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Assessment of Construction Fatalities to Predict Cause Factors by Neural Network Analysis

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Abstract

The number of fatalities in construction industry is third highest among the nine major industrial categories. The University of Tennessee, Construction Industry Research and Policy Center (CIRPC) houses the most comprehensive OSHA fatality case file collection. A review of this database indicates that there is both a lack of relevant information and inability to utilize the current database in a predictive manner to impact the number of fatalities. This paper proposes a new format for data collection and analysis in a manner that allows capturing underlying contributing factors related to fatality such as size and organizational structure of employer, short term contracting and temporary employment, multiple employer worksites and multi-cultural personnel. This data collection model is based on analysis of neural networks (ANNs) and categorical regression analysis of the current fatality database. In addition, a predictive model based on ANNs of factors is proposed to gauge the probability of occurrence of fatality accidents of the company and advocate coherent event based safety programs. The results emphasize on the effectiveness of current hazard prevention mechanism and provide insight to improve training programs which supports the primary goals of OSHA in reducing fatalities.

Keywords
Construction fatality, organizational structure and size, neural network analysis, organizational behavior, and prediction of fatality.

1. Introduction

Construction workers accounted for 1 in 5 on-the job fatalities and 1 in 10 nonfatal workplace injuries and illness as reported in year 2004 [1]. In 2009 the construction industry incurred the most number of fatal injuries in the private sector as compared to fifteen other industrial areas [2,3]. Several research studies have concurred that the work place environment in the construction industry is evidently one of the most hazardous industries in many countries [4,5,6]. In conjunction with the human loss construction accidents also delay project progress, damages contractor reputation and incurs large monetary loss [4]. Human errors like in aviation accounts for majority of the accidents caused in construction industry as the direct cause. However, the underlying factors leading to occurrences of human action failure are present across multiple levels within organizations, as apparent within the construction industry. This paper highlights the importance of the organizational factors namely; size and organizational structure of employer, short term contracting and temporary employment, multiple employer worksites and multi-cultural personnel which are inherent to the construction industry [7]. The employers in construction industry are widely divided in the single contractors, small group contractors and large companies. This makes it difficult to comply with different set of rules at all levels of operation. The pilot data analysis of the OSHA accident fatality database revealed the presence of large proportion of small entity employer all across the construction industry. Approximately 35% of the employers have ten or less than ten total employees. Fifty percent of the employers consist on twenty or less than twenty total employees. This statistic is important because these fifty percent of employers nurture the underlying conditions of almost 50% of the environmental cause factors leading to a fatal accident. The OSHA database is used as a training set to understand the underlying cause factors within the current available database. This allows estimating the probability of occurrence of a fatal event in presence of different combination of factors.

2. Background and Literature Review

Historically, many studies have been conducted to investigate human error rather than organizational issues in terms of managerial and organizational communications level [8]. The fatality report analysis has been looked at from several perspectives, namely, different production techniques, work force turnover, crew management, different production techniques, available tools and workers attitude [9,10]. Studies have reported that factors like production schedules, budget constraints also effect the project conditions and in the sense working conditions for individuals [11]. Training and human awareness programs have been initiated to reduce the fatality rate among workers [12]. The organizational structure and project composition factors have not been explored in detail so far due to its complexity and volatile nature. This is considered an essential part of the analysis since it reveals the underlying causes for inadequately trained worker characteristics, use of defective equipment, insufficient or lack of personal protection equipment, etc.

3. Fatality Data Collection

This paper proposes a modified data collecting catalog to reflect efficient systematic information for mitigation of accident fatalities. The primary purpose for analyzing any accident or incident database is to learn the factors causing accidents and initiate change which will report accurate information. We performed a neural network analysis on the OSHA data base to find out the model fit. It was then followed by a categorical analysis to compare the causal factors with the organization size factors.

3.1 Analysis of Neural Networks (ANNs)

ANNs is used in forecasting applications for is generality and flexibility. It is a data driven approach which captures nonlinear data structures without prior assumptions about the underlying relationships among factors. This is particularly suits the data set available for construction accident fatalities.

