JIMMA UNIVERSITY
JIMMA INSTITUTE OF TECHNOLOGY
SCHOOL OF GRADUATE STUDIES
FACULTY OF CIVIL AND ENVIRONMENTAL ENGINEERING
CONSTRUCTION ENGINEERING AND MANAGEMENT CHAIR

DEVELOPING CONSTRUCTION LABOUR PRODUCTIVITY MODEL USING ARTIFICIAL NEURAL NETWORKS FOR BUILDING PROJECTS OF CONCRETING ACTIVITY IN ADDIS ABABA CITY

A Thesis submitted to School of Graduate Studies, Jimma University, Jimma Institute of Technology, Faculty of Civil and Environmental Engineering in Partial Fulfillment of the Requirements for the Degree Master of Science in Construction Engineering and Management

By

Dawit Benti Abdissa

January, 2020

Jimma, Ethiopia

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Advisor: Engr. ALEMU MOSISA (ASSISTANT. PROF)

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DEVELOPING CONSTRUCTION LABOUR PRODUCTIVITY MODEL USING ARTIFICIAL NEURAL NETWORKS FOR BUILDING PROJECTS OF CONCERNING ACTIVITY IN ADDIS ABABA CITY

DAWIT BENTI ABDISSA

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DECLARATION

I declare that this research entitled "Developing Construction Labour Productivity Model Using Artificial Neural Networks for Building Projects of Concreting Activity in Addis Ababa City" is my own original work, and has not been submitted as a requirement for the award of any degree in Jimma University or elsewhere.

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As research Adviser, I hereby certify that I have read and evaluated this thesis paper prepared under my guidance, by Dawit Benti Abdissa entitled "DEVELOPING CONSTRUCTION LABOUR PRODUCTIVITY MODEL USING ARTIFICIAL NEURAL NETWORKS FOR BUILDING PROJECTS OF CONCRETING ACTIVITY IN ADDIS ABABA CITY" and recommend and would be accepted as a fulfilling requirement for the Degree Master of Science in Construction Engineering and Management.

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ABSTRACT

We cannot imagine the success of labor intensive construction projects by neglecting construction labor productivity. Therefore, improving construction labor productivity (CLP) is a vital task to increase project quality and decrease project cost and time. There are various modeling techniques adopted for predicting production rates of labor that incorporate the influence of various factors but neural networks are found to have strong pattern recognition and higher accuracy to get reliable estimates. Therefore the overall aim of this study was to develop a model using Artificial Neural Networks (ANN) for estimating the CLP of concreting activity for building projects in Addis Ababa city.

The CLP data was collected through questionnaire and direct observation of concreting activity. Both primary and secondary data sources were used. From review of past literatures numerous context specific CLP influencing factors were identified. The most critical influencing parameters were selected by calculating the relative importance index (RII) of questionnaire survey data. The productivity data that was used for further analysis and modeling was collected by direct observation of concreting activity. The strength of relationship between CLP and influencing parameters was analyzed using correlation coefficient results generated by Python. CLP model which represents the output of crew within a certain factors was successfully developed using Python.

Five objective and six subjective critical influencing parameters were selected using RII. Crew experience, age of workers, and placement technique are the top three influencing parameters which have a strong relation with CLP with correlation coefficient values of 0.5681, 0.5349, and -0.5227 respectively. The model developed within these influencing parameters have higher capability to predict the output of a labor with coefficient of determination (R^2) value of 92% and mean squared error value of 0.316%.

The CLP model was successfully developed within the identified most critical eleven influencing parameters using ANN's. Therefore the researcher strongly recommends the application of this model for accurate estimation of productivity. For any interested users the final optimal model can be easily accessed in Python, Excel programmed sheet and mathematical formulas.

Keywords: *ANN, Building projects, Concreting, Influencing Factors, CLP, Model, Python*

ACKNOWLEDGMENTS

First of all, I would like to take this opportunity to thank God Almighty for giving me enough wisdom to accomplish this research.

My sincere gratitude goes to my main advisor, Ass. Professor Alemu Mosisa, and Co-advisor Engineer Lelise Birhanu for their kind encouragement, guidance, supervision, and support throughout the preparation of this research, from Jimma University, Institute of Technology, Faculty of Civil and Environmental Engineering. Their accessibility, willingness to help, inspiration, advice, and camaraderie, made it easier to meet the ultimate goal of this paper.

I am deeply grateful to all who have given assistance in obtaining the information and data related to this paper. Especially to those who have helped me fill the questionnaires and give me their precious time to let me interviewed them. And also, for those who have contributed to the success of this thesis.

I would like to express my sincere appreciation to Mettu University for the sponsorship provided for me to study my Master's Degree at Jimma University. I am also grateful for the funding received to accomplish this study from the cooperation of Jimma University and Ethiopian Road Authority.

Furthermore, but not the least and last, my special thanks and love should go to my families and friends for their encouragement, help, and advice through my journey of life as well as in the preparation of this research.

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ABBREVIATIONS

ABM	Agent Based Modeling
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Networks
BNN	Backpropagation Neural Network
BP	Back Propagation
CLP	Construction Labour Productivity
DES	Data Envelopment System
FIS	Fuzzy Inference System
GRNN	General Regression Neural Network
MAE	Mean Absolute Error
MLP	Multilayer Perceptron
MSE	Mean Squared Error
NN	Neural Networks
R^2	Coefficient of Determination
RBFNN	Radial Base Function Neural Network
TFP	Total Factor Productivity

CHAPTER ONE

INTRODUCTION

1.1. Background

Productivity is described as the quantitative measure between the numbers of resources used and the output produced, generally referred to as man-hours required to produce the final product in comparison to planned man-hours. Productivity is a key element in determining the success and failure of any construction project (Golnaraghi et al. 2019). The most common construction productivity metrics are unit rate (ratio of labor cost to units of output); labor productivity (ratio of work hours to units of output); and productivity factor (ratio of scheduled or planned to actual work hours) (Gouett et al. 2011). The efficiency of activity level systems, focusing on the labor resource of the construction process, is measured using construction labor productivity (CLP). Because of different ways of defining construction labor productivity, arriving at a common definition of productivity is a confusing task. Strictly speaking, productivity is a quantitative assessment of the correlation among a number of resources used and the amount of output produced, therefore, it is a component of cost and is not a method of estimating the cost of resources (Khan 2005). In this thesis, CLP is defined as the ratio of units of output produced to units of input work hours; as shown in Eq. (1.1)

$$\text{Construction labour productivity (CLP)} = \frac{\text{Output (quantity produced)}}{\text{Total labor work-hours}} \qquad (1.1)$$

In this paper construction, labor productivity was modeled using Artificial Neural Networks (ANN). Modeling of CLP using ANN involves input, hidden and output layers. Construction labor productivity, considered as an output layer, which shows how much end product is produced by using different inputs (materials, energy, equipment, and etc.) to produce outputs (project products). The hidden layer is nonlinear combinations of the network inputs that are computed. A sigmoid function was used in the program which represents the nonlinear function.

A number of researchers have applied ANN's in construction management, principally for decision-making, forecasting, and optimization. ANN's is a technique for Artificial Intelligence programs and one of the most common approaches to machine learning. These programs invest learning capabilities in intelligent systems that can improve their performance over time (Negnevitsky 2005).

In addition, when ANNs are exposed to a sufficient quantity of data to be processed, they have the ability to learn from experience to improve performance behavior in processing samples. Moreover, "ANNs can generalize to others they have not yet encountered" (Negnevitsky 2005). However, ANNs are simultaneously storing and processing data throughout the entire network model instead of in a limited space, which means it must be considered as a global feature rather than a local one (Negnevitsky 2005).

Researchers throughout the world were adopted available productivity estimation techniques to develop a model for estimation of CLP. The first technique is statistic-based called the multivariable linear regression. It attempts to map the relationships between the influential factors and productivity with the explicit mathematical functions. However, the statistical technique could oversimplify the relationships compared with the neural network technique (Sonmez and Rowings, 1998). The second technique that has been widely used in recent research for identifying the relationships and modeling of CLP is the neural network. The neural network technique imitates a pattern recognition process of a human brain (Wasserman, 1989). And also, currently, different techniques have emerged that can be used for the development of the productivity models. Inference system like expert system and fuzzy inference system (FIS), data envelopment analysis (DEA), and agent-based modeling are some of the emerged techniques used for the development of CLP models.

ANN is a branch of Artificial Intelligence (AI) in which structures are based on the biological nerves systems. It can exhibit a surprising number of human brain characteristics e.g. learn from experience and generalize from previous examples to new problems. Generally, the aim of this paper was to develop a CLP estimation model for building projects of concreting activity using the modeling technique of ANN.

1.2. Statement of the Problem

As many construction operations are labor-intensive, the question of labor productivity becomes paramount especially as higher productivity levels typically translate into superior profitability, competitiveness, and income (Rojas and Aramvareekul, 2003). Labour is one of the major factors used to convert construction inputs to outputs/project products. In developing countries, labor counts 30-50% of total project cost (Harmon and Cole 2006). CLP is an efficiency measure of an activity that deals with the process of converting inputs (total labor work-hours) to outputs using labor as the transformation mechanism. Therefore, CLP is defined as the ratio of output to input (Rojas &Aramvareekul, 2003).

