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Analysis of Labor Productivity of Brick Masonry Work in Building Construction in Kathmandu Valley

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Abstract

Construction labor productivity is the most determinant of success of any construction project. Labor is considered as more variable and unpredictable cost component for the successful accomplishment of construction projects. The main aim of this research is to develop an artificial neural network (ANN) model to predict the production rate for brick masonry work by assessing the various factor affecting labor productivity. Out of forty-four factors selected from a literature review, the top thirteen factors were selected for model development after the questionnaire survey and ranking them based on Relative Importance Index (RII). The model was developed in Neurosolution version 7.1.1.1 using the various input data set collected from active construction site of brick masonry. 65% of data set were used for training, 20 % of data set were used for cross-validation and remaining 15 % of data set were used for testing. The error between actual productivity and estimated productivity was computed using Mean Square Error (MSE) which was 0.019 which verified that the estimated production rate was within an acceptable range. After the successful testing of model, a sensitivity analysis was performed to analyze the order of most influencing factors affecting labor productivity. The developed ANN model can be used for estimating the labor productivity of brick masonry work for any building construction project by incorporating the influence of selected parameters or factors.

***Keywords**: Labor, Building project, Labor Productivity, Brick masonry, Kathmandu Valley, Artificial Neural Network (ANN)*

1. INTRODUCTION

Construction industry is one of the nation's largest and challenging industries. Construction accounted for 10-11 % nation's gross domestic product (GDP) of Nepal. About 60% of the nation's development budget is spent through the use of contractors. Construction productivity needs to measure to develop construction industry as it is the major sector having positive impact on overall improvement of the nation's economy and provides employment to a large number of people [1].

Productivity in construction can be called performance factor, production rate, unit person-hour rate and many others. However, productivity traditionally means the ratio of input to output. In construction, the output is measured in terms of weight, length or volume and input resource in terms of cost of labor or man-hours [2]. Productivity in engineering terms may be defined as measure of the technical or engineering efficiency of production[3]. Construction productivity is one of the important indicators of the performance of the project. Construction is a labor-intensive industry, so workforce is the dominant productive resource; thus, construction productivity is primarily dependent on human effort and performance [4].Hence, it is crucial for productivity measurement. Productivity can be shown in equation as:

$$\text{Productivity}=\frac{\text{Output}}{\text{Labor Cost}}=\frac{\text{Output}}{\text{Labor Cost}} \quad (1)$$

Labor costs generally make up 33 to 50 % of total project cost [5]. Hence, for the contract work to be financially successful, productivity must be improved so that labor costs and total project costs can be reduced [3]. To improve labor productivity, numerous factors influence productivity but vary according to projects or even between tasks within the same project. Contractors have often focused on labor productivity rates as the primary source of the overall success or failure of a project [6]. According to a study conducted by [7], only 56.92% and 55.74% of time were spent by skilled and unskilled workers for productivities. According to Mishra [1],labor productivity must be improved to reduce labor costs. This will help in the overall performance management and help to understand potential areas of improvement in the construction projects resulting into optimized cost and better resource management.

The impact of those factors can be quantified in productivity models. These models play an important role in planning, scheduling, and estimating cost [3].Due to complex nature of construction labor productivity, it has been a complicated task to determine realistic productivity value. Thus, recent research has shown that artificial intelligence applications provide a flexible environment to deal with such complexity. Most of these studies employed supervised methods in Artificial Neural Networks (ANN). Use of neural networks has been growing widespread attention in the construction industry to aid in many different applications for productivity prediction [8].

Construction Productivity Model

Construction productivity models explain productivity variations by the factors included in the model. These models are needed for construction planning, estimating, and scheduling. In planning, productivity models of controllable factors (such as crew size or scheduled overtime) are needed for maximizing labor productivity to achieve lower labor costs and shorter project duration. In estimating, productivity models are used to predict labor costs; and finally in scheduling, productivity models are needed to forecast activity durations [9].The model developed so far are limited in explaining the variations of productivity. Most of these models included a single factor while neglecting the variations caused by other factors. Some of the modeling techniques used are statistical model, action response model, factor model, linear regression model, etc. Artificial Neural Network (ANN) has been considered as a reliable modeling technique with dynamic learning mechanism and effective recognition capabilities to estimate the production rates under any specific condition. The model consists of 3 layers: Input, Hidden and Output layers. The data/ factor is fed in the hidden layers. A large number of neurons are fed in hidden layer as weights and bias. Various types of activation functions are used to convert the input into the desired output [2].

During the process called training, the network generalizes the knowledge and becomes capable of providing solutions to the new problems even if only incomplete or noisy data are available. Once a network is trained using an adequately representative training set, it can be used to classify or to predict the output of the modeled system for a given input pattern. One of the attractive properties of such networks is their capacity for tolerating moderate amounts of noise and variations in the input.

Neuro Solution

Many design software is used for creating neural network models. Like SPSS, MATLAB, etc. Neuro Solutions is the premier neural network simulation environment. As mentioned in [10] Neuro Solutions combines a modular, icon-based network design interface with an implementation of advanced artificial intelligence and learning algorithms using intuitive wizards or an easy-to-use Excel™ interface. Neuro Solutions are more powerful and flexible, easy to use and many researchers used NeuroSolution application in building their neural networks that it achieved good performance and it has multiple criteria for training and testing the model [10].