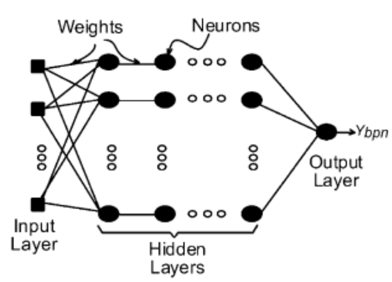


Figure 1: Multilayer Feed Forward ANN Structure. (Reprinted from reference 13)

The Figure 1 shows the model of ANN used in this study. This model has three types of layers, namely, the input layer, the output layer and the hidden layer. There may be one to two hidden layers in a model. The layers are connected to each other with neurons and the neurons connected with weights. The weights and biases are optimized when the AANs is trained using Back-propagation algorithm. The objective function optimizes the sum of square of the difference between the desirable output and the estimated output. Commonly used models are based on linear regression and do not perform well on non-linear databases [13]. In this paper we first use 13 factors from the OSHA data set to predict the fatality cause. Figure 2 shows the analysis of neural network model used to predict the fatality accident data. The model fit output of analysis is displayed in Figure 3. A second set of neural network analysis was conducted to measure the influence of workers human related factors on the fatality categories.

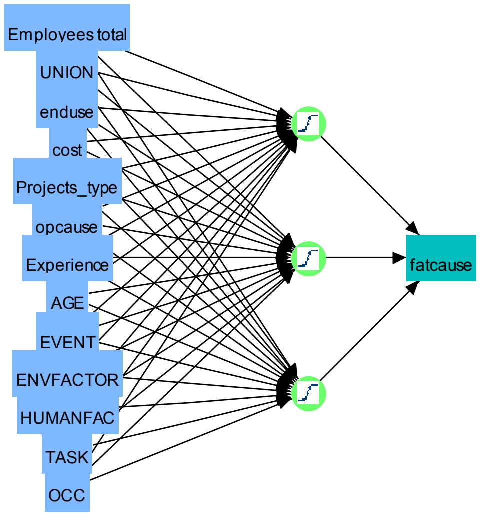


Figure 2: ANNs for full factor analysis

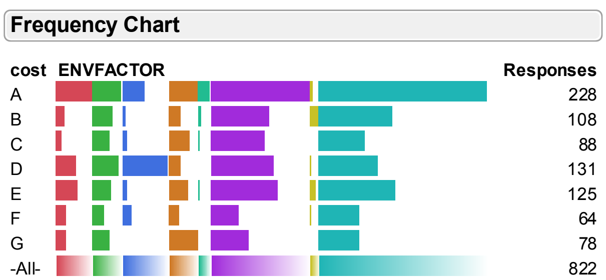
Training

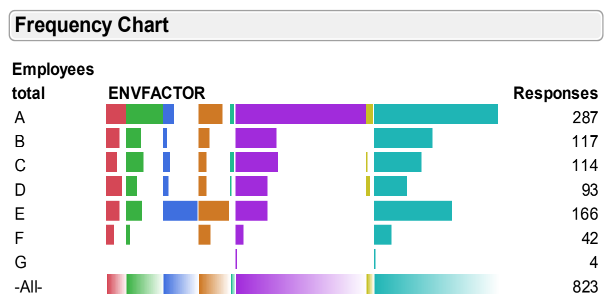
fatcause	Measures
Generalized RSquare	0.9576148
Entropy RSquare	0.7794604
RMSE	0.306611
Mean Abs Dev	0.1717096
Misclassification Rate	0.0976645
-LogLikelihood	168.55431
Sum Freq	471

Figure 3: ANNs model fit results

3.2 Categorical Regression Analysis

The relationship of employer size and cost of the project with environmental cause factors and human cause factors is represented by performing categorical regression analysis on these three variables. The frequency charts obtained from categorical analysis shows that the conditions favorable for causing an accident due to environmental factors and human error factors occur more frequently in employer groups A and B. Group A represents employer have ten or less than ten employees and group B represent twenty or less than twenty employees. Also, as the cost of the project goes down the frequency of environmental factors and human error factors goes up.