In developing countries like Ethiopia where the availability of machines is low construction operations are largely labor intensive. Therefore, the project's success is greatly influenced by the labor's productivity performing the job. The performance of construction industry is best described by its construction labor productivity, but most construction projects fail to correctly imitate the construction labor productivity, this failure is mainly due to the lack of having construction labor productivity estimation models which is very crucial for the industry to indicate the performance.

The construction industry has lacked developed CLP models which are capable of explain which parameters cause productivity to change and by how much, therefore the industry is constantly searching for ways to improve labour productivity (Tsehayae 2015).

Lack of having developed CLP model increases the uncertainty of the construction projects which intern decreases the success, profitability, and competitiveness of the company, so the aim of this study was to develop construction labor productivity estimation model using ANN's for building construction projects in Addis Ababa city.

1.3. Research Questions

1. What are the parameters that can influence CLP in building projects for concreting activity?
2. Which of the identified influencing factors are strongly correlated to CLP?
3. Can we develop CLP model using ANN's?

1.4. Objectives

1.4.1. General Objective

The general objective of this thesis is to develop a model using ANN for estimating labor productivity of building projects in Addis Ababa city.

1.4.2. Specific Objective

- To identify, classify, and quantify factors that can influence construction labor productivity in building projects for concreting activity.
- To measure the strength of the relationship between the identified factors and the construction labor productivity.
- To develop a construction labor productivity model using ANN for concreting activity.

1.5. Scope of the Study

This study was conducted in Addis Ababa city building construction work projects, which were active projects and was on the stage of concreting activity. The data collected, the model developed and the conclusions that are evolved from this study is only applicable for the building projects of concreting activities for columns, beams, and slabs in Addis Ababa city. And also, since the CLP is affected by numerous parameters at a different level this study was focused on those factors which can affect productivity at the activity level because the summation of success of all activities will lead to the success of the project and the industry at all.

1.6. Significance of the Study

Construction industries in developing countries are largely labor-intensive, therefore the CLP is paramount to the success of this industry. This research was conducted to eliminate the problems related to the estimation of labor in a certain parameter. After identifying the factors influencing CLP a model was developed which is helpful for construction stakeholders for estimating the CLP that was obtained in a required level of factors. Therefore, the reason behind conducting this paper was to develop a CLP estimation model that is helpful to improve profitability, success as well as the competitiveness of the construction industries.

1.7. Limitation of the Study

The developed model was only based on the data that was collected by direct observation from active construction projects of concreting activity, so that this developed model is only applicable to the estimation of labour productivity of concreting activity in Addis Ababa city. There are different types of construction productivity metrics; unit rate, labor productivity, and productivity factor metrics. In this thesis, therefore the focus is on CLP, which is defined as the ratio of units of output to units of input work hours, where higher values are better than lower values.

CHAPTER 2

LITERATURE REVIEW.

2.1. Concept of Labour Productivity

The meaning of labor productivity for the construction industry varies with its application in different areas. The overall measure of productivity can be defined by the total factor productivity (TFP). TFP is an economical model, in which both input and output are measured in terms of finance (birr). Because of difficulties in predicting the various inputs, TFP is not very useful for contractors as it can be highly inaccurate (Sonmez 1996).

Construction labor productivity (CLP) is an efficiency measure of an activity that deals with the process of converting inputs to outputs (project components) using labor as the transformation mechanism. Therefore, CLP is defined as the ratio of output to input (Rojas &Aramvareekul, 2003). Labour productivity is of critical importance to the construction industry, as it directly affects the profitability and competitiveness of construction companies, and it is, therefore, a frequently researched topic. The construction industry is constantly searching for ways to improve labor productivity, but the industry has lacked crew-level CLP models capable of explaining which parameters cause productivity to change and by how much. (Tsehayae 2015).

2.2. Available Productivity Estimation Techniques

Productivity estimation modeling is based upon the assumption that productivity and its influential factors have a relationship in the past events. Therefore, the productivity of future events can be estimated by determining these relationships and specifying values for the influential factors. Several past studies have quantified the impact of different parameters on CLP using factor models. Factor modeling is a multivariate approach to modeling crew-level productivity using influencing parameters (factors and practices) as independent variables and productivity as the dependent variable.

Model development involves gathering and measuring of input parameters, and identify the key independent variables and to model the complex relationship between these variables and dependent variable which is CLP (output) using appropriate analysis methods. Accordingly, numerous context-specific parameters that can influence CLP were identified from the review of literature and critical variables or parameters were identified using a questionnaire survey. Different data analysis methods have been adopted to model CLP including regression analysis, artificial neural networks, expert systems, inference systems, and other emerging methods. This section investigates available techniques for modeling CLP.

2.2.1. Linear Regression

The first technique is statistic-based called the multivariable linear regression. The method relies on actual data between numerous parameters as independent variables and productivity as the dependent variable. Most existing models address the effect of a single input variable, like temperature, on CLP (Yi and Chan 2014). Regression analysis method has a number of major limitations for representing the complex relationship between input variables and CLP (Lu 2001) additionally, multiple regression analysis requires each input variable to have a linear relationship with CLP, input variables not be correlated with one another. However, the input variables (factors) in CLP analysis are often related to one another (Nasirzadeh and Nojedehi 2013), and the relationship between input variables and CLP is highly complex and nonlinear.

2.2.2. Neural Network

The second technique that has been widely used in recent research for identifying the relationships is the neural network. More recent CLP studies focus on the use of artificial neural networks (ANN's). AbouRizk et al. (2001) developed a two-staged neural network-based CLP model for industrial welding and pipe installation activities. Mosehli et al. (2005) utilized NN for modeling the impact of change orders on labor-intensive operations based on historical company-specific data. Neural networks provide an effective tool for complex problems, such as modeling CLP where the relationships between inputs and output cannot be easily represented by mathematical functions (Moselhi et al. 1991).

2.2.3. Emerging Methods

Recently a number of advanced methods are being employed in modeling CLP. Song and AbouRizk (2008) studied steel fabrication and steel drafting activities and combined discrete-event simulation with a neural network to model the productivity of a production system that had a number of related activities. The NN was used to model individual activities and the complex relationship between productivity and influencing factors, and discrete-event simulation was used to simulate the entire shop fabrication production process. Numerous authors adopted different techniques for modeling labor productivity including; Fuzzy inference system (FIS), data envelopment analysis (DEA), and agent-based modeling (ABM).

2.3. Definitions and Basic Concept of ANN's

Artificial Neural Networks is one of the most common approaches to machine learning, and also is a technique for Artificial Intelligence (AI) program. These systems possess a "machine learning mechanisms form" that is considered fundamental for adaptive systems to work (Negnevitsky 2005). In other words, the human brain is a basic model in fundamental approaches for neural networks that are created based on a biological concept (Negnevitsky 2005).

Many definitions for the term machine learning have been devised by specialist researchers and scientists. Learning is system merit that denotes changes in the system based on its ability to achieve a similar task with more efficiency in the future (Frantz 2003). Learning produces or improves the system is based on experience drawn from work done previously (Michalski et al. 2013)

Artificial neural networks contain links between input and hidden layers and also between hidden and output layers that connect neurons in the model. It can be arranged in different layers: input, hidden, and output. The hidden layer has no connections to the outside world because they are connected only to the input and output layers Zayed and Daniel (2005). Each link has a numerical weight to identify the effect of each neuron (see fig. 2.1). ANNs have long-term memory that considers weights essential in achieving the model goal (Russell and Norvig 2010, Negnevitsky 2005) and Moreover, these weights show the strength for each input; in other words, they show the importance each neuron has for the input layers. The repetitive style of the weights' adjustment processes leads to learning in a neural network (Russell and Norvig 2010, Negnevitsky 2005)

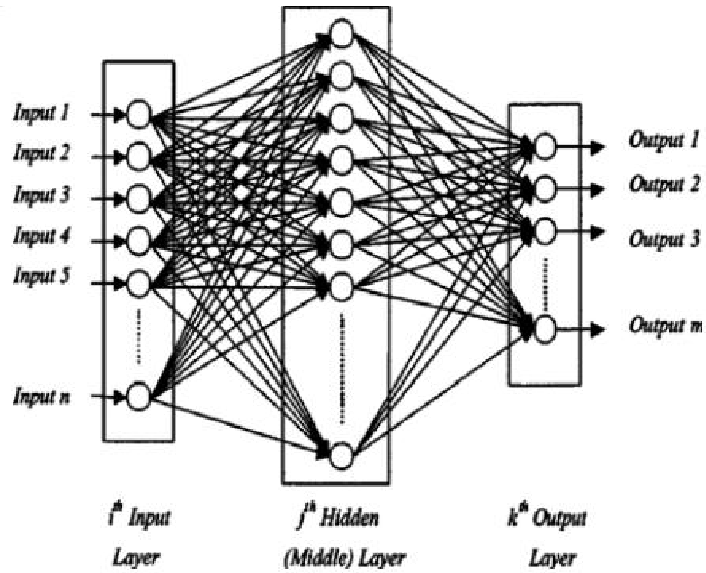

Figure 2. 1: Typical Structure of Feedforward ANN (Zayed and Halpin 2005)

Connecting links transfers a number of input signals to a hidden neuron, then neurons compute a new activation level to produce a result value, then it will be produced as output signal through output links (see fig 2.2). Neurons yields only a single output signal, which is a final solution to the problem, or an input to other neurons, regardless of the number of input signals (Hassanean 2018)