2. OBJECTIVE

This research aims to present a field study that determines the effects of a set of variables on labor productivity of brick masonry work. To achieve the aim of the research, this research has the following objectives:

i. To identify different factors that affect the labor productivity.
ii. To predict labor productivity of brick masonry work using Artificial Neural Network model.
iii. To analyze the variations in the labor productivity of brick masonry work due to changes in the selected factors using Artificial Neural Network.

3. RESEARCH METHODOLOGY AND DATA COLLECTION

In this study, both quantitative and qualitative approaches were used. The qualitative approach was used to determine the main factors affecting labor productivity and a quantitative approach was used for predicting the labor productivity which was collected in numeric form. Various factors affecting labor productivity are identified through the literature review. A questionnaire survey was conducted to identify the most influencing factors. Pretesting was done by interviewing with 7 specialists and their suggestions were considered and some modifications were carried to prepare a final questionnaire.

Studied population includes site engineer, site supervisor, contractor representative, project manager working in active construction site of Kathmandu valley. The sample size was computed using Cochran's Formula for large population:

$$n_0 = \frac{Z^2 pq}{e^2}$$

Where,

n_0 = Cochran's sample size recommendation

e = Desire level of precision

p = Estimated proportion of population which has the attribute

q = (1-p)

z = value from table (depend upon confidence level= 90%)

$$n_0 = \frac{1.64^2 \text{x} 0.5 \text{x} (1-.5)}{0.1^2} = 67.24 \approx 68$$

For 90% confidence level, 68 questionnaires should be distributed.

In this research, to select the most suitable factors affecting labor productivity during brick masonry work, ordinal scales were used.

Table 1: Ordinal Scale used for data measurement

Item	**Very High Effect**	**High Effect**	**Medium Effect**	**Low Effect**	**Very Low Effect**
Scale	5	4	3	2	1

The Relative Importance Index method (RII) is used here to determine the most important factors that affect labor productivity in brick masonry work.

$$\text{Relative Importance Index (RII)} = \frac{5n_5 + 4n_4 + 3n_3 + 2n_2 + 1n_1}{5N}$$

Where,

N = the total number of respondents

n1 = number of respondents who answered "Very Low effect"

n2 = number of respondents who answered "Low effect"

n3= number of respondents who answered "Medium effect"

n4 = number of respondents who answered "High effect"

n5 = number of respondents who answered "Very high effect"

Based on ranking of the factors obtained through RII with a value greater than 0.8 and further consultation with quite similar factor selected in [11] and [8], 13 factors were selected as the input variables for the model and the productivity rate (m^3/man-day) will be the output of the model.

The data should be fed in the model in the integer form. All the factors used for the input are not in the numeric format. So, all the collected data was encoded into a numeric format.

Table 2: Input and Output Encoding

S.No.	Input Factor	Code
1	Experience	Number
2	Crew Size	Number
3	Labor percent (unskilled/skilled)	Number
4	Floor Height	Number
5	Labor Behavior and thinking	Unsatisfied and disloyal=1
		Satisfied and loyal =2
6	Use of alcohol and drug	No = 1
		Moderate = 2
		Excess = 3
7	Lack of labor Surveillance	Low Surveillance=1
		Medium Surveillance=2
		High Surveillance=3
8	Material availability	Low Quantity=1
		Medium Quantity=2
		High Quantity=3
9	Equipment and tool	Hand mix=1
		Machine mix=2
10	Bonus, incentive, extra wages	Bonus or Extra wage for overtime=1
		No Bonus and Extra Wage for overtime = 2
11	Alterations in design or drawing	Low alteration=1 (negligible change)
		Medium Alteration
		High Alteration (major changes causing delay at work)
12	Haulage of material within construction site	Difficult = 1 (travel distance more than 20 ft.)
		Medium = 1 (travel distance between 10- 20 ft.)
		Easy = (travel distance less than 10 ft.)
13	Wages	Daily=1
		Weekly=2
		Monthly=3
		Lump sum=4
No	**Output Parameter**	**Code**
1	Labor Productivity	M^3/man-day (Working hour = 8 hours)

For the model development, 35 sets of data were collected from 7 active construction sites through direct site observation for predicting productivity using Artificial Neural Networks (ANNs).In this study, a convenience sampling method is used for the collection of data from the site, which is one of the non-profitability sampling techniques. Readily available sites were chosen where brick masonry work was going.

In this research, Neuro Solution version 7.1.1.1 application was selected to develop ANN model as it is more powerful and flexible as well as easy to use. As per the requirement of ANN model, among 35 data sets available, 65% of the data which is 23 set is used for training phase, 20% of the data which is 7 is used for cross-validation and 15 % of the data which is 5 is used for testing purpose. The model was developed using 1 hidden layer with 30 neurons. The model was run for 1000 epoch for each training. The model used tanh activation function. The choice of artificial neural networks in this study is based on prediction using feed forward neural network architectures and back propagation learning techniques. To create a successful model and to determine the accuracy of the model Mean Square Error was computed.

$$\text{MSE}=\frac{1}{\text{N}}\sum(\text{Actual rate} - \text{Predicted rate})^2$$

4. RESULT AND DISCUSSION

Determining the possible factor affecting labor productivity in building construction is one of the objectives of this study. One of the most significant keys in building the neural network model is identifying the factors that have a real impact on labor productivity for brick masonry work in building projects.

Factor Affecting labor productivity

The questionnaire included 44 factors under 8 different groups, listed as an output of the literature review and pretesting of the draft questionnaire. Relative Importance Index (RII) for each of the 44 factors were determined and the factors were ranked accordingly.