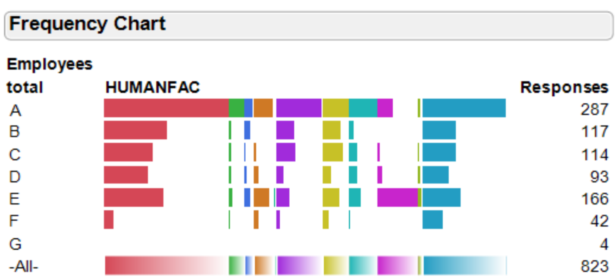


Figure 4: Frequency chart for Environmental factors and human factors with respect to amount of project cost and size of employer organization.

4. Fatality Prediction Model

Analysis of neural networks prediction profiler was used to estimate probability of occurrence of each fatality cause under different levels of cause factors. The prediction profiler reports each response level in a separate row. The profiler traces the predicted response of the fatality causes as one variable is changes and other are held constant at certain values. It uses the data set to train the algorithm and assign weights to the relationship between predictors and response variables. The prediction profiler output for the construction fatality database is shown in figure 5. The y axis represents the probability of each fatality cause factor in different rows. The x axis represents the levels or categories of influencing factors. The blocks which have an approximate straight line denotes that there will be no change in the probability of occurrence for the corresponding fatality category even if you change the level of cause factor. Similarly the graphs in the blocks which higher displacement denote that the probability of occurrence for the corresponding fatality category will either increase or decrease as you change the level of cause factors.

