Comparison of Modelling Tools in Assessing Safety Performance of Construction Site

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Abstract. Safety performance is the key factor in construction sites as it figures out the unsafe act, condition and supervision of the worksite. Three different modelling tools such as Artificial Neural Network (ANN), Genetic Programming (GP) and Multi-linear Regression (MLR) are used to assess the performance of the site. Furthermore, the performance of these models is also analysed with respect to various conditions to assess its suitability. Results indicates that all the three models can be used to predict the safety performance but GP based models have higher flexibility in extrapolating the results outside the training range with highest accuracy. Thus, it is recommended to employ GP based models in predicting safety performance in construction sites.

Keywords: Construction, Safety, Artificial Neural Network, Genetic Programming

1. Introduction

Despite automations in construction activities, the demand for skilled construction workers continues to increase. The successful completion of any project depends not only on timely/cost effective manner but also on the minimal or no site safety related accidents, the responsibility for which depends on the contractors/builders. It is required to analyze the performance of each construction site with respect to its preparation towards ensuring such safety and evolve methods and means to actually improve the site safety. From the selection of appropriate parameters which determine the site safety to analyzing such data is a challenging task. Most of such data are obtained only in the form of questionnaire survey and it is difficult to extract scientifically meaningful inferences from that. There are lot of recordable and non-recordable injuries /accidents in construction sites and hence safety has a significant role. So, the safety performance of each construction site should be assessed to compare safety aspects with other construction sites [1]. When the safety performance of each construction sites is addressed, then the builders/owners will take suitable steps to mitigate the accidents through
assigning competent safety engineers/supervisors as well as the performance of the workers can be improved.

The conventional method which is used to identify safety performance is TR safety index. It consists of questions according to the safety standards which are in the form of a checklist. The assessors will perform a walk around audit and respond to the checklist. From the data safety performance is calculated using equation 1 [2, 3].

\[
TR = \frac{\text{No. of agreement}}{\text{No. of agreement} + \text{No. of disagreement}} \times 100
\]  

(1)

The checklist consists of unsafe conditions and in some cases the previously occurred accidents in the particular site. A workplace cannot be certified as safe until the workplace holds competent workers, engineers, supervisors and availability of Personal Protective Equipment’s (PPE). So, this research made an attempt to determine the safety performance using seven parameters such as frequency of tool box talk, safety supervision, safety training, availability of PPE, its usage, type of accidents that occurred and competent of the workers. The relative severity of the parameters in the site safety, if ascertained, will help the site engineers/supervisors to take appropriate decisions to ensure better safety. This can be done by appropriately modelling of the inputs and output governing the site safety. Modelling has not received much attention so far in the construction safety studies. Over the last couple of decades, many data driven methods have found their application in diverse fields of engineering. How suitable these models are in arriving at meaningful inference from data generated through questionnaire survey is important to be explored. Unlike the regular or natural processes, the construction management related studies have to rely on questionnaire surveys which comes with the obvious problem of inability of such data to represent clearly the underlying process being studied. This is the actual challenge associated with the modelling of these data.

Conventionally, the Relative Importance Index (RII) is used to rank the data. For instance, RII is used in different applications such as causes and effects [4, 5] of construction delays, ranking the key quality factors in construction sites [6], assessment of construction safety factors [7] and so on. However, arriving at decisions on construction safety only with ranking approach is not fully complete. For a complete picture, modelling of the inputs and outputs have to be carried out which gives a better insight into the whole phenomena. Since, different modelling techniques different in their characteristics, it is necessary to evaluate different models. Towards this end, this study adopts some of the machine learning modelling tools such as Artificial Neural Network (ANN) and Genetic Programming (GP) to predict safety performance of the site, besides using the conventional methods like Multilinear Regression (MLR). The suitability of these models is also analysed and recommendations are given.