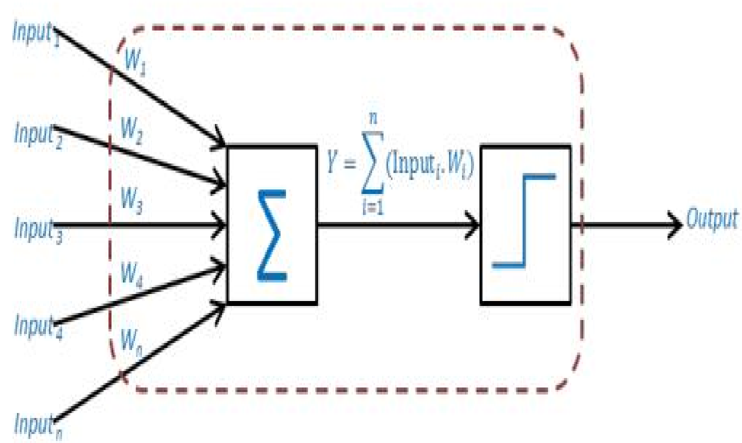

Figure 2. 2: Typical input/output signal process of neurons (Hassanean 2018)

Building artificial neural networks follows significant steps. (1) The network architecture must be designed, which involves deciding on the number of neurons, how the neurons are to be connected to form a network, on kind of neuron to be used, and on the number of hidden layers the network will have. (2) The type of learning algorithm to use is decided. (3) Neural networks must be trained which involves initializing weights and then updated from a set of training examples. Finally, the model will be developed (Russell and Norvig 2010).

The simplest way of finding a result is through a neuron. The values of each input signal received from an adjacent node and the weights on each input connection are dominant factors on the activation level in the computation processes (Russell and Norvig 2010). The computation process is divided into input function and activation function categories. The input function is a linear component which is used to compute the weighted sum of input values, were as activation function is a nonlinear component which is used to transform the weighted sum into the final value. (Russell and Norvig 2010).

In ANN's learning is the process of the weights that are adjusted into NNs to achieve some desired behavior of the network, which is also referred to as Training (Negnevitsky 2005). There are different learning algorithm styles that are used in artificial neural networks (see Fig. 2.3);

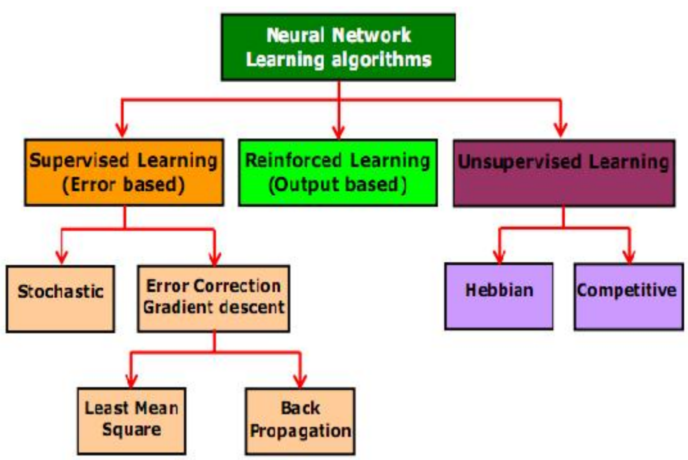

Figure 2. 3: Classification of Learning Algorithm (Krenker 2010)

Supervised learning, gradient descent, backpropagation NN learning algorithm is a learning style that is teacher existence during the learning process and for expected outputs. The learning process is based on generating error correlation between computed output and correct expected output. The "error" generated is used to change the weights of the neural network parameters such that a result is instantaneously used to improve the network's computational performance (Krenker et al. 2011).

There are various types of ANN techniques including General Regression Neural Network (GRNN), Backpropagation Neural Network (BNN), Radial Base Function Neural Network (RBFNN), and Adaptive Neuro-Fuzzy Inference System (ANFIS). Sana et al. (2011) were used Various ANN techniques to compare the statistical performance of the developed models and "BNN outperformed the techniques of RBF, ANFIS, and GRNN". AL-Zwainy et al. (2013) developed a model for estimating construction labor productivity in marble finishing works. They used multilayer perceptron training through a BNN algorithm.

2.3.1. Mathematical Steps for the Training Algorism into ANN's

The systematic steps, with equations, for the workflow in an ANN through the forward and backward propagation can be set out as follows:

Step 1: preparation, preprocessing and scaling of data: Set all the weights and threshold levels of the network to random numbers, uniformly distributed inside a small range (Haykin 1999) (see eq.2.1). Data preprocessing stage is necessary to facilitate network training which can then perform preliminary processing on the data, in order to make the data easier for the neural network training to extract the relevant information Beale et al. (2010)

X_std= (X - X.min(axis=0)) / (X.max(axis=0) - X.min(axis=0))

X_scaled = X_std * (max-min) + min………………………………… (2.1)

Where: X_std = standard deviation

X_scaled= the normalize/scaling value data

Xmin= the minimum value of data

Xmax= the maximum value of data

Min, Max = feature range.

Data scaling is one of the important procedures for preprocessing the data in NNs. The significant reason for data scaling is to equalize the importance of variables, to improve the training of the neural network, and to avoid the slowing down of the learning rate near the edges of specifically the output range due to the property of the sigmoid function, which is asymptotic to values 0 and 1 for logistic function (sig), for this function the scaling ranges between 0.1 to 0.9, and the linear scaling formula can be expressed by equation (2.1). The network's task is made much easier and meaningful if it is provided with data scaled in a way that helps to maintain all weights within a small set of predictable ranges Beale et al. (2010). Furthermore, it is a standard practice to normalize the inputs before applying them to the artificial neural network Beale et al. (2010). Initializing the neural network weights to tiny random values ensures that the product of the input weight will be small Beale et al. (2010).

Step 2: The input vector (data or signal) is presented to the input layer, which computes the input to the hidden layer by applying inputs (x1,x2,x3,…., XP) for each iteration, and desired outputs (yd1,yd2,yd3,….,ydp) for each iteration, to calculate the actual outputs of the neurons in the hidden layer ($y_j{}^q$) (see eq. 2.2):

$$y_j^q(I) = sigmoid\left[\sum_{i=1}^{p} x_i\,(I).\,w_{ij}(I) + \theta_j\right] \qquad \text{……………………………….. (2.2)}$$

Where:

$y_j{}^q$: the actual outputs of the neurons in the hidden layer for each iteration,

Xi: the value of the input parameter i for each iteration,

Wij: the weight of input i,

P: the number of neuron j in the hidden layer, and

θj: the threshold applied to the neuron (i.e. bias function of hidden layer).

Step 3: The hidden layer takes its input for neuron from equation 2.2 and uses it as the argument for a sigmoid function to produce the actual output of the neurons in the output layer (y_k^r) (see eq. 2.3):

$$y_k^r(I) = sigmoid\left[\sum_{j=1}^{q} x_{jk}(I).w_{jk}(I) + \theta_k\right] \quad \text{……………………………. (2.3)}$$

Where:

Y_k^r: the actual outputs of the neurons in the output layer for each iteration,

Xjk: the value of output parameter I for a hidden layer for each iteration,

Wjk: the weight of input j to the output layer,

q: the number of neuron k in the output layer, and

θk: the threshold applied to the neuron (i.e. bias function of output layer).

Sigmoid: the sigmoid activation function

Step 4: The procedure of backward propagating the error associated with output neurons to modify the weight's parameter in the back-propagation network. The error gradient and weight correction are thereby computed for the neurons in the output layer, and then in the hidden layer see eq. 2.4-2.10):

$$e_k(I) = y_{d,k}^r(I) - y_{a,k}^r(I) \quad \text{………………………………………………………. (2.4)}$$

$$\delta_k(I) = [e_k(I)].y_k^r(I).[1 - y_k^r(I)] \quad \text{…………………………………………. (2.5)}$$

$$\Delta w_{jk}(I) = \alpha.y_j(I).\delta_k(I) \quad \text{…………………………………………………….... (2.6)}$$

$$w_{jk}(I+1) = w_{jk}(I) - \Delta w_{jk}(I) \quad \text{……………………………………………..... (2.7)}$$

$$\delta_j(I) = \left[\sum_{k=1}^{r} \delta_k(I).w_{jk}(I)\right].[y_j^q(I).[1 - y_j^q(I)].] \quad \ldots\ldots\ldots\ldots\ldots\ldots (2.8)$$

$$\Delta w_{ij}(I) = \alpha.x_i(I).\delta_j(I) \quad \ldots\ldots\ldots\ldots\ldots\ldots (2.9)$$

$$w_{ij}(I+1) = w_{ij}(I) - \Delta w_{ij}(I) \quad \ldots\ldots\ldots\ldots\ldots\ldots (2.10)$$

Where:

ΔWij(I): The weight correction for the input layer with hidden layer,

Δwjk(I): The weight correction for the hidden layer with output layer,

α: learning rate,

Xi: The weight of input i,

δj(I): The error gradient at neuron j in the hidden layer.

δk(I): The error gradient at neuron k in the output layer at iteration I.

r: The number of neurons in the output layer

Yj(I): The output of neuron j in the hidden layer

I: the number of iterations.

q: the number of neurons in the hidden layer

^{q}: The value of the output of the hidden layer,

After executing equation 2.10, one iteration of the training algorithms is completed. The next stage is a return to step 2 and a repetition of all the succeeding steps in the process until the detected error criterion is satisfied, or the error values remain minimum.