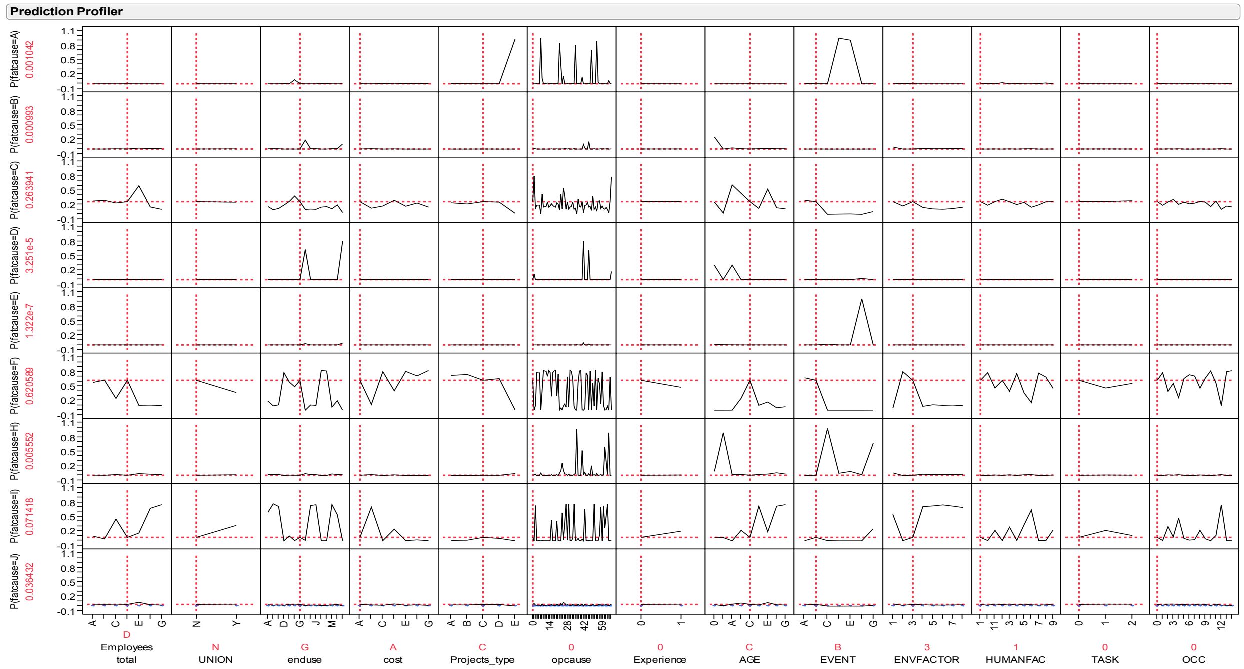


Figure 5: Prediction Profiler graphs for fatality categories with respect to 13cause factors.

5. Results

5.1 Fatality Data Collection

The R square measure (0.9576) in figure 3 shows how well the neural network analysis model predicts the fatality cause factor. The root mean square analysis value measures the difference between values predicted by a model and values actually observed from the data set. The model root mean square error indicates the scope of improving the database information to reduce the size of residuals in the model. The R square (0.8924) for human related cause factors model revealed that person related cause factors are highly correlated to fatality occurrences. The results of both ANNs and categorical regression demonstrated that although there is no direct influence of organizational factors on fatality cause factors, they act as moderator variables that affect the direction and/or strength of the relation between environmental and human factors and fatality occurrences. Misjudgment of hazardous situation, malfunction of procedure for securing operation, insufficient or lack of protective work clothing and equipment were the top three categories in person related cause factors. This proposes the inclusion of detailed person related information in the database, concerning culture, physiological conditions, psychological conditions and job aptitude. Highly rated cause factors like lack of training, lack of experience, defective or improper safety equipment and their use are responsibility of the employer. The frequency charts displayed that majority of the construction industry is comprised of small entity employer concerned with low budget projects. The accident reports should therefore investigate what characteristics of the small entity employer hinders them from complying with safety related procedures during projects.

5.2 Fatality Prediction Model

The snapshots of results for the fatality prediction models are displayed in the figure 6, 7, and 8. The probability prediction of each fatality category is calculated using the combination of each cause factors. The prediction profiler has a dotted red line which can be moved across the block graph to see the change in probability of occurrence. The results displayed in figure 6 indicates that fatality category 'H' (Fall from any height) has a 98.92% probability of occurrence when the person has experience (1), falls between the age group of 41 – 50 years (D), under the category C event (fall) when the environmental cause factor is overhead moving and/or falling object action (2) and human cause factor is safety device removed or inoperative (5). However if you change the category of event details to rubbed /abraded (D) and keep the rest of the factors unchanged, probability of fatality category from fall decreases to 49.45% as displayed in figure 7.

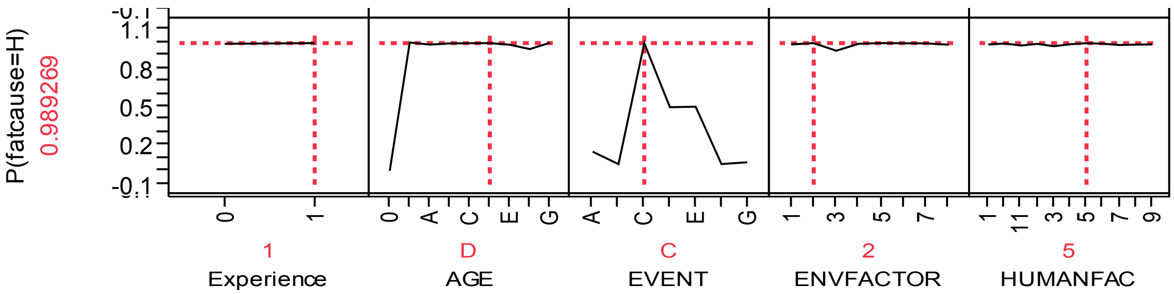


Figure 6: Prediction Profiler graph for fall fatality with respect to experience, age, event detail, environmental factor and human factor.

