing sets, and is especially useful for small datasets (Fu, 1994; Dong and Wang, 2010). The average RMS error of the 10 experiments is then used to guide the suitability of the network configuration.

The usual two hidden layers configuration (Flood and Kartam, 1994; Chua *et al.*, 1997) were used in the model. The numbers of neurons in the hidden layers are bounded by the number of neurons in the input and output layers (13 and one) and minimized to reduce the rigidity of the network and ensure that accurate output can be generated for unseen data inputs (Chua *et al.*, 1997). Experiments were conducted using the software NeuroShell 2 (Ward Systems Group, 2008) to identify the best configuration with the lowest average RMS error. As a result, four neurons were placed in the first hidden layer and another two were placed in the second hidden layer. The logistic function was used as the scaling function and as the activation function for the neurons in the input layer. In addition, the hyperbolic function was used as the activation function in the neurons of the hidden and output layers. All models in the experiments were back-propagation networks using generalized delta rule.

*Sensitivity analysis and model modification*

Using the initial model as a starting point, sensitivity analyses were conducted to identify significant OSHMS elements influencing the occurrence and severity of accidents. The set of input OSHMS elements were then amended progressively based on the results of the sensitivity analysis. At each stage the model was further validated using the leave-one-out cross-validation technique. The output scales were defined such that a higher value indicates lower accident severity (see Table 2). Thus, when the input value of an important OSHMS element was increased by 5%, the corresponding output value should increase by more than 5%.

The results of the sensitivity analysis of the initial model are summarized in Table 4. As can be observed, four of the elements produced negative changes in the output. This anomaly will be discussed subsequently. The element with the lowest percentage change was then eliminated from the

**Table 3** Leave-one-out cross-validation technique

| Experimental cycle number | Training example | Testing example |
|---|---|---|
| 1 | Dataset 2, 3, 4, 5, 6, …, n | Dataset 1 |
| 2 | Dataset 1, 3, 4, 5, 6, …, n | Dataset 2 |
| 3 | Dataset 1, 2, 4, 5, 6, …, n | Dataset 3 |
| . | . | . |
| . | . | . |
| . | . | . |
| *n* | Dataset 1, 2, 3, 4, 5, …, n-1 | Dataset *n* |

**Table 4** Changes in accident severity (output) caused by +5% change in input values of initial model

| No. | OSHMS element | % Change in output due to +5% change in input |
|---|---|---|
| 4 | Group meetings | 62 |
| 5 | Incident investigation and analysis | 49.49 |
| 10 | Maintenance regime for all machinery and equipment | 48.69 |
| 1 | Safety policy | 35.25 |
| 11 | Hazard analysis | 18.98 |
| 8 | Evaluation, selection and control of subcontractors | 11.97 |
| 2 | Safe work practices | 8.24 |
| 13 | Emergency preparedness | 7.4 |
| 12 | The control of movement and use of hazardous substances and chemicals | 4.06 |
| 7 | Safety promotion | –4.68 |
| 9 | Safety inspections | –10.25 |
| 6 | In-house safety rules and regulations | –44.42 |
| 3 | Safety training | –63.15 |

model and the leave-one-out cross-validation technique was conducted on the new model. The sensitivity analysis, model amendment and cross-validation process were then repeated until all OSHMS elements that produced negative changes in the output were eliminated. The final set of input OSHMS elements is shown in Table 5. The final model only consists of OSHMS elements that produced at least +10% change in the output. The final model configuration produced an average RMS error of 0.29 (maximum average RMS error = 0.57 and minimum average RMS error = 0.003) when tested using the test set.

## Results

The prediction performance results of the final neural network model are summarized in Tables 6 and 7. The results show that as a whole the prediction performance of the neural network model is reasonably accurate. Table 6 shows that for the training set, out of 72 serious accident examples only three examples (4%) were misclassified, i.e. the network has prediction accuracy of about 96% for serious accidents. For no or minor accident examples, the network has prediction accuracy of about 89%. For the prediction of specific output categories, 78% of C case examples, 83% of B case examples, 100% of A case examples and 69% of no accident examples are predicted within one degree of deviation from the expected category, i.e. error tolerance of one category away from the expected category (see cells with bold font in Table 6).

For the test set (Table 7), with the exception of the no accident category, the model prediction for specific categories is 75% accurate for an allowance of one degree of deviation from the expected category. In the case of no accident output category, the model is 50% accurate (one degree of deviation from

**Table 5** Input OSHMS elements of final model and respective percentage change in accident severity (output)

| No. | OSHMS element | % Change in output given +5% change in input |
|---|---|---|
| 5 | Incident investigation and analysis | 73.39 |
| 13 | Emergency preparedness | 63.35 |
| 4 | Group meetings | 62 |
| 11 | Hazard analysis | 29.52 |
| 1 | Safety policy | 27.23 |
| 2 | Safe work practices | 18.24 |
| 12 | The control of movement and use of hazardous substances and chemicals | 18.2 |
| 10 | Maintenance regime for all machinery and equipment | 14.89 |
| 8 | Evaluation, selection and control of subcontractors | 11.97 |