2.4. Applications of ANN's in Construction

Nowadays ANN's have a number of applications in construction industries, projects, and activities management practice, principally for forecasting, decision making, and optimization.

Many applications of NN in construction research have been found including the estimation of cost, quality, and productivity. William (1993) developed back-propagation networks for predicting changes in the construction cost index. McKim et al. (1996) used a neural network to predict the effectiveness of a construction firm. Sana et al. (2011), Faiq et al. (2012), Aswed (2016), Golnaraghi et al. (2019) were used neural networks for the prediction of construction labor productivities of activities.

Researchers have been applied ANN's in construction for decision making. Murtaza and Deborah (1994) used an unsupervised neural network with the Kohonen Algorithm for decision-making on construction modularization. Soemardi (1996) used two fuzzy neural networks for solving group decision-making in selecting a wall system under multiple criteria.

ANN's can also be applied for the design, planning, and management of construction. Chua et al. (1997) used ANNs to identify the key management factors affecting budget performance in a project. Al- Tabtabai et al. (1997) used a BP network to capture the decision-making procedure of project experts involved in schedule monitoring and prediction for multistory building projects under construction. Therefore, the application of ANNs for construction management research plays a vital role in the industry.

2.5. Identification of Input Parameters Influencing CLP

Through a literature review of past studies, various factors that can affect construction labor productivity are identified. Scholar's generally grouped different parameters in the category and varying numbers of parameters were established. Sana et al. (2011) identified 5 factors influencing CLP- weather, lack of availability of material and equipment, location of the project, site condition, and a number of workers. Faiq et al. (2012) identified 10 influencing factors grouped under objective and subjective variables. Al-Zwainy et al. (2013) identified 10 influencing factors grouped under objective (age, experience, number of labor, the height of the floor, and size of marble tile) and subjective variables (security conditions, the health status of worker team, site condition, site condition, and availability of construction materials). Zayed and Attia (2015) identified 8 influencing factors- temperature, humidity, precipitation, wind speed, floor height, work type, gang size, labor percent, and time. Tsehayae (2015) identified 145 activity level input parameters grouped under- labor and crew, materials and consumables, equipment and tools, task property, location property, foreman, and Engineering and instructions. Aswed (2016) identified 13 influencing parameters and grouped under objective variables (age, experience, gang number, wall thickness, wages, and wall thickness) and subjective variables (gang health, weather, site condition, material availability, mortar type, and security condition). Golnaraghi et al. (2019) identified 9 influencing factors grouped under weather, crew, and project. The summary of the identified parameters from the literature is presented in Appendix 1.

Various previous studies have been identified various factors that have been influencing the labor productivity of different construction activities. A questionnaire survey has been carried out to identify the most important of all those context-specific factors identified through literature, those factors have been divided into two categories; quantitative (objective) factors and qualitative (subjective) factors which are strongly related to concreting activity for building projects in Addis Ababa City.

Table 2. 1: Some Literature Summary of Key Input Parameters Influencing CLP

Study Details	Key Input parameters Influencing CLP
Golnaraghi et al. (2019): 9 factors	Temperature, humidity, wind speed, precipitation, gang size, labor percentage, work type, floor height, and work method.
Aswed (2016): 13 factors	Age, experience, gang health, gang Number, weather, wages, site condition, material availability, wall length, wall thickness, wall height, mortar type, and security in a site.
Zayed and Attia (2015): 8 factors	Temperature ºC, humidity (%), precipitation, wind speed (km/h), floor height, work type, gang Size (workers), labor Percent (%), time(min).

Faiq et al. (2012): 10 factors	Age, experience, number of labor, the height of the floor, size of the marble tile, security condition, health status of the work team, weather condition, site condition and availability of construction materials.
Sana et al. (2011): 5 factors	Weather, lack of availability of material and equipment, location of project, site conditions, and a number of workers.

2.6. Quantification of Output Parameters

In this thesis, CLP is defined as the ratio of a unit of output produced to the unit of input work hours (Khan 2005). The unit of output produced is the physical measure of quantity completed (concrete cast) which can be measured by simple mathematics. The unit of input work hours can be computed using total labor work-hours and recorded based on the total man-hours the crew used to complete a given quantity of concrete on a cumulative basis. The output produced or the quantity cast were recorded using the cubic meter (m^3) of concrete cast or produced, and the total labor work-hours are the total time used for final placing and finishing of the installed quantities of concrete.

2.7. Programming Languages

There are numerous programming languages that are used in today’s world for modeling different situations. Python is a widely used high-level programming language for general-purpose programming, created by Guido van Rossum and first released in 1991. Python features a dynamic type system and automatic memory management and supports multiple programming features. It has a large and comprehensive standard library. (Www.goalKicker.com)

Python is the first top popular general purpose programming languages. Python is used throughout the world by numerous professional like software engineers, mathematicians, scientists, data analysts, network engineers, students and others. Python is a language that is easy to learn, free, cross-platform, has a great developer community support, and good in-built features that could help development of models. (Www.hackr.io/blog/python)

2.8. Evaluating Model Performances

The model development process should always evaluate the performance of the model before using for the intended purpose. Artificial Neural Networks model do the evaluation when it performs backpropagation (as the fundamental of evaluating a model is to compare the predicted values with the actual values which is something done in part during backpropagation). Some of the techniques used to evaluate the performance of multilayer perceptron neural network model are discussed in the following subheadings.

Mean Absolute Error (MAE): is a measure of difference between two continuous variables. Assume *X* and *Y* are variables of paired observations that express the same phenomenon. Examples of *Y* versus *X* include comparisons of predicted versus observed, subsequent time versus initial time, and one technique of measurement versus an alternative technique of measurement. Consider a scatter plot of *n* points, where point *i* has coordinates (x_i, y_i) Mean Absolute Error (MAE) is the average vertical distance between each point and the identity line. MAE is also the average horizontal distance between each point and the identity line. (Lehmann 1998).

The mean absolute error is given by:

$$\text{MAE} = \frac{\sum_{i=1}^{n}[Y - X]}{n} = \frac{\sum_{i=1}^{n}[e]}{n}, \ldots \quad (2.11)$$

The mean absolute error is an average of the absolute errors, ei=Yi-Xi

Where $y_{i\,=}$ is the prediction

$X_{i\,=}$ the true value.

Note that alternative formulations may include relative frequencies as weight factors.

Mean Squared Error (MSE): of an estimator (of a procedure for estimating an unobserved quantity) measures the average of the squares of the errors—that is, the average squared difference between the estimated values and the actual value. MSE is a risk function, corresponding to the expected value of the squared error loss. The fact that MSE is almost always strictly positive (and not zero) is because of randomness or because the estimator does not account for information that could produce a more accurate estimate. (Willmott 2005).

The Mean Squared Error is given by:

$\mathrm{MSE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i-n}}^{\mathrm{n}}[\mathrm{Yi} - \mathrm{Yi}]^{2}$………………..…………………………………………... (2.12)

R-Squared (R^2): is a statistical measure that represents the proportion of the variance for a dependent variable that's explained by an independent variable or variables in a regression model. Whereas correlation explains the strength of the relationship between an independent and dependent variable, R-squared explains to what extent the variance of one variable explains the variance of the second variable.

The Formula for R-Squared is:

$\mathrm{R} - S \qquad = 1 - \frac{E \qquad V}{T \quad V}$…………………………………………. (2.13)

2.7. Research Gaps

Despite its obvious importance in construction project management, developing accurate and interpretable CLP models for analysis and improvement of construction productivity has not been fully achieved (Yi and Chan 2014). Even if CLP is a key to the success of construction projects, there is a limited number of researches were done in developing counties and throughout the world to develop a model for the estimation of productivity. Since the availability of construction machines used to convert construction inputs to outputs or project products are very low in Ethiopia, the construction industry is largely labor-intensive. In spite of this, there was no research performed in Ethiopia to develop CLP estimation models which are very crucial and important for the success of construction projects in the country. Therefore, in order to fill this research gap and to enhance the profitability, income, and competitiveness of the construction projects this paper is very important for the country as well as for the construction stakeholders in Ethiopia.