ANN has been used in diverse applications in construction management related problems such as to predict labour productivity [8], construction workers near miss falls [9], workplace injuries, safety climate and behaviours [10], site overhead cost [11] and so on. It is demonstrated that ANN has a potential and is a promising tool in construction site management. Unlike ANN, GP has not received much attention in the studies related to construction site. A few works are reported on GP applications in predicting the settlement of shallow foundation [12], compressive strength of concrete [13], pollutant removal from bioreactor [14], prediction of algal blooms [15] and so on. GP differs from the conventional multi-linear or non-linear models in the sense that GP offers a flexible form of the model unlike the conventional models where the form of the models is pre-fixed.

The remaining part of the manuscript is organized as follows. The next part deals with the overall methodology of the study followed by the case study description. Results obtained from the modelling tools are then discussed and finally conclusions are drawn.
2. Modelling Tools

2.1 Multilinear Regression
MLR is a statistical tool which is used to model the relationship between the dependent variable and one or more independent variables. The output of this model is in the form of an equation which is derived using non-linear predictor functions. These models can be used prediction and forecasting [16]. In this research the non-linear regression model is developed using Minitab software to determine the safety performance of a construction site using seven input variables. The validity of the model is determined by the number of matches with the actual output.

2.2 Artificial Neural Network
ANN is a type of soft computing tool which follows the basic principle of the human brain and falls under the category of supervised learning. ANN consists of three layers such as input layers, hidden layers and the output layers which are also called as neurons. Each neuron are interconnected with each other which form a network architecture. In order to get an ANN model, the data are trained, tested and then validated with the existing output. Usually a three-layer feed forward network is found to be suitable for civil engineering problems. To measure the performance of the identified model a set of output values has to be known. It can be measured using mean squared error, absolute error, percentage error, mean absolute percentage error, correlation coefficient and so on [17]. In this research ANN models are identified using Neuroshell software and performance of the model is measured using the number of matches between the existing output and the predicted values.

2.3 Genetic Programming
GP adopts the principle of Darwinian theory of survival of the fittest. GP forms an algorithm by using several parameters such as crossover, mutation, multiple regression and fitness function to solve a problem. The set of functions which is used in GP are addition, subtraction, multiplication, division, arithmetic, logical, trigonometric, conditional and comparison. The most commonly used primitive functions are arithmetic and mathematical functions. The outputs of the GP models are in the form of an equation through which the desired solution can be obtained [18]. In this research GP models are identified using Discipulus software and performance of the identified equations is measured using the number of matches with the actual output.

3. Case Study

This research considered building construction sites in southern part of India which follows all the rules and regulations as mentioned in Indian standard code of practice. A questionnaire survey is conducted for about one week with 116 workers in a construction site to determine the safety performance of the particular site. The first part of the questionnaire consists of basic details of the workers such as name, age and experience whereas the second part consists about the frequency of tool box talk, safety supervision, safety training and availability and use of PPEs. Other details such as type of accidents that occurred in the particular site and competency of the worker have been extracted from the particular site data book. In addition to this, two safety engineers and project manager are also consulted to discuss about the parameters that involved in the questionnaire survey which is sufficient to determine the safety performance.

4. Results and Discussion

4.1 Data pre-processing
The level of agreement which is extracted from the questionnaire survey is scaled into three levels such as low ‘1’ to high ‘3’ as shown in Table 1. This is done to eliminate the dominations among the variable and make the calculations simple. Tool box talk is a primary parameter that is to be
considered for the safety of the workers in which the safety engineers/supervisors will explain about the safe operating procedures of the work so as to enable the workers to get a clear picture of the task before they start. For instance, if the workers receive tool box talk rarely from safety engineers/supervisors, it is classified as low and accordingly.