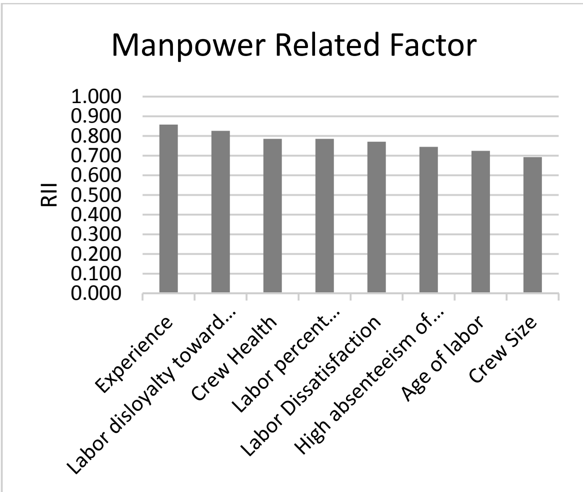

Fig 1: Ranking Manpower related factor

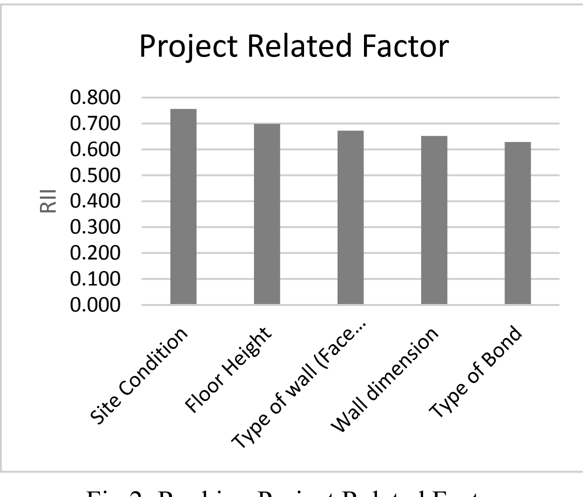

Fig 2: Ranking Project Related Factor

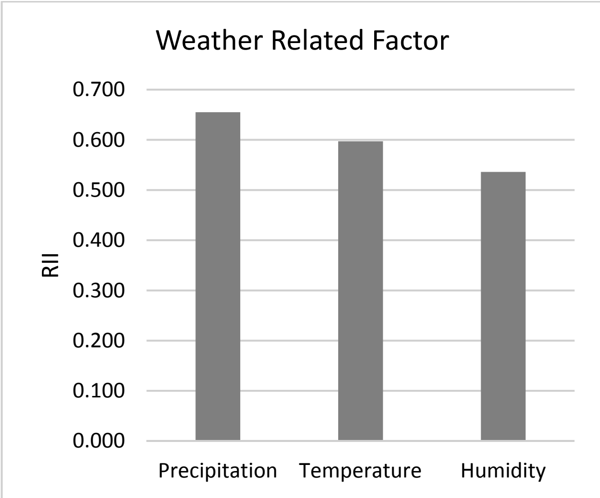

Fig 3: Ranking Weather-Related Factor

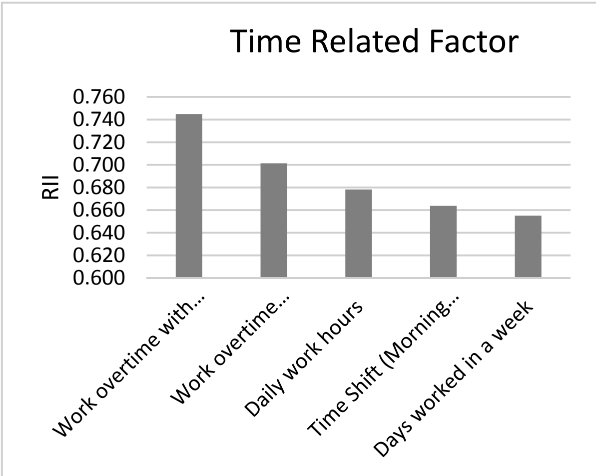

Fig 4: Ranking Time Related Factor

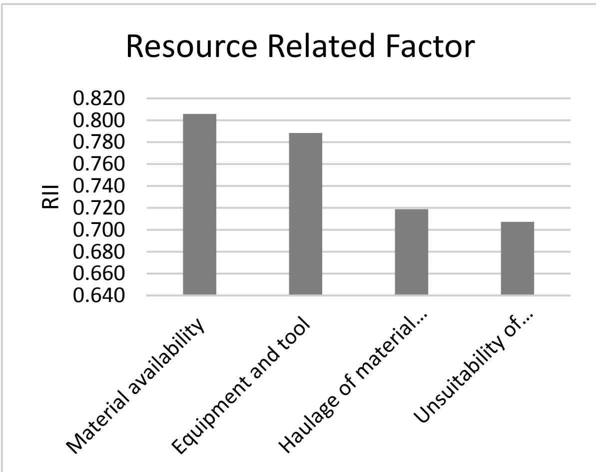

Fig 5: Ranking Resource Related Factor

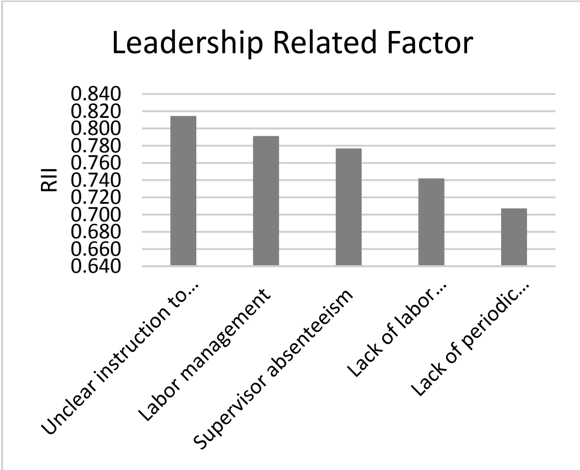

Fig 6: Ranking Leadership Related Factor

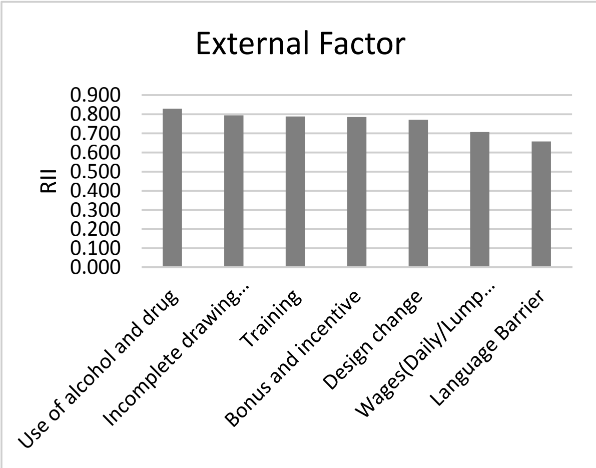

Fig 7: Ranking External Factor

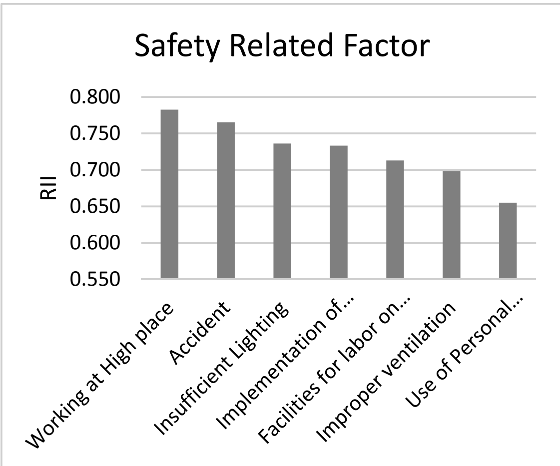

Fig 8: Ranking Safety Related Factor

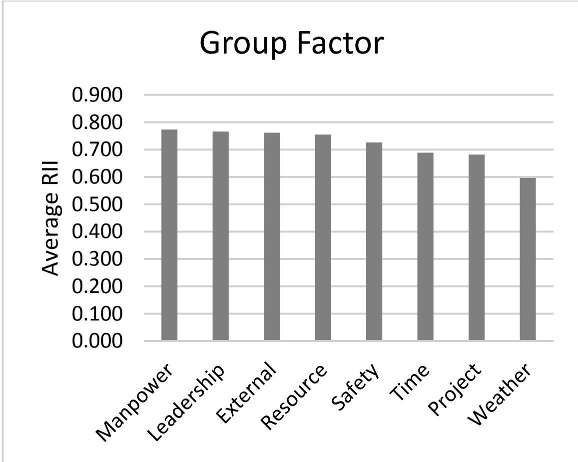

Fig 9: Ranking Group Factor

Cronbach's alpha α is used to check the reliability using the formula

$$\alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{K} \sigma_{yi}^{2}}{\sigma_{x}^{2}}\right)$$

Where,

K= no. of component

σ_x^2=variance of the observed test scores

σ_{yi}^2=variance of component i for the current sample of persons

Using the above formula, the value of α obtained is 0.99 which is within the acceptable limit (internal consistency as excellent under its commonly accepted rule).

Model Result and Analysis