CHAPTER 3

RESEARCH METHODOLOGY

3.1. Study Area

This study was conducted in Addis Ababa, Ethiopia. Addis Ababa is the Federal Capital city of Ethiopia, located between 8055' and 9005' North Latitude and between 38040' and 38050' East Longitude. The total land area of the city is 54,000 hectares, with a population of more than 3 million. The average elevation of the city is 2,500 meters above sea level, and hence has a fairly favorable climate and moderate weather conditions. (www.addisababa.gov.et)

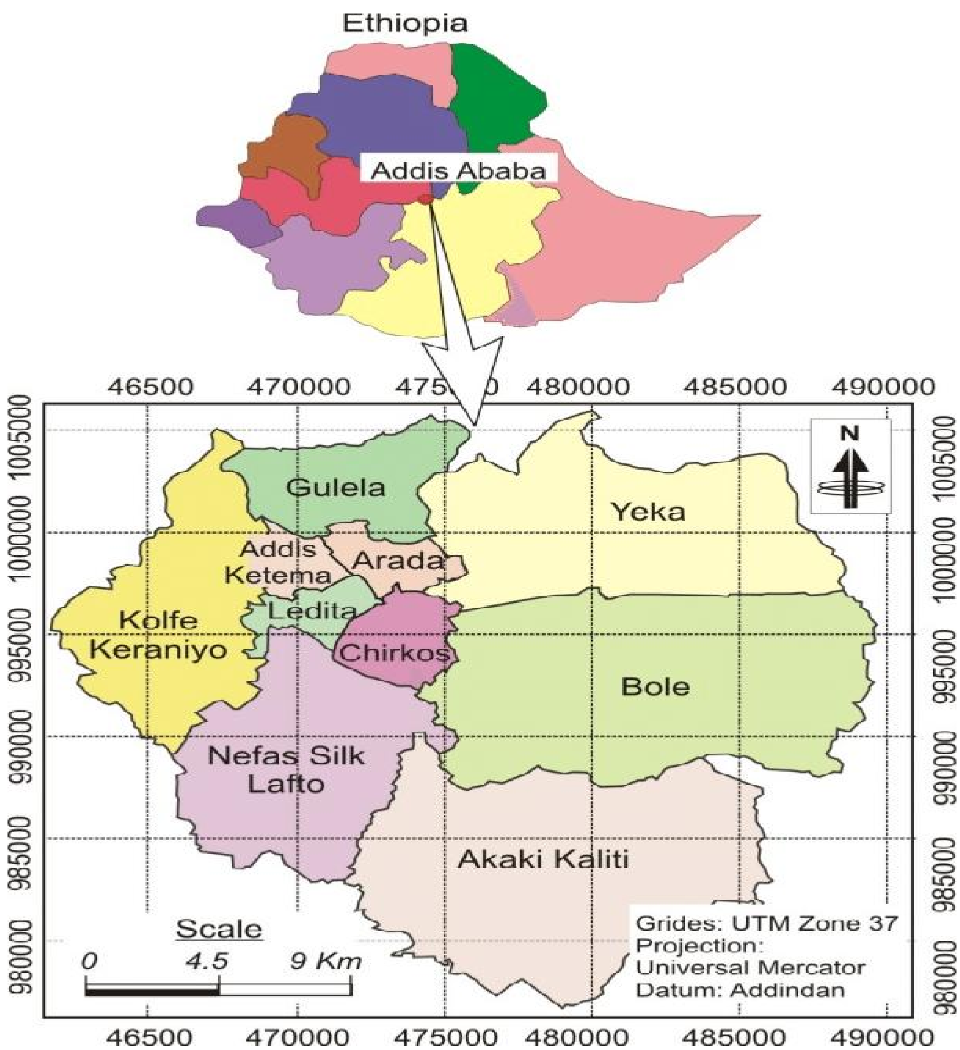

Figure 3. 1: Location Map of Study Area (www.researchgate.net)

3.2. Research Design

Mixed type of research design was adopted in order to fully answer research objectives of this study. Saunders et al. (2009) states that descriptive research is used to describe an accurate profile of a situations. Correlation type of research design was adopted to answer the second research objective of this study. This design offers the researcher to describe the strength of relationship between the identified critical influencing factors (independent variables) and CLP (dependent variable).

A simulation type of research design was adopted to meet the objective of this study. Simulation involves devising a representation in a small and simplified form (model) of a system, which can be manipulated to gauge effects. Models can be mathematical (number-crunching in a computer) or physical, working with two- or three-dimensional materials (Walliman 2011). Also, this research can be categorized as applied based on purpose and primary and secondary based on the source of data.

3.3. Sample Size and Sampling Techniques

The model was developed using the data collected from active constriction projects which was on the concreting stage and located in Addis Ababa city. Therefore, no other sample selection formulas were used or the method adopted to distribute the questionnaire and to collect the data was by direct observation and it is therefore purposive sampling.

3.4. Study Variable

3.4.1. Dependent Variable

The dependent variable of this research was construction labour productivity.

3.4.2. Independent Variable

Some of the independent variables that can influence CLP are:

- ✓ Crew Experience
- ✓ Age of Workers
- ✓ Placement Technique
- ✓ Number of Workers Performing the Task

3.5. Data Collection Procedure

To achieve the research objectives different data collection procedures was adopted. Data was gathered through questioner survey, and by direct observation of the concreting activity. Primary data sources was used in order to get firsthand information from the construction projects and it helped in providing information for specific purpose of addressing the problem at hand that interview was conducted with stakeholders, and critical observation of the activity concreting was also done in order to obtain reliable information about the factors that affect productivity of concreting activity. Secondary data was gathered through reviewing, examination of documents, reports, and records of published sources and other pieces of literature related to factors or parameters that can affect construction labor productivity and the respective modeling techniques used to develop the model for estimating CLP.

Numerous researchers have identified that a suitable method of data collection influenced the accuracy of the production rate values. A questionnaire survey is the most common data collection method adopted by the researchers to collect information on the critical factors and on the output produced within these factors in a cost-effective way but the reliability and accuracy of the results cannot be proved. Therefore, the researcher adopted a direct observation method to collect productivity data of concreting activity on the site, so that the accuracy of data can be improved which leads to the overall accuracy of the model.

3.6. Data Processing and Analyzing

To achieve the initial part of the research objective a literature of past labor productivity studies was reviewed to identify, and classify influencing inputs or parameters presented together with the quantification of the parameters for field data collection, the different identified factors was grouped in to subjective and objective variables and their frequency of occurrence was counted and selection of factors was done by using RII on the data obtained through questionnaire survey. Using the results of RII most critical elven influencing parameters was selected for further analysis, for field data collection and for development of the model.

The eleven most critical influencing factors (five objective and six subjective) identified through the questionnaire survey were then recorded simultaneously during measurement of production rates of concreting activity in the site using the data collection form as shown in appendix 8. The selected influencing factors were chosen since they were considered the most critical by construction stakeholders to influence productivity rates. Thus, it is worthwhile to consider the above-mentioned critical construction labor productivity factors to model labor productivity. The correlation coefficient of these factors was calculated and used to investigate the strength of relationship between the identified most critical factors and the CLP, so that at this point the second objective of the paper was successfully achieved.

The data which was collected by direct observation from active building construction projects, which were on concreting stage was first systematically arranged in an excel spread sheet and imported into a programming software for further analysis and modeling. The ANN model was developed using python 3.7 version and the codes were presented and coded in Jupyter notebook with lots of Tensorflow libraries which were used for modeling the CLP of concreting activity for building projects in Addis Ababa city.

Data collecting, analysis, and modeling were follow the following simple procedure:

- ✓ Identification of CLP influencing factors from different kinds of literature.
- ✓ Preparing questioners and distribute to construction stakeholders then collect the questioners and identify the factors which are highly significant for CLP at the site. (Research objective one was achieved)
- ✓ After identifying the most critical factors that can influence CLP, data was collected by direct observation for concreting activity from different building projects located in Addis Ababa city.
- ✓ By applying correlation coefficient on the data’s collected from direct observation the strength of relationship between the identified factors and CLP was investigated. (Research objective two was achieved)
- ✓ Finally, CLP model was developed using Python programming language (Research objective three was achieved)

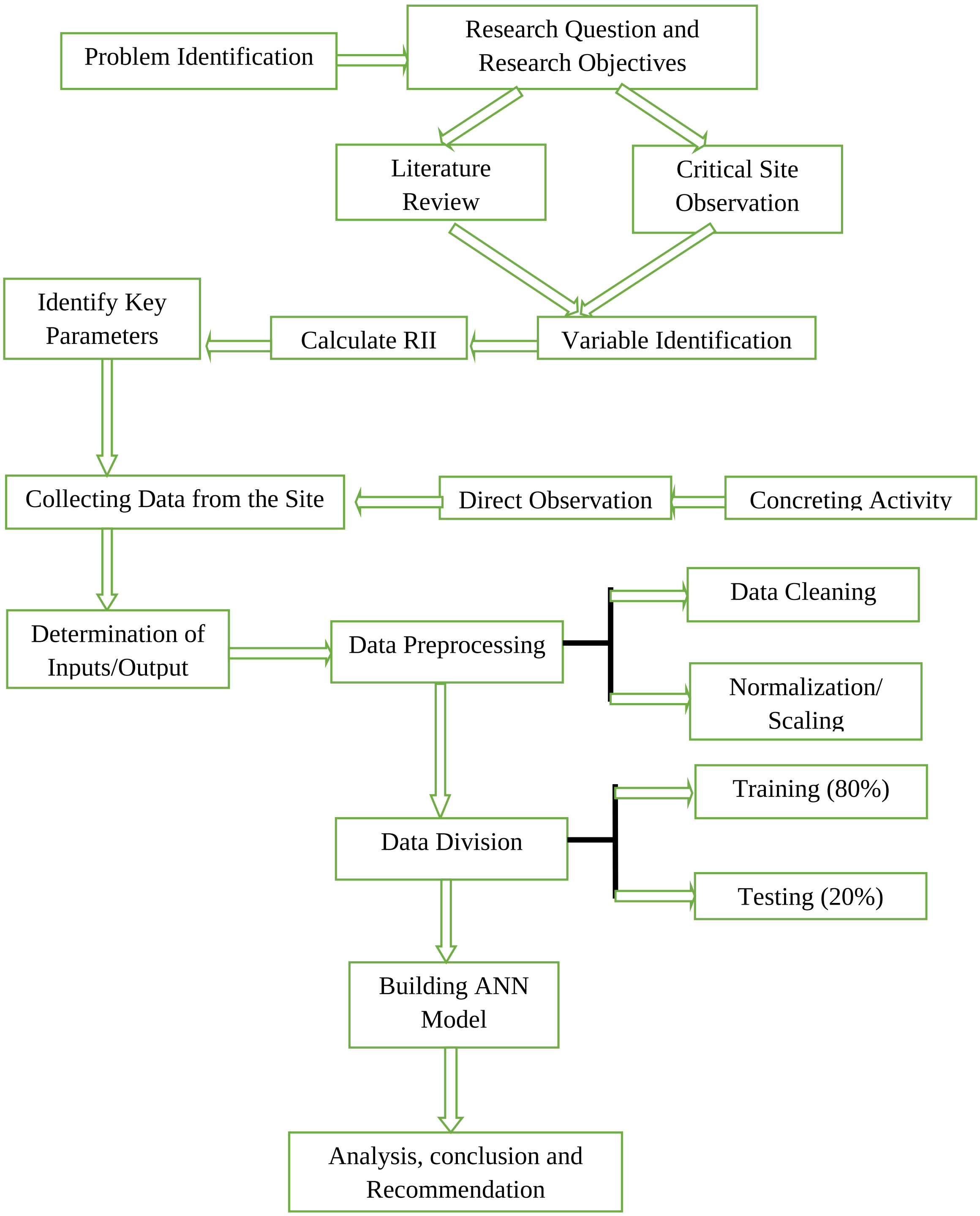

Figure 3. 2: Overall Summary of the Study (Researcher Design)