Similarly, regular safety supervision, safety training and availability of PPE have significant roles in construction sites. Safety supervision may help to reduce accidents that can occur in the site which can favor the welfare of the workers. Safety training may give certain ideas about the accidents, its consequences and mitigations measures of construction hazards. In case of any damage that occurred to the PPE, it should be replaced and the worker should not use the damaged PPE. So, in order to ensure the PPE availability in the site, proper inspection has to be done. The severity of the hazards can be reduced if the worker uses proper PPE. Thus, safety supervision, safety training, PPE availability and usage have key roles in assessing safety performance of the site.

### Table 1 Data pre-processing

| S.No | Inputs                        | Frequency                        | Level |
|------|-------------------------------|----------------------------------|-------|
| 1.   | Tool box talk                 | Rare                             | 1     |
|      |                               | Occasional                       | 2     |
|      |                               | Every time before starting the task | 3     |
| 2.   | Safety supervision            | Rare                             | 1     |
|      |                               | Occasional                       | 2     |
|      |                               | Almost certain                   | 3     |
| 3.   | Safety training               | Rare                             | 1     |
|      |                               | Occasional                       | 2     |
|      |                               | Almost certain                   | 3     |
| 4.   | PPE – availability            | No additional PPE                | 1     |
|      |                               | 50% is additional                | 2     |
|      |                               | More than enough                 | 3     |
| 5.   | PPE – usage                   | Only helmets                     | 1     |
|      |                               | Both helmets & footwear’s        | 2     |
|      |                               | Use all required PPE’s           | 3     |
| 6.   | Type of accidents that occurred | Lost time injury             | 1     |
|      |                               | First aid                        | 2     |
|      |                               | No accidents                     | 3     |
| 7.   | Competency                    | Unskilled                        | 1     |
|      |                               | Semi-skilled                     | 2     |
|      |                               | Skilled                          | 3     |

Possibility of accidents increases with lack of safety training and supervision. Hence accidents are considered as the important parameter in determining safety performance. As accidents are the negative parameters among all, the classification made here is little different. For instance, if there are no accidents it is classified as high level ‘3’. Apart from the organizational support to the worksite, the worker should also be competent to handle unexpected hazards in the task. The competency of the worker can be improved by additional safety trainings but the builders/owners have to select a competent person before assigning the task. Based on the inputs from the safety engineers a set of IF THEN rules are framed to determine the actual performance of the site through the data collected from each worker. For example, some of the IF THEN rules will look like
IF the frequency of tool box talk is LOW, safety supervision is LOW, safety training is LOW, PPE availability is LOW, PPE usage is LOW, type of accident is LOW and competent of the worker is LOW, THEN the performance of the site is LOW.

IF the frequency of tool box talk is MEDIUM, safety supervision is MEDIUM, safety training is MEDIUM, PPE availability is MEDIUM, PPE usage is MEDIUM, type of accident is MEDIUM and competent of the worker is MEDIUM, THEN the performance of the site is MEDIUM.

IF the frequency of tool box talk is HIGH, safety supervision is HIGH, safety training is HIGH, PPE availability is HIGH, PPE usage is HIGH, type of accident is HIGH and competent of the worker is HIGH, THEN the performance of the site is HIGH.

4.2 Conditions for the models
To predict safety performance using ANN, the inputs are given as, frequency of tool box talk ($I_1$), safety supervision ($I_2$), safety training ($I_3$), availability of PPE ($I_4$), its usage ($I_5$), type of accidents that occurred ($I_6$) and competence of the workers ($I_7$) whereas in GP the inputs are from $I_0$ to $I_6$ with all the above-mentioned parameters. In order to identify the versatile model, models are analyzed for their performance against four different conditions such as checking the ability of the tool to extrapolate the validation set ($C_1$), to predict the low performance in the validation set ($C_2$), to predict the medium performance ($C_3$) and to predict the performance of the mixed-up data ($C_4$).