The purpose of testing phase of ANN model is to ensure that the developed model was successfully trained and generalization is adequately achieved. The best model that provided more accurate productivity estimate was structured of General Feed Forward (GFF).

Table 3: GFF model architecture

Architecture of the model	
Model Type	Generalize Feed Forward
Transfer Function	Tanh
Gradient Search	Levenberg Marqardt
No. of PEs in the input layer	13
No. of hidden layer	1
No. of PEs in the hidden layer	4
No. of PEs in the output layer	1

Table 4: Results of neural network at testing phase

No.	Actual Productivity	Estimated Productivity	Absolute Error	Absolute Percentage Error (%)	Mean Square Error
1	0.6766	0.6280	0.0486	7.75	0.019
2	0.7204	0.7387	0.0183	2.48	
3	0.6521	0.8320	0.1799	21.62	
4	0.8405	0.7703	0.0702	9.12	
5	0.4211	0.6556	0.2345	35.77	

During training phase, MSE versus Epoch of training and cross-validation data sets are shown in figure 10.

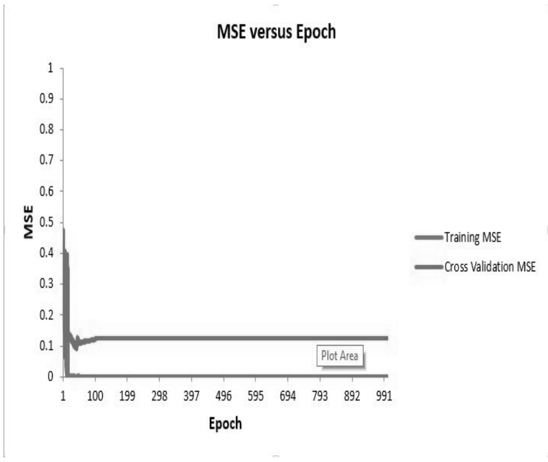

Fig 10: Training and Cross-validation MSE vs Epoch

Table 5: Training and Cross-validation Result

Best Network	Training	Cross-Validation
Epoch when min error	122	7
Minimum MSE	0.0013	0.0611
Final MSE	0.0013	0.1243

Results of training data sets are shown in figure 11 and 12.