**Table 6** Prediction performance—training set

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Predicted output | No or minor accident | No accident (NA) | | | | | | | **12 (33%)** |
| | | Between NA & A | | | 1 (3%) | | **3 (8%)** | | **13 (36%)** |
| | | A case | 1 (3%) | | 1 (3%) | | **28 (78%)** | | *8 (22%)* |
| | Serious accident | Between A & B | 1 (3%) | | **8 (22%)** | | **5 (14%)** | | 3 (8%) |
| | | B case | *6 (17%)* | | **6 (17%)** | | | | |
| | | Between B & C | **22 (61%)** | | **16 (44%)** | | | | |
| | | C case | **6 (17%)** | | *4 (11%)* | | | | |
| | | | C case | Between B & C | B case | Between A & B | A case | Between NA & A | No accident (NA) |
| | | | Serious accident | | | | No or minor accident | | |
| | | | Expected output | | | | | | |

*Note*: Percentages in parentheses are the percentages of examples of the relevant output category (rounded off to nearest %).

the expected category). At a broad level, the network has a prediction accuracy of 100% for serious accidents and 87.5% for no or minor accident examples. The prediction performance of the model for both the training set and test set is comparable to the results of Chua *et al.* (1997) and Dikmen and Birgonul (2004).

## Discussion

### Critical OSHMS elements

As expected, most of the OSHMS elements are able to generate significant improvement in accident severity of a project. Based on the results of the final neural network model (Table 5), improvement in incident investigation and analysis (element 5), emergency preparedness (element 13) and group meetings (element 4) have the biggest positive impact on accident occurrence and severity. Within CP79:1999 (Singapore Productivity and Standards Board, 1999), the element incident investigation and analysis places strong emphasis on the determination of OSHMS root causes of incidents (including near misses) and implementation of measures to prevent recurrence. This is in line with OSH literature (e.g. Kletz, 2002; Chua and Goh, 2004) that emphasizes the importance of learning from incidents. Furthermore, CP79:1999 requires detailed analysis of incident

**Table 7** Prediction performance—test set

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Predicted output | No or minor accident | No accident (NA) | | | | | *1 (25%)* | | **1 (25%)** |
| | | Between NA & A | | | | | **3 (75%)** | | **1 (25%)** |
| | | A case | | | | | | | *1 (25%)* |
| | Serious accident | Between A & B | | | **1 (25%)** | | | | *1 (25%)* |
| | | B case | *1 (25%)* | | **0 (0%)** | | | | |
| | | Between B & C | **1 (25%)** | | **2 (50%)** | | | | |
| | | C case | **2 (50%)** | | *1 (25%)* | | | | |
| | | | C case | Between B & C | B case | Between A & B | A case | Between NA & A | No accident (NA) |
| | | | Serious accident | | | | No or minor accident | | |
| | | | Expected output | | | | | | |

*Note*: Percentages in parentheses are the percentages of examples of the relevant output category (rounded off to nearest %).

statistics for sites with sufficient size and duration, but contractors in Singapore typically do not record non-injury incidents due to the transient nature of construction projects, the lack of resources and tight deadlines. Hence, sites having a high score in the element of incident investigation and analysis are probably companies with greater OSH commitment and hence stronger OSH resourcing. This postulation appears to be supported by the observation that projects with higher scores in incident investigation and analysis are usually of bigger contract sum or have government clients that tend to place more emphasis on OSH. Generally, projects with greater OSH commitment are less likely to have accidents and even if they have accidents they should be of lower severity. OSH commitment is thus a possible confounding factor that the critical OSHMS elements are associated with.

Based on CP79:1999, emergency preparedness includes having systematic plans and resources to deal with a range of emergency situations, and frequent emergency drills and first aid programmes to mitigate the severity of accidents. It is not surprising therefore, that improvement in emergency preparedness can lead to a significant decrease in accident severity.

The group meetings element in CP79:1999 refers to safety committee meetings, tool box meetings, safety briefings and coordination meetings. These meetings constitute the key forums for OSH communications that formally address OSH issues and decide on appropriate actions. In accordance with CP79:1999, the group meetings, particularly the safety committee meetings, are to be attended by different trades and subcontractors to facilitate participation and open communication. The identification of group meetings being a critical OSHMS element is in line with recent studies that have shown that safety culture, including OSH management, is influenced by trust (Conchie *et al.*, 2006) and trust, in turn, is influenced by communication (Conchie and Burns, 2008). It was also shown that high safety performance teams have frequent safety communications from top management, and the use of multiple modes of safety communication improves safety performance (Alsamadani *et al.*, 2012). Thus improvement in safety communication, safety culture and OSH management is expected to lead to lower likelihood and severity of accidents.