3.7. Ethical Consideration

Before starting the data collection process the researcher was obtained ethical clearance from Jimma University, Institute of Technology, Department of Construction Engineering and Management. Official letters were written from the Department of Construction Engineering and Management to concerned construction offices. The purpose of the letter was explained to the subjects. Saunders et al. (2009) states that respondents and participants during research data collection should participate on the basis of informed consent. Since the study was conducted only for academic purpose there were no conflicts between the researcher and the respective project stakeholders. Therefore construction labour productivity data's with their influencing parameters was successfully collected by direct observation at the project sites.

3.8. Data Quality Assurance

The quality of the data which were obtained from different journals was assured by using only those data obtained from predatory journals. The data obtained from questioners were properly analyzed using different statistical methods and computer software's like Microsoft excel and Python 3.7. All the obtained data were recorded and collected in due care that it was reliable and accurate.

CHAPTER FOUR

RESULT AND DISCUSSION

4.1. General Background

The topic of this research was developing a construction labor productivity model using ANN's for building projects in Addis Ababa city. This research was conducted on Addis Ababa city building construction work projects which were active (ongoing) and also on the stage of concreting activity.

The overall aim of this paper was to identify and classify different factors or parameters that can influence CLP, to investigate the impacts of the identified factors on CLP, and finally to develop a model for estimating CLP of building projects for concreting activity. Tables 4.1 and 4.2 show the context-specific objective (quantitative) and subjective (qualitative) variables which were identified by a critical review of numerous published documents, reports, records, and books. Those factors which can cause variation of productivity on a daily basis or on the short term are the primary selection criteria that were adopted to select context-specific parameters.

Table 4. 1: Context Specific Objective Variables

SN.	Objective (Quantitative) factors
1	Crew Size (number of workers):
2	Crew experience (seniority)
3	Age of workers
4	Average wind speed
5	Number of consecutive days worked
6	Number of languages spoken
7	Number of craftsperson technical training

8	Level of overtime
9	Level of interruption and disruption
10	Foreman experience
11	Distance to temporary material storage to casting place
12	Space of casting (volume of work)

Table 4. 2: Context Specific Subjective Variables

SN.	**Subjective (Qualitative) factors**
1	Weather condition (comfort level)
2	Location of project
3	Comfortability of materials storage for work
4	Scaffold requirement
5	Skill level of labor
6	Congested work area (arrangement of falsework)
7	Communication problems with workers
8	Alcoholism
9	Disruption of power/water supplies
10	Health status of workers
11	Extent and quality of supervision
12	Safety requirements
13	quality requirements
14	Crew flexibility (crew willingness in performing other members task)

15	Building element (footing, grade beam, column, slab…)
16	Cover from weather effect
17	The working condition (noise)
18	Placement technique (Pump, Crane, bucket, direct chute…)

4.2. Identification of Critical Influencing Parameters

As discussed in section 2.4 and summarized in appendix 1 numerous input parameters that can influence CLP have been identified from the review of the literature. The identified 30 context-specific factors were grouped under two main categories: 12 objective (quantitative) and 18 subjective (qualitative) variables. A questionnaire survey was conducted in Addis Ababa City construction stakeholders with 32 respondents from project managers, contractors, consultants, masons, and foremen to identify the most critical factors from the identified 30 factors and consequently to establish a top 11 factors: 5 objective and 6 subjective factors as shown in table 4.3 and 4.4. The responses to each parameter were systematically arranged in an excel worksheet and are then used to calculate RII using equation 4.1. In this research, RII is named as the parameter index (PI) and is used to rank each parameter. The summary of PI for all factors is summarized in table 4.3, figure 4.1 and appendix 6.

PI= ∑W/A*N

PI= [1*n1 + 2*n2 + 3*n3 + 4*n4 + 5*n5]/ A*N…………………………………... 4.1

Where: W = Weight given to respondents to each parameter ranging from 1 to 5

n1 = Number of respondents for unimportant

n2 = Number of respondents for moderately important

n3 = Number of respondents for no idea

n4 = Number of respondents for very important

n5 = Number of respondents for extremely important

A = Highest weight (i.e. 5)

N = Total number of responses collected for the ordinal scale

Table 4. 3: Most Critical Factors Influencing CLP

SN	Influencing Factors	PI	Rank
Objective Variables			
1	Crew Size (number of workers)	0.913	1
2	Crew experience (seniority)	0.838	6
3	Age of workers	0.769	11
4	Level of interruption and disruption	0.781	10
5	Distance to temporary material storage to casting place	0.875	3
Subjective Variables			
1	Weather condition (comfort level)	0.869	4
2	Congested work area (arrangement of falsework)	0.825	7
3	Health status of workers	0.888	2
4	Crew flexibility (crew willingness in performing other members task)	0.806	9
5	Building element	0.856	5
6	Placement technique	0.819	8

Table 4.3 and Figure 4.1 shows the ranking of the most critical factors influencing CLP. A crew size or a number of workers was ranked 1st from identified context-specific factors that can influence CLP, with an RII value of 0.913. Crew size has a great influence on productivity. This result is supported by Golnaraghi (2019) who found that the crew size affects labor productivity. This conclusion is also supported by Aswed.G (2016) concluded that crew size affects job-site productivity.

The health status of workers ranked the 2nd to affect construction labor productivity with an RII value of 0.888. As discussed in section 2.4 the health status of workers is one of the most important parameters to affect CLP. This conclusion is supported by Al-Zwainy et al. (2013).

Distance to temporary material storage to casting place was found to be the 3rd most critical factor that can influence CLP with and RII value of 0.875. Tsehayae.A. (2015) argues that the final placing distance to the material mixing distance can affect CLP. Transporting the mix to the final casting place requires considerable time which consequently affects productivity.

The 4th identified parameter that can affect CLP is weather conditions (comfort level) with an RII value of 0.869. This conclusion is supported by numerous CLP authors like Sana et al. (2011), Zayed and Attia (2015). Weather is one of the conditions that can facilitate or hiders the activity and productivity of workers even extreme conditions may stop the execution of the activity.

Building elements ranked the 5th to affect construction labor productivity with an RII value of 0.856. The building element refers to the element of the building/plant under construction. The element of the building can be beam, column, and slab. Building element affects CLP as each building elements have different ease of placement.

Crew experience has a great influence on productivity and ranked 6th from the 30 factors identified from the literature, with an RII value of 0.838. This result is supported by Faiq et al. (2012) who found that the craftsmen’s experience affects labor productivity. This conclusion is also supported by Aswed (2016) who established that the knowledge of the craftsman affects job-site productivity. Experience improves both the intellectual and physical abilities of workers in return, increases labor productivity.

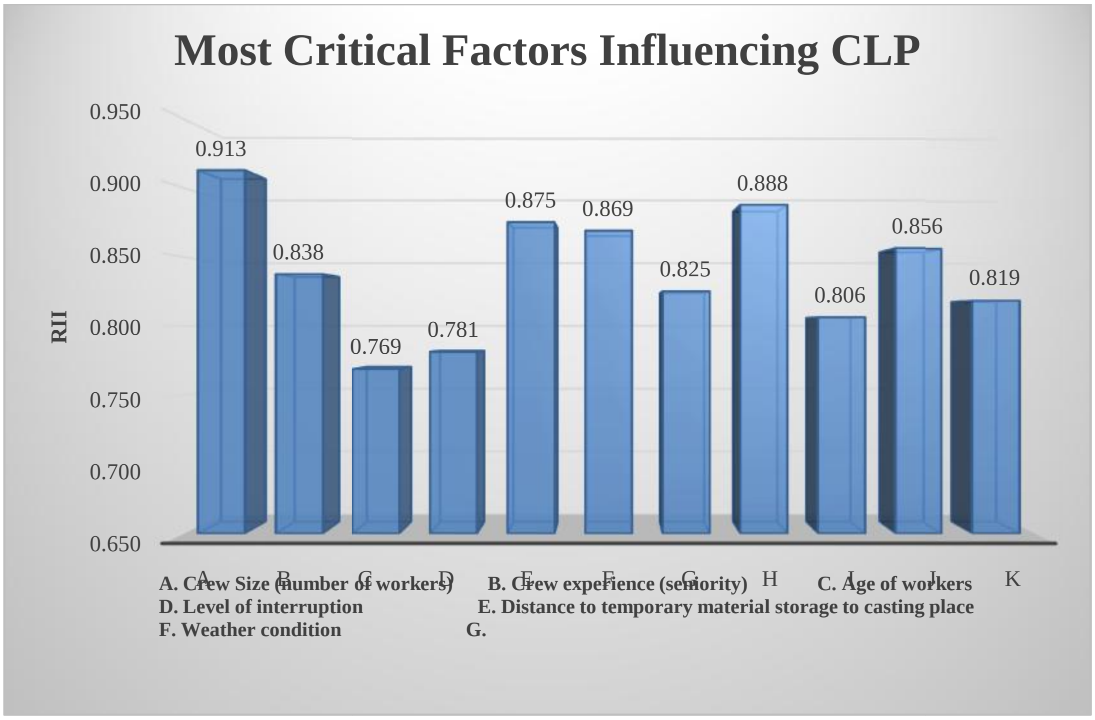

Figure 4. 1: Most Critical Factors Influencing CLP

Congested work area/arrangement of falsework was the 7th most critical parameter which was identified from the questionnaire with an RII value of 0.825. This result is supported by Liberda et al. (2003) who found that the congested work area affects labor productivity. Congested work area hiders ease of movement of workers performing concreting activity which consequently affects CLP.