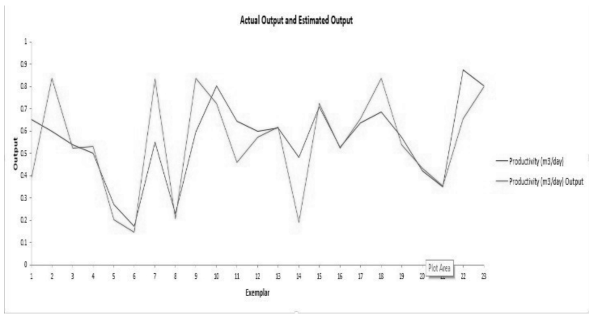

Fig 11: Comparison between actual productivity and estimated productivity for training data sets

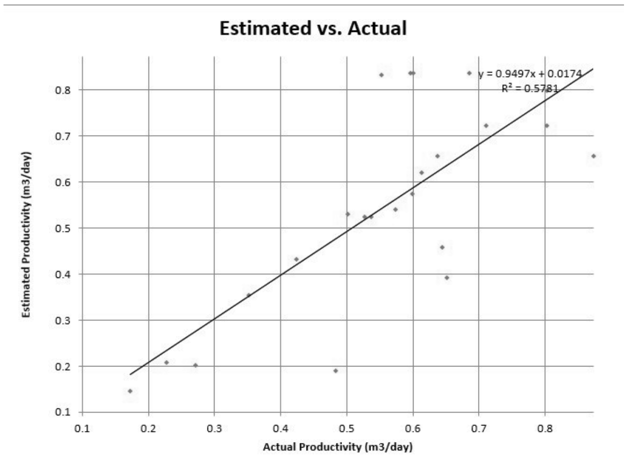

Fig 12: Graph between Estimated and actual productivity for training data sets

Results of cross-validation data sets are shown in figure 13 and 14.

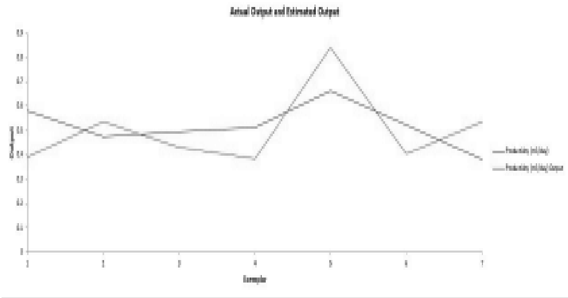

Fig 13: Comparison between actual productivity and estimated productivity for Cross-validation data sets

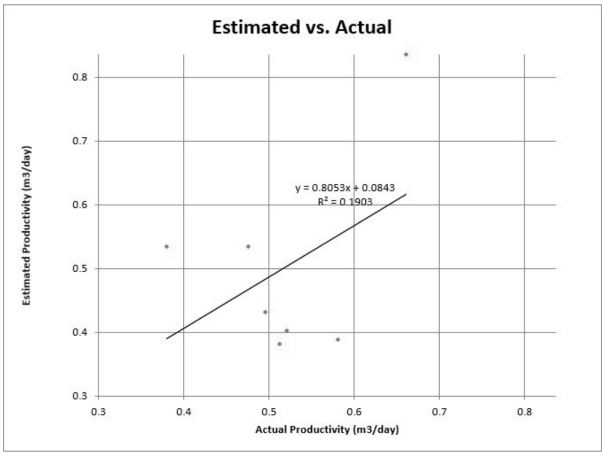

Fig 14: Graph between Estimated and actual productivity for cross-validation data set

Results of test data set are shown in figure 15 and 16.

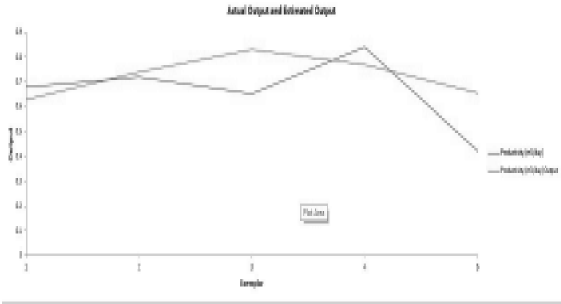

Fig 15: Comparison between actual productivity and estimated productivity for test data set

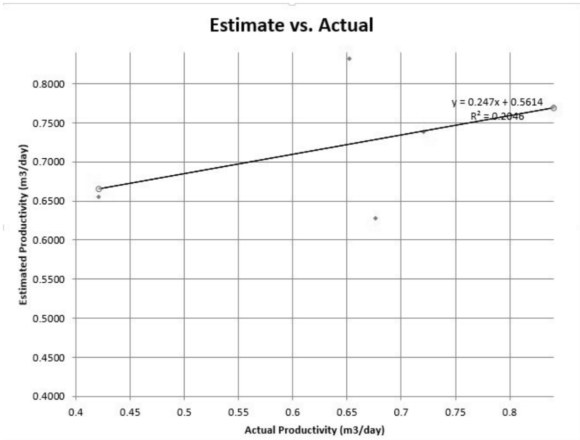

Fig 16: Graph between Estimated and actual productivity for test data sets

Figures 11, 13 and 15 show that the difference between the two lines is the error between the desired and actual productivity for the training, cross-validation and testing set of data. The MSE of testing data set was obtained to be 0.019 as shown in table 4 which is an acceptable limit.