4.3 Model using Artificial Neural Network
To develop an ANN model, the data set are separated into training, testing and validation sets. Model parameters such as the number of hidden neurons, learning rate, momentum rate and initial weights are chosen randomly, and are refined on trial-and-error basis. The effect on model accuracy due to changes in the hidden neurons are shown in Table 2. The performance of the model is measured based on 80% exact matches with the actual and predicted output. From the results it is known that the ANN models are not much effective in extrapolating the data but in case of mixed up data, it shows satisfaction by predicting the number of data as fixed in the performance measure. Several run has been performed with “Logistic” as an activation function and it is found that three-layer back propagation neural network 7-7-1 is a suitable model to predict safety performance for $C_4$.

| Condition | Data Sets | No. of data | No. of matches | Percentage | Hidden neurons |
|-----------|-----------|-------------|----------------|------------|----------------|
| $C_1$     | Training  | 10          | 9              | 100        | 8              |
|           | Testing   | 7           | 5              | 71         |                |
|           | Validation| 5           | 1              | 20         |                |
| $C_2$     | Training  | 10          | 9              | 90         | 7              |
|           | Testing   | 7           | 6              | 86         |                |
|           | Validation| 5           | 3              | 60         |                |
| $C_3$     | Training  | 10          | 9              | 90         | 7              |
|           | Testing   | 7           | 6              | 86         |                |
|           | Validation| 5           | 5              | 100        |                |
| $C_4$     | Training  | 10          | 9              | 90         | 7              |
|           | Testing   | 7           | 6              | 86         |                |
|           | Validation| 5           | 4              | 80         |                |
4.4 Model using Genetic Programming
The performance of the model is measured with the 80% of the exact matches with the output performance. The data sets which is used for training, testing and validation is as shown in Table 3. GP run with an initial program size of 80 and maximum of 512, crossover rate of 50 and mutation rate of 95. The initial population size is set as 500, where it is increased to 1500 for C₁ and 1000 for remaining conditions. The GP models are effective in predicting the output in all conditions as compared to ANN. It can be seen in extrapolating GP performance beyond the training data set, GP showed 60% of the exact matches for C₁ and 80% for all other conditions. It is seen in all equations that I₅ appears in all equations which indicate the safety performance of the construction site depends on the accident history of the worker. A single accident may create lot of damages to the worker and workplace, changes in time schedule and budget. Hence the accident history of the worker has to be known by the safety engineers and while conducting tool box talk, he should address the causes and consequences of such task to create awareness among the workers. Also, if the worker who is involved in large number of accidents/first aid case, he won’t be allowed to do work in high risk areas. In condition C₁ & C₃ the parameters I₁, I₄, and I₅ are common which indicates safety supervision, PPE usage and accident history of the worker. From the equation it can be said that by proper supervision and usage of PPE while working may reduce the accidents in the worksite. As these are the key factors, these must be emphasized while determining safety performance.

Table 3 Results of GP

| Condition | Data Sets | No. of data | No. of matches | Percentage | GP evolved equations |
|-----------|-----------|-------------|----------------|------------|----------------------|
| C₁        | Training  | 10          | 8              | 80         | \(SP = \frac{I₅(0.18 - 0.1I₄)}{I₁} + I₄\) |
|           | Testing   | 7           | 5              | 71         |                      |
|           | Validation| 5           | 3              | 60         |                      |
| C₂        | Training  | 10          | 8              | 80         | \(SP = \left(\frac{I₁I₅(I₆ - 1)}{I₆}\right)^{1/2} + 0.66\) |
|           | Testing   | 7           | 7              | 100        |                      |
|           | Validation| 5           | 4              | 80         |                      |
| C₃        | Training  | 10          | 8              | 80         | \(SP = (I₅I₄)^{1/4} \times I₄^{1/2}\) |
|           | Testing   | 7           | 5              | 71         |                      |
|           | Validation| 5           | 5              | 100        |                      |
| C₄        | Training  | 10          | 8              | 80         | \(SP = (I₀I₄(I₅+I₃) - I₀)^{1/4}\) |
|           | Testing   | 7           | 6              | 86         |                      |
|           | Validation| 5           | 4              | 80         |                      |