The 8th ranking factor with the RII value of 0.819 was placement technique. The placement technique adopted for concreting activity can be using cranes, winches, buckets or other mechanisms which greatly alters the productivity rate produced. This result is acceptable because the productivity produced by different concrete placement techniques are different. This result is supported by Tsehaye.A. (2015)

Crew flexibility is the 9th parameter which was identified from the questionnaire survey. Crew flexibility refers to the ability and willingness of crew members in performing other member’s tasks. This result is also supported by Tsehaye.A. (2015)

The level of interruption and disruption is the total time lost in minutes due to different external and internal reasons. This result is supported by Tsehaye.A. (2015). Level of interruption and disruption were ranked the 10th factor with an RII value of 0.781. This result is acceptable because interruption of the work by any means can cause, completely or partially stopping the construction work and affecting labor productivity.

The age of workers was ranked 11th, with an RII of 0.769 among all the 30 factors that affected labor productivity (Table 4.1 and 4.2). (Aswad (2016) and Faiq et al. (2012)) Supported this result, citing that the age factor generally affects job-site productivity.

4.3. Quantification of Input Parameters

Quantification of input parameters (independent variables) is the vital and starting point for the analysis and modeling of CLP studies. However, the parameters influencing the CLP variable are complex leading quantification and data collection process a challenging task. Additionally, quantification of factors or parameters is complicated as the factors are a mix of objective and subjective variables and therefore quantification requires proper and understandable measurement schemes.

Subjective parameters like weather condition, the health status of workers, placement technique and the likes require detailing of parameters, so that accurate data can be collected. Whereas parameters having objective concepts like crew size, age of workers, crew experience and the like can be easy to carry out the data collection process. As a result, first, the researcher identified the most critical influential parameters or factors from the collected questionnaires before completing detailed measurement, so the data collection process was simplified.

For each identified most critical factors a measurement scale that is used to data collection must be developed, so as to quantify the input parameters and simplifies the construction site data collection process. The quantification in this research is done for all critical parameters which were identified from questionnaires' respondents as shown in table 4.3 and also for other parameters which were identified from the review of documents as shown in appendix 7.

Objective variables can be quantified by well-defined numerical values (e.g. distance from mixing place to casting place is measured in terms of average distance from mixing place to the final placement of concrete). Whereas, subjective variables lack well defined numerical measures (e.g. weather condition is measured by the comfort level of the atmosphere). Hence for subjective variables, a pre-defined rating scale (1-4) has been developed based on sub-parameters. The purpose of this sub-parameter is to assist the data collection process when the parameter cannot be measured directly so that these sub-parameters are used to suggest the extent of the parameter's existence. Sub-parameters are based on measurable concepts that are always associated with the parameters and enables measurement of parameters by a pre-determined rating scale. For example, weather parameter sub-parameter was defined based on sunny (1), moderately sunny (2), moderately rainy (3), and rainy (4). This type of sub-parameters enables the development of a rating scale which are capable of measuring the parameters. Detail of the critical input parameter quantification can be seen in appendix 7 and table 4.4.

Table 4. 4: Critical Input Parameters Quantification

ID	Parameter	Description	Measurement scale (unit)	Data source
		Objective Variables		
N	Crew Size (number of workers)	The total number of the crew performing the actual task	Integer	DC
E	Crew experience (seniority)	The average years of experience of the crew members on concreting activity	Real number	F+CM
A	Age of workers	The average age of workers performing the actual work in years.	Real number	F+CM
I	Level of interruption and disruption	The time lost and delay events caused due to several reasons, which may disrupt the crew from performing the assigned tasks.	Integer (total minutes spent)	DC
D	Distance from mixing place to final casting and finishing place	The average distance between mixing place to final placing and finishing	Integer	DC

Subjective variables				
W	Whether condition	The atmospheric weather condition of the site during performing the required task	1-4 pre-determined rating shown below 1- Sunny 2- Moderately sunny 3- Moderately rainy 4- Rainy	DC
C	Congested work area	Arrangement of falsework and ease of the site to perform the task in question	1-4 pre-determined rating shown below 1- Completely uncongested 2- Somewhat congested 3- congested 4- completely congested	DC
H	Health status of workers	Health status of workers during the execution of the task	1-4 pre-determined rating shown below 1- Very good 2- Good 3- Moderate 4- Bad	CM
F	Crew flexibility	Crew willingness in performing other members task	1-4 pre-determined rating shown below 1- Completely willing 2- Willing 3- Somewhat willing 4- Completely unwilling	DC
B	Building element	Beam, column, slab…	1-4 pre-determined rating shown below	DC

			1- Slab 2- Beam 3- Column 4- Septic tank	
P	Placement technique	Pump, winch, bucket, direct chute…	1-4 pre-determined rating shown below 1- Pump 2- Winch 3- Direct chute 4- Bucket	DC

Note: DC= data collector, F= foreman, and CM= crew member

Data can be gained from the following sources: researcher (data collector), foreman, and crew members), this data sources would be assigned to each parameter and sub-parameter based on the respondent's knowledge about the source of data in question. Data's which can be collected by direct observation like weather condition can be collected by researcher or DC. For this research, the preferred criterion for direct observation data collection is summarized as shown in figure 4.2.

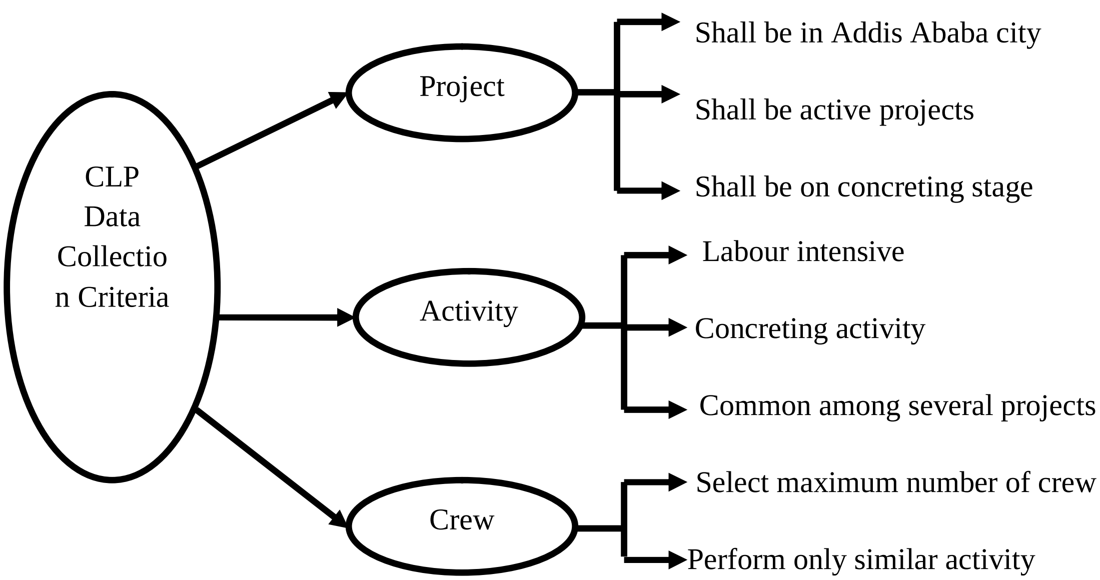

Figure 4. 2: Criteria for Selecting Building Projects for Data Collection

4.4. Data Analysis

All the data's collected by direct observation from the construction site are first tabulated and saved in CSV format in excel spread sheet then imported into Python. The descriptive statics of the collected data were shown in table 4.5 which can clearly show the summary of the collected dataset.