The minimum and maximum productivity obtained from actual conditions are 0.4211 m^3/day and 0.8405 m^3/day respectively. Similarly, the minimum and maximum productivity obtained from model are 0.6280 m^3/day and 0.8320 m^3/day respectively. Similarly, minimum and maximum differences obtained from the model in the testing phase are 0.0183 m^3/day and 0.2345 m^3/day respectively. Figures12, 14 and 16 show that agreement between the actual and estimated values draws a 45-degree line, which reassembles that actual productivity values are similar to the estimated productivity. In test data graph, there is a slight change in angle it may be due to the least number of data in testing phase.

Sensitivity Analysis

The NeuroSolution program provides a useful tool to identify sensitive input variables called ‘‘Sensitivity about the Mean’’. The sensitivity analysis was run by batch testing on the GFF model after fixing the best weights then started by varying the first input between the mean ± one standard deviation, while all other inputs are fixed at their respective means. The network output was computed for 20 steps above and below the mean. This process was then repeated for each input. Finally, a report summarizing the variation of output with respect to the variation of each input was generated.

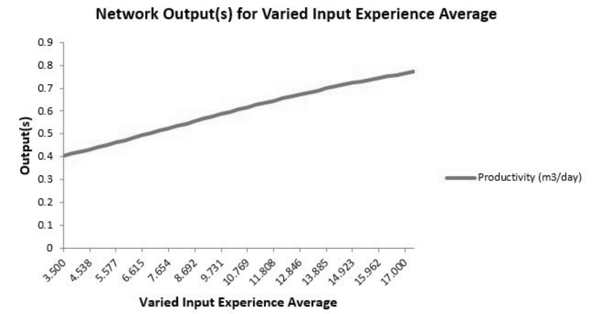

Fig 17: Sensitivity for Average Experience of labor

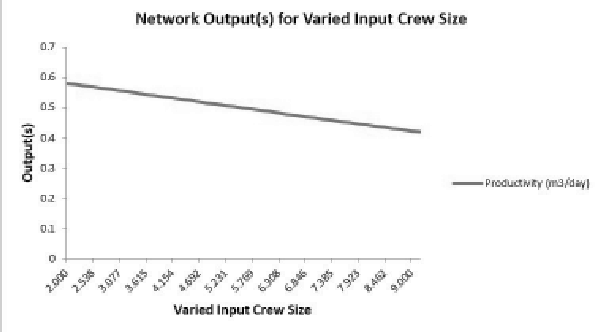

Fig 18: Sensitivity analysis for Crew Size

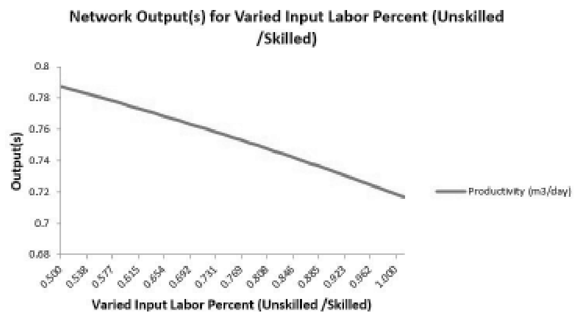

Fig 19: Sensitivity Analysis for Labor Percent

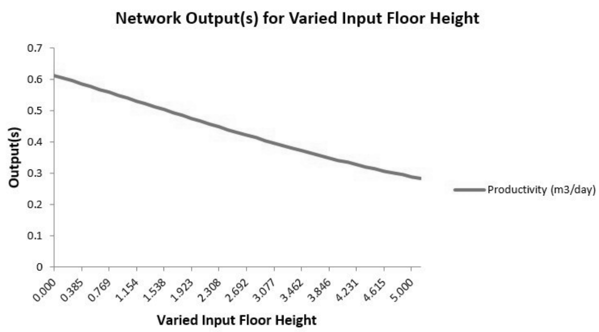

Fig 20: Sensitivity Analysis for Floor Height

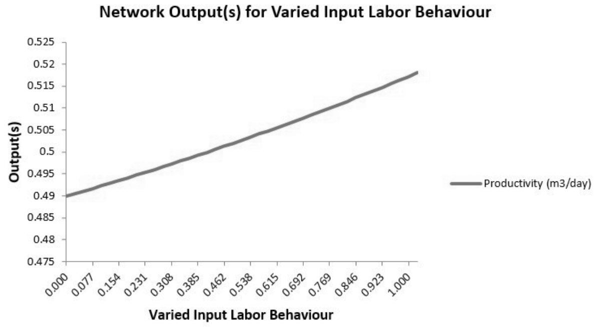

Fig 21: Sensitivity Analysis for Labor Behavior

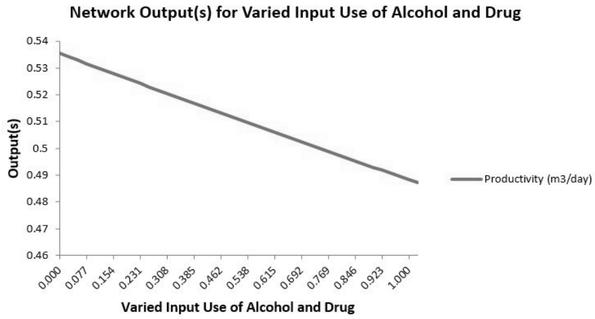

Fig 22: Sensitivity Analysis for use of alcohol and drug

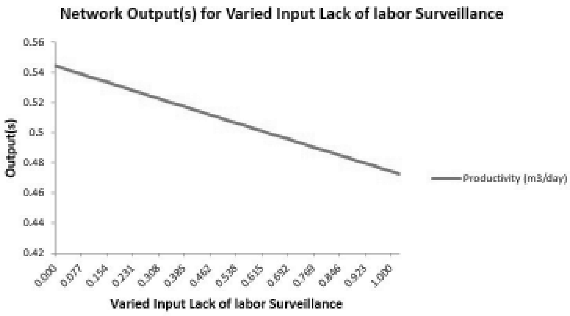

Fig 23: Sensitivity analysis for Lack of labor Surveillance

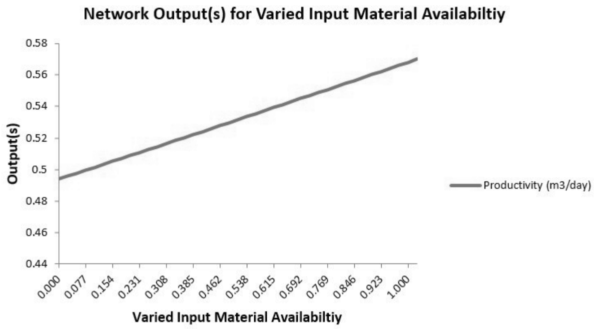

Fig 24: Sensitivity analysis for Material availability

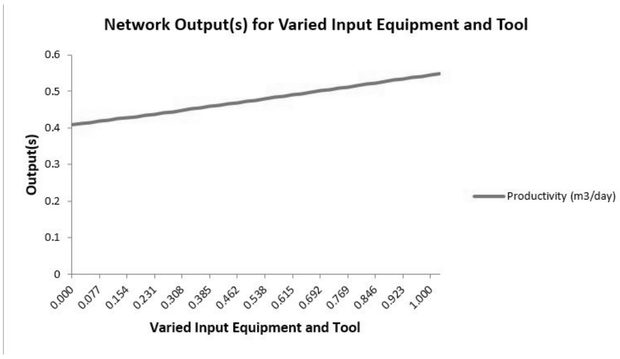

Fig 25: Sensitivity analysis for Equipment and tool

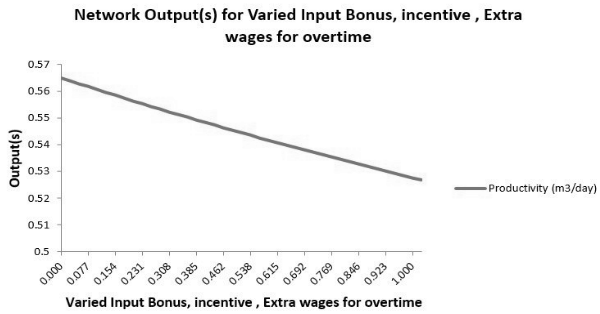

Fig 26: Sensitivity analysis for Bonus, incentive, extra wages for overtime

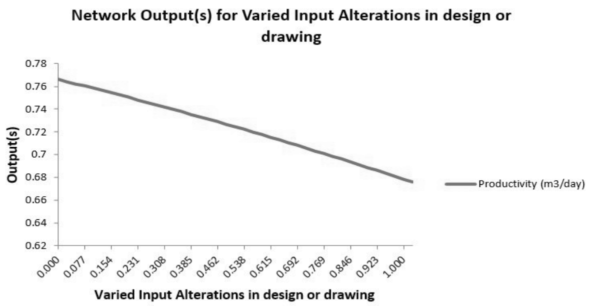

Fig 27: Sensitivity analysis for Alteration in design or drawing

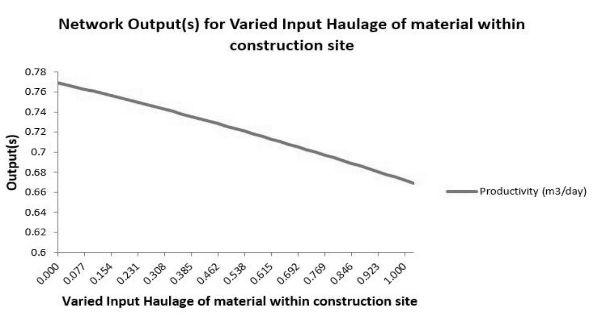

Fig 28: Sensitivity analysis for Haulage of material

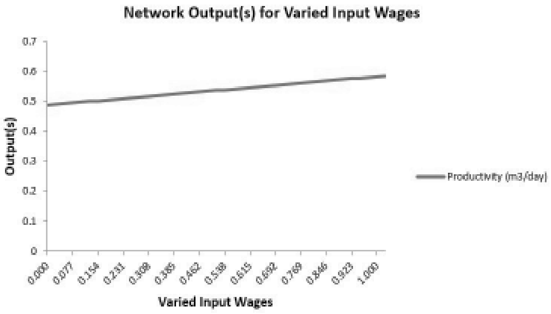

Fig 29: Sensitivity analysis for Input wages

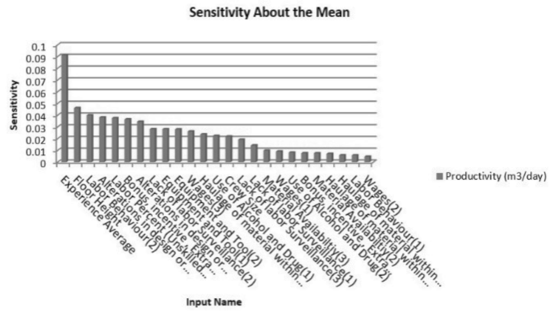

Fig 30: Sensitivity about mean