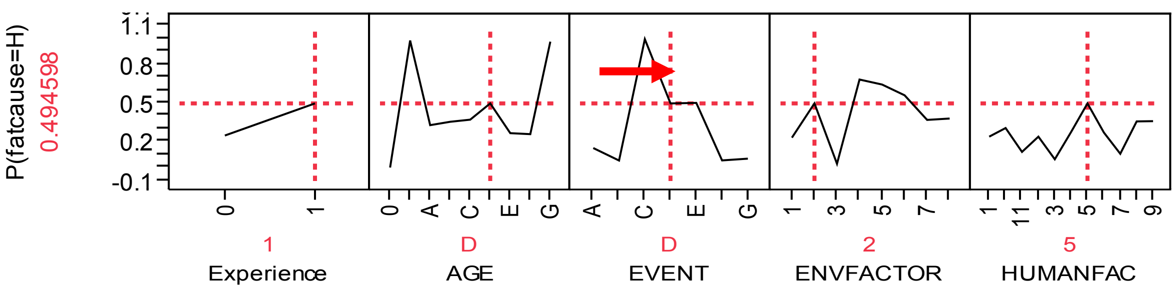


Figure 7: Prediction Profiler graph for fall fatality with respect to experience, age, change in event detail, environmental factor and human factor.

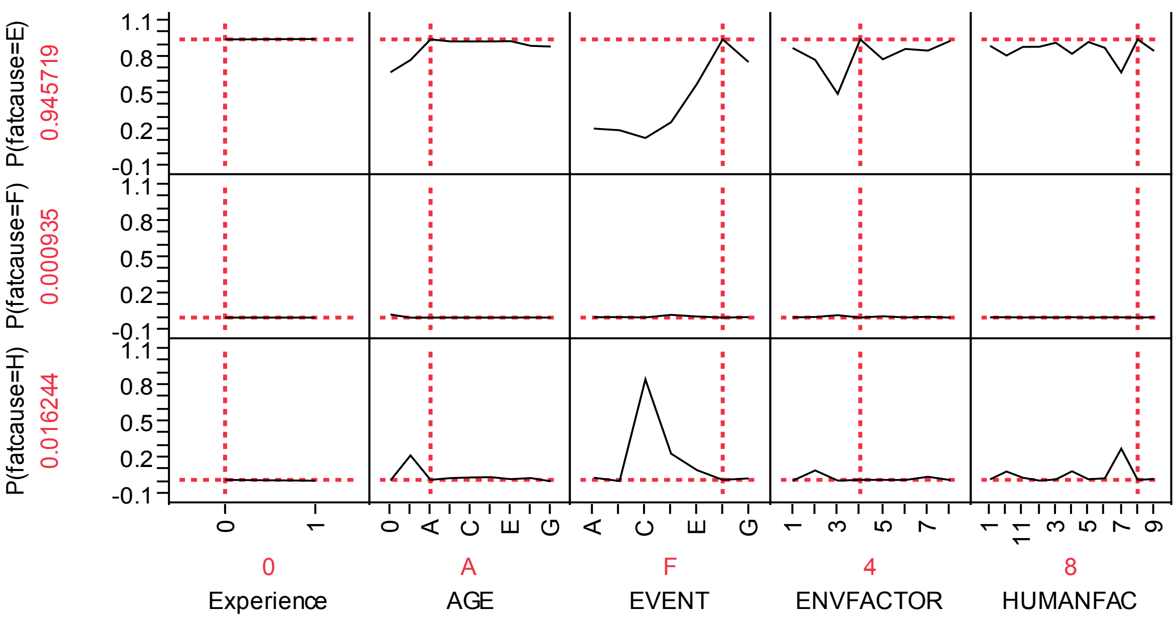


Figure 8: Prediction Profiler graph for electrocution, drown, and fall fatality with respect to experience, age, event detail, environmental factor and human factor.