Based on the study by Hallowell and Gambatese (2009) the most effective OSHMS elements are upper management support and commitment and strategic subcontractor selection and management, and the least effective elements are recordkeeping and accident analyses and emergency response planning. The differences in findings may be due to the differences in definition of OSHMS elements. For instance, Gambatese and Hallowell (2009) grouped recordkeeping and accident analyses as one single element. The recordkeeping portion may have significantly lowered the importance of the combined element. Furthermore, upper management support and commitment may have underlying confounding factors that are very similar to those of group meetings in CP79:1999. It should also be noted that Gambatese and Hallowell (2009) relied primarily on subjective data while this study utilized objective sources.

### Negative changes in output

The analysis identified that improvement in safety promotion (element 7), safety training (element 3), safety inspections (element 9) and safety rules and regulations (element 6) are associated with negative changes in accident severity (Table 4). It is possible that the OSH elements, despite having a positive causal relationship with the network output, are simultaneously related to unidentified confounding factors that are negatively related to the network output. One such possible confounding factor is worker empowerment (as opposed to tight management control). Lund (2004) argued that top down control of workers degrades work sustainability including OSH because management devised controls may not be effective due to the dynamic nature of the work environment. This view is supported by Daltuva *et al.* (2009) who emphasized the importance of worker participation in OSH. Hence top down controls such as safety inspections and safety rules and regulations can potentially result in reduced worker empowerment and hence poorer safety performance. In the context of Singapore, most safety promotion and safety training controls in the construction industry were focused on mandatory requirements that workers are expected to follow. Contractors frequently send their workers for safety training only if they are required by law and the demand for effective training is relatively low. It is noted that the problem of ineffective mandatory safety training is also observed in the US (Wilkins, 2011). Therefore, over-focus on rules and regulations in training and promotion is likely to enhance the perception that the employers are only interested in legislative requirements and the effectiveness of these interventions will be negated by the reduction in worker empowerment.

## Conclusions and further research

An occupational safety and health management system (OSHMS) is a common safety intervention in the construction industry. However there have been debates about its effectiveness in improving the safety performance of construction worksites. The most likely case is that certain elements of an OSHMS are more critical than other elements. At the same time the relationship between OSHMS elements and safety performance is most likely non-linear. In this case, application of soft computing techniques such as artificial neural network is suitable for the nature of the problem. The predictive accuracy of the model suggests that a neural network approach, as a research method, can be used to understand the relationship between OSHMS elements and safety performance. At the same time critical OSHMS elements that have significant influence on the occurrence and severity of accidents in Singapore have been identified. Thus, a neural network approach is feasible for analysing the relationship between OSHMS elements and safety performance, and the present methodology can be adapted by future researchers to suit their research question. Based on the study, the three most significant OSHMS elements of CP79:1999 that influence the occurrence and severity of accidents in Singapore construction projects are: incident investigation and analysis, emergency preparedness, and group meetings. The analysis shows that learning from incidents, well-prepared consequence mitigation strategies and open communication can reduce the severity and likelihood of accidents on Singapore construction worksites.

Owing to the complex interactions between the elements of an OSHMS and the possible influence of project characteristics, the study should be deemed as exploratory in nature. In addition, the data used in this study are from Singapore and constrained to large government projects. Thus the findings will be more applicable to countries and projects of a similar profile. Nevertheless it is interesting to note that the finding in this study contrasted with earlier findings by Hallowell and Gambatese (2009). The study by Hallowell and Gambatese (2009) highlighted upper management commitment and subcontractor management as the most effective OSHMS elements with recordkeeping and accident analyses and emergency response planning as the least effective elements. The variation may be due to differences in classification of OSHMS elements, research method and data sources. Future research is encouraged to investigate the differences further so as to derive stronger theoretical background for implementation of an OSHMS in different types of project and environment.

The study has also provided a rich foundation for further research in numerous areas. The neural network output of this study is based on the occurrence and severity of an accident, which is an important determinant of safety performance. Other important safety outcomes that can be studied are the frequency of OSH incidents and risk (frequency $\times$ severity). OSH risk provides a more holistic picture of safety performance and a neural network model that predicts OSH risk provides a leading indicator (Harrington *et al.*, 2009) to facilitate proactive improvements. In addition, as recommended by Ciarapica and Giacchetta (2009) a wide range of soft computing tools should be applied in the OSH context to facilitate knowledge discovery. Some promising tools include case-based reasoning (Goh and Chua, 2009, 2010), fuzzy logic (Mure and Demichela, 2009) and Bayesian network (Martin *et al.*, 2009). Further research should explore the different tools in a range of OSH issues and assess the corresponding advantages and disadvantages. As indicated earlier, lack of worker empowerment and tight management control may negate the positive influence of OSH management system elements. The study by Sherratt *et al.* (2012) has shed some light on the interaction between engagement and enforcement, but as suggested by Sherratt *et al.* (2012), this is an area that requires detailed examination in future studies. Similarly, the findings of this study can also be used to develop propositions for further research on the impact of safety communication and top management commitment on the effectiveness of the OSHMS.

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