This study shows that average experience has the most influence on productivity followed by floor height, labor behavior (loyal and satisfied). Similarly, wages (weekly) have the least influence on labor productivity.

5. Conclusion and Recommendation

Construction industry has been rated as one of the key industries which help in developing and achieving the goal of society. Prior knowledge of construction labor productivity plays a significant role and it can lead to save money and time. This research is intended to find out the probable factor affecting labor productivity in building construction, predict labor productivity rate through ANN model and perform the sensitivity analysis to study the influence of adopted factors on labor productivity. The performed sensitivity analysis was in general logical where average experience has the most influence in the productivity followed by floor height, labor behavior (loyal and satisfied). Similarly, wages (weekly) has the least influence on labor productivity. This result is justified as experience improves the intellectual and physical abilities of labor which consequently increases labor productivity. With the increase in floor height, the vertical transport of material becomes difficult and also the fear of working in high place reduces labor productivity.

6. Recommendation

- The result from the research specially the ability of ANN model to predict productivity rates could be used for predicting the labor productivity by construction companies in future for planning, scheduling of projects and even estimating the costs.
- Other neural network can be developed and use for other construction work apart from brick masonry like plastering, tiling, painting, etc.
- Construction parties are recommended to be aware of estimating productivity and using these techniques.
- Construction companies are recommended to have their own database system for the actual production rate of the different construction operations.

7. Limitation of the Study

This research is predicting labor productivity of brick masonry. Building construction sites of Kathmandu Valley are only considered.

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Reference

1. Mishra, A., & Regmi, U. (2017). *"Effects of Price Fluctuation on the Financial Capacity of "Class A" Contractors."* International Journal of Creative Research, 1920-1938.
2. Joshi, P., & Shrestha, S. K. (2019). "*Analysis of Labor Productivity During Concreting Operation in Building Construction of Kathmandu Valley".* Journal of Advanced Research in Construction and Urban Architecture, 1-7.
3. Loganathan, S., & Kalidindi, S. (2015). "*Masonry labor construction productivity variation : An indian case study."*