Similarly, the results in figure 8 can be interpreted as, when an inexperienced person from age category less than 20 years working as an electrician (event category F) is performing work related activity concerning material handling equipment (4) encounters malfunction of procedure in lock out - tag out (8) the probability of fatality category in electrocution increases to 94.45%. However there still hold a 1% chance of occurrence for fall fatality under these circumstances. In the above figure the prediction profiler indicates that experience does not affect the probability of occurrence of any of the given E, F, H fatality categories. This format of results gives us a comprehensive understanding of relationships between cause factors and various categories of fatalities.

7. Conclusion and Future Work

We have shown that by adding the employer organizational characteristics like, size of the employee, sub contracting level, multi employer project, etc., to the current fatality database can be improved to prediction accuracy. A future goal for this work would be to identify moderation effect of these organizational characteristics on each direct cause variables. The neural network prediction model helped understand the relationship of casual factors to occurrences of fatality accidents. This model can predict more accurately as additional factor are included in the training dataset. This model can be made available to employers to run on their hazard occurrence database. This can provide a customized list of causation factors based on a standard industry wide prediction procedure. The output of this model can be used to customize training programs for each employer class based on the factor characteristics. For example by using the results of the improved data set and neural network analysis we will be able to confirm whether there is a relation between small entity employer and environmental cause factor of inadequacy/absence of training program. The outcome of this project will initiate channelized investigation programs for specific fatality accidents. The construction sector poses many challenges and opportunities for improvement. Recognizing the conditions affecting construction working environment will help mitigate fatality accidents at a large scale.

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References

1. Meyer, S.W., Pegula, S.M., 2004, “Injuries, Illnesses, and Fatalities in Construction, 2004,” Compensation and working conditions Online, U.S. Bureau of Labor Statistics, May 24, 2006.
2. “National Census of Fatal Occupational Injuries in 2009 (Preliminary Results)” Released August 19 2010, Bureau of Labor Statistics, U.S. Department of Labor. http://www.bls.gov/news.release/pdf/cfoi.pdf
3. Dong, S., (2009), “Challenges and opportunities of aging construction workers. Healthy aging for sustainable workforce, A February 17-18, 2009 Conference Report, Society of Occupational and Environmental Health, P – 20.
4. Silver Spring, MD Carter, G., & Smith, S., 2006, “Safety hazard identification on construction projects.” Journal of Construction Engineering and Management, 132(2), 197−205.
5. Wang, W., Liu, J., & Chou, S., 2006, “Simulation-based safety evaluation model integrated with network schedule. Automation in Construction”, 15(3), 341−354.
6. Camino, M. A., Ritzel, D. O., Fontaneda, I., & González, O. J., 2008. “Construction industry accidents in Spain,” Journal of Safety Research, 39(5), 497−507.
7. Gillen, M., Gittleman, J.L., 2010, “Path forward: Emerging issues and challenges.” Journal of Safety Research, 41, 301-306.
8. Shappell, S.A., & Weigmann, D.A., (2000). “A human error approach to accident investigation: The taxonomy of unsafe operations.” International Journal of Aviation Psychology. 8, 269-291.
9. Hinze, J., and Wiegand, F. _1992_. “The role of designers in construction worker safety.” J. Constr. Eng. Manage., 118_4_, 677–684.
10. Abdelhamid, T., and Everett, J. _2000_. “Identifying root causes of construction accidents.” J. Constr. Eng. Manage., 126_1_, 52–60.
11. Jaselskis, E. J., Anderson, S. D., and Jeffrey, S. R. _1996_. “Strategies for achieving excellence in construction safety performance.” J. Constr. Eng. Manage., 122_1_, 61–70.
12. Garrett, J.W., Teizer, J., 2009, “Human factors analysis classification system relating to human error awareness taxonomy in construction safety. Journal of Construction Engineering and Management, Vol: 135, No: 8.
13. Balestrassi, P.P.; Popova, E.; Paiva, A.P.; Marangon Lima, J.W., (2009), “Design of experiments on neural network's training for nonlinear time series forecasting.” Neurocomputing, Volume 72, Issue 4-6, Pages 1160-1178.