Table 4. 5: Summary of the Collected Data Set

	count	mean	std	min	25%	50%	75%	max
CLP	114.0	4.242018	4.501959	0.34	1.515	2.12	5.467500	20.000000
Crew Size	114.0	8.649123	1.021733	6.00	8.000	8.00	9.000000	11.000000
Crew Experience	114.0	5.083114	2.615161	2.00	3.220	3.89	6.570000	10.400000
Age	114.0	26.251534	3.378545	22.00	24.000	25.50	27.700001	34.000000
Interruption level	114.0	8.053509	13.652800	0.00	0.000	2.25	8.870000	86.000000
Distance	114.0	29.779823	10.321677	7.50	21.100	29.95	38.200001	49.799999
Whether	114.0	1.780702	0.817494	1.00	1.000	2.00	2.000000	4.000000
Congested Area	114.0	1.921053	0.705788	1.00	1.000	2.00	2.000000	3.000000
Health Status	114.0	1.631579	0.484506	1.00	1.000	2.00	2.000000	2.000000
Crew Flexibility	114.0	1.859649	0.689712	1.00	1.000	2.00	2.000000	3.000000
Building Element	114.0	2.008772	0.825432	1.00	1.000	2.00	3.000000	3.000000
Placement Techniques	114.0	2.122807	1.090103	1.00	1.000	2.00	2.000000	4.000000

To measure the strength of the relationship between construction labor productivity and its critical influencing factors and also between the independent variables a correlation coefficient was calculated using python 3.7 as shown in table 4.6 and appendix 10. A correlation coefficient is a number that can describe the degree of relationship between two variables such as "X" and "y".

The correlation coefficient shown in table 4.6 is computed by considering the construction labor productivity rate of concreting activity as "y" and it's all critical influencing factors as "X". The values shown the strength of a linear relationship of collected data between CLP and its influencing factors. If the sign of the R is positive, the value of CLP increases when influencing factors increases. If the sign is negative CLP decreases as the influencing factor increases.

Table 4. 6: Correlation between CLP and Influencing Factors

Influencing Factors	Correlation(R)
Crew Size	0.1160
Crew Experience	0.5681
Age	0.5349
Interruption level	-0.0573
Distance	-0.1201
Whether	-0.0748
Congested Area	-0.1944
Health Status	-0.1984
Crew Flexibility	-0.0912
Building Element	0.1266
Placement Techniques	-0.5227

Always correlation coefficient ranges between -1 and +1. A strong relation between variables is identified by larger absolute coefficient values. An absolute R-value 1 specifies the perfect linear relationship between variables. From table 4.6 result it is clear that none of the influencing factors are over correlated to CLP and therefore there is no overestimation between variables.

From table 4.6 it is observed that crew experience and age of workers have higher correlation coefficient (R) values than other influencing factors with a value of 0.5681 and 0.5349 respectively. The higher positive values of correlation for crew experience and age of workers imply that the production rate of concreting activity has a high direct linear relationship with these factors. As the year of experience of workers in concreting activity increases production rate also increases. Similarly, as the age of crew performing concreting activity increases the production rate also increases.

Placement technique is the third most influencing factor to correlate with construction labor productivity with an R-value of -0.5227. Placement technique is a subjective variable that was quantified in section 4.3 in the Linkert scale of 1 to 4: pump, winch, direct chute, and bucket respectively. This correlation coefficient value shows a strong relationship of placement technique with CLP but the sign indicates a decrease in production rate as we go down the Linkert scale. In other words production rate dramatically decreases while the activity is performed in a bucket than in the pump. From this result, we can conclude that using a pump for placing concrete dramatically increases the production rate.

Next to the placement technique, the health status of workers and arrangement of falsework have higher correlation coefficient values of -0.1984, and -0.1944 respectively. The negative sign shows the decrease in production rate as we go down the Linkert scale. The health status of workers was ranked 1 to 4: very good, good, moderate, and bad respectively. During the execution of concreting activity as the health status of workers is going bad their productivity is also decreased. Ease of the site or arrangement of falsework to perform the task in question is scaled 1 to 4: completely uncongested, somewhat congested, congested, and completely congested respectively. This result shows that as the place of performing the task becomes more congested production rate decreases.

The concreting activity can be performed in different parts of a building. The researcher was therefore considered column, slab, beam, and septic tank; as these concreting activities are the major activities for most building projects. The building element was ranked on the Linkert scale of 1 to 4: slab, beam, column, and septic tank respectively. But due to the unavailability of the data septic tank was excluded from further analysis and modeling. From the R-value of 0.1266, we can conclude that the building element productivity rate of labor for a column is higher than the beam and slab.

Distance is the total length from the mixing place of concrete to the final casting place of concrete. The R-value of -0.1201 shows that as the distance of concrete placement gets longer the productivity rate decreases. And the other influencing factor with an R-value of 0.1160 is crew size. We can conclude that the productivity rate of labor increases as the number of the crew performing the activity increases.

The R values of -0.0912 and -0.0748 are the values of correlation for crew flexibility and whether respectively. It can be easily understood that as the willingness of the crew performing the task decreases the productivity is also decreases. Similarly, the weather condition is also another influencing factor that can alter the productivity of labors. The final factor which was used in this study was the interruption level of the activity by any means. The interruption level was correlated to CLP with R-value of -0.0573 which shows that as the time of interruption increases productivity rate drops down.

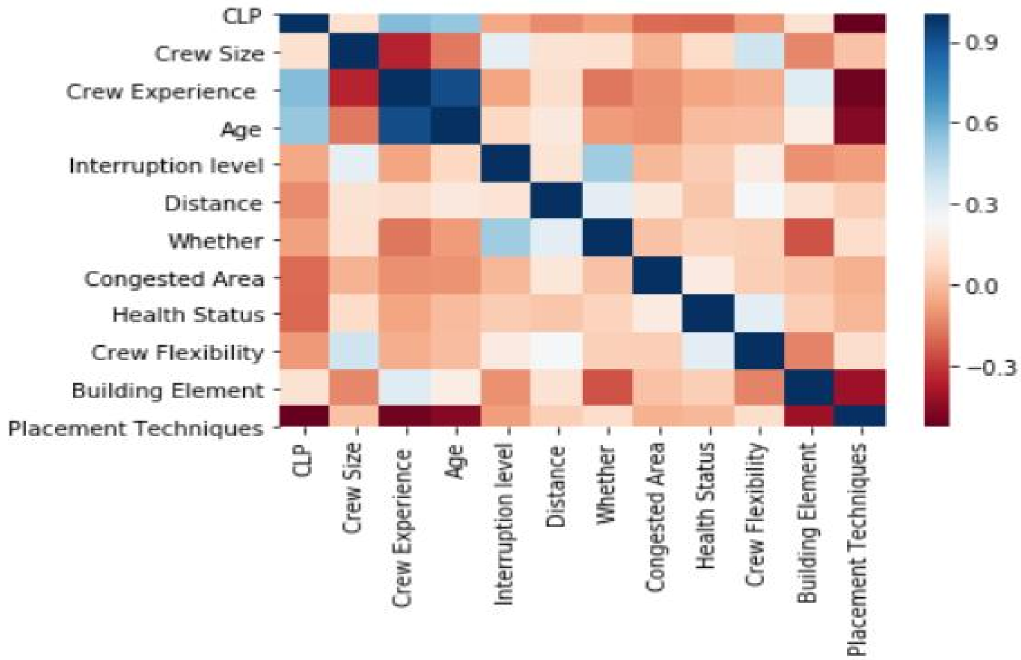

Figure 4. 3: Correlation Heat Map

In figure 4.3 it is clearly observed that strongly correlated factors have dark red and dark blue colors whereas, the strength of the relationship between variables decreases as the colors contrast decreases. Along the diagonal, it is shown that everything is perfect dark blue this is because along the diagonal correlation is 1, which is the correlation of variables with itself.

The strength of relationship between all variables for the collected datasets by direct observation are shown in the appendix 10 numerically from the correlation result generated by Python and also in figure 4.3 by color contrasts generated using plot heat map function of python in Jupyter notebook. From figure 4.3 and appendix 10 we can conclude that placement technique and crew experience, weather condition and interruption level, placement technique and age of workers, building element and placement technique have high contrasting red and blue colors in the correlation heat map and also high numerical absolute values of greater than 4.00. Therefore construction stakeholders at site should consider the combination of these independent variables as the impact of one variable have stronger influence on the others.

4.5.Model Development

Researchers were used several functions to study the relationship among a given data which was discussed previously in previous sections. Backpropagation Neural Network was adopted in this research since BNN is the most widely used type of function to analyze this type of data and it connected by interconnections called synapses and it consists of processing elements called neurons. Sana et al (2011), and AL-Zwainy et al (2013) were applied BNN's for developing construction labor productivity models.

In the process of developing this model all the inputs are multiplied with the weights, bias is added and moved forward through the network to predict the output. The weights and biases are arbitrarily assigned by the network during the forward pass to predict the output of the network. The predicted output or the machine guess were compared to the target output and their difference which is the error (MSE) is propagated in the opposite direction of the forward pass to adjust the weights and biases of the network. The weights and biases are adjusted in each step so that the gradient results in smaller errors until the error minimum is reached.

Training the network is all about adjusting the weights and biases in order to improve the performance of the network. The learning algorithm style adopted for this model development was supervised learning, error correction gradient descent, backpropagation, which is a teacher's existence learning process for expected outputs. The network consists of three-node levels layers which are input, hidden, and output layers. Hence it consists of more than two layers and each layers consists of more than two nodes the structure of the network is a multilayer.

4.5.1. Data Preparation and Preprocessing

In the process of developing the construction labor productivity model all data's that were obtained and collected from direct observation are converted to numeric values and inserted in an excel spreadsheet and saved in the CSV format. The second step followed was importing the data frame into Jupyter notebook and preprocessing the data that involves tasks of removing duplicates and no values