4. Jarkas, A. M. (2010). "*Analysis and Measurement of Buildability Factors Affecting Edge Formwork."* Journal of Engineering Science and Technology Review, 142-150.
5. Jergeas, G. (2009). "*Improving Construction Productivity on Alberta Oil and Gas Capital Projects."*
6. Missbauer, H., & Hauber, W. (2006). *"Bid calculation for construction projects, regulations and incentive effects of unit price contracts".* European Journal of Operational Research, 1005-1019.
7. Maskey, A., & Mishra, A. (2018). "*Labor productivity assessment of armed police force Nepal building construction project."* International Journal of Current Research, 10(11), 75315-75324.
8. Gerek, I. H., Erdis, E., Mistikoglu, G., & Usmen, M. (2015). "*Modelling masonry crew productivity using two artificial neural network techniques".* Journal of Civil Engineering and Management, 231-238.
9. Sonmez, R. (1996). *"Construction labor productivity modeling with neural networks and regression analysis".*
10. NeuroDimension. (2020). *"Home: NeuroDimension."* Retrieved 7 5, 2020, from NeuroDimension: http://www.neurodimension.com/
11. Aswed, G. K. (2016). *"Productivity estimation model for bracklayer in construction projects using neural networks". Al-Qadisiyah Journal For Engineering Sciences*, 183-199.
12. Attar, A., Gupta, A., & Desai, D. (2013). *"A Study of Various Factors Affecting Labour Productivity and Methods to Improve It."* IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE), 11-14.
13. Chavan, S., & Salunkhe, H. (2016). *"A study on labor productivity in construction industry".* International Journal of Engineering Research, 247-249.
14. Golnaraghi, S., Zangenehmadar, Z., Moselhi, O., & Alkass, S. (2019). "*Application of Artificial Neural Network(s) in Predicting Formwork Labour Productivity."*
15. Gundech, M. (2012). *Study of factors affecting labor productivity at a building construction project in the USA: Web Survey.* North Dakota State University Of Agriculture and Applied Science.

16. Kshirsagar, P., & Rathod, N. (2012). "*Artificial Neural Network*." International Journal of Computer Applications.
17. Mady, M. (2013). *Prediction Model of Construction Labor Production Rates in Gaza Strip using Artificial Neural Networks.*
18. Rasoon, S. H., & Zwainy, F. M. (2016). "*Estimating Productivity of Brickwork item using Logistic and Multiple Regression Approaches."* Scholars Journal of Engineering and Technology (SJET), 234-243.
19. Singh, M. S., D.N, T., Narwade, R., & Nagarajan, K. (2019). *"Factors affecting the labor productivity of brickwork and analyzing them using RII method."* International Journal of Advanced Technology and Engineering Exploration, Vol 6(54), 143-151.