4.5 Model Using Multilinear Regression
The best fit MLR model for the data with least error is identified through the following equations. The regression equation (2) is applicable for C₁ whereas equation (3) is applicable for C₂, C₃ & C₄.

\[
\text{SP} = [-0.258 + (0.027I₁+0.004I₂+0.123I₃+0.085I₄+0.283I₅+0.238I₆+0.297I₇)]
\]

\[
\text{SP} = [-0.314+ (0.090I₁+0.107I₂+0.011I₃+0.026I₄+0.274I₅+0.285I₆+0.314I₇)]
\]

Whereas SP is the Safety Performance (Output)
I₁, I₂..., I₇ is the input

It can be seen from both the equations that I₅, I₆ and I₇ i.e. PPE usage, type of accidents and competent of the workers have the major impacts and it denotes vital role in determining safety performance of the construction sites. The overall exact matches for C₁ is 60% and 50% for C₂, C₃ and C₄.
5. Conclusion

This research applied three different tools such as artificial neural network, genetic programming and multi-linear regression to determine safety performance of construction site. In C1, MLR showed 60% of the better results as compared to all other conditions. In all other conditions GP showed better results than ANN. Hence GP is suggested for determining safety performance in construction sites. ANN has an obvious disadvantage of its inability to offer relationship between inputs and output in mathematical form. GP models are more meaningful in the sense that they have a flexible form. Of course, these models have absolute validity because data are derived from questionnaire surveys which involves lot of subjectivity. Nevertheless, the models do offer some inference which is useful for engineers and supervisors to get a better idea to manage site safety.

Reference

[1] Gunduz M Birgonul M T and Ozdemir M 2018 Autom. Constr. 85 pp 124-134
[2] Laitinen H Marjamäki M and Päivärinta K 1999 Accid. Anal. Prev. 31(5) pp 463-472
[3] Gunduz, M and Laitinen H 2018 KSCE J. Civil Eng. 22(2) pp 440-446
[4] Odeh A M and Battaineh H T 2002 Int. J. Project Manage. 20(1) pp 67-73
[5] Aibinu A A and Jagboro G O 2002 Int. J. Project Manage. 20(8) pp 593-599
[6] Shanmugapriya S and Subramanian K 2015 Int. Res. J. Eng. Technol. 2(7) pp 907-913
[7] Gunduz M and Ahsan B 2018 Int. J. Ind. Ergon. 64 pp 155-162
[8] Heravi, G and Eslamdoost E 2015 J. Constr. Eng. Manage. 141(10) 04015032
[9] Zhang M, Cao T and Zhao X 2019 J. Constr. Eng. Manage 145(1) 04018120
[10] Abubakar A M, Karadal H, Bayighomog S W and Merdan E 2018 Int. J. occup. Saf. Ergon. pp 1-11
[11] Leśniak A and Juszczyk M 2018 Arch. Civ. Mech. Eng. 18(3) pp 973-982
[12] Rezania M and Javadi, A A 2007 Can. Geotec. J. 44(12), pp 1462-1473
[13] Velay-Lizancos M, Perez-Ordoñez J L, Martinez-Lage I and Vazquez-Burgo P 2017 Const. Build. Mater. 144 pp 195-206
[14] Sharma N K, Suganya K, Sivapragasam C and Matheswaran M 2019 IEEE Int. Conf. Intell. Tech. Control, Optim. Signal Process. pp 1-4
[15] Sivapragasam C, Muttil N, Muthukumar S and Arun V M 2010 Mar. Pollut. Bull. 60(10) pp 1849-1855
[16] Vigneshwaran S, Uthayakumar M and Arumugaprabu V 2020 J. Test. Eval. 48(2)
[17] Kulkarni P Londhe S and Deo M 2017 J. Soft Comput. Civil Eng. 1(2) pp 70-88
[18] Koza, J R 1994 Stat. Comput. 4(2) pp 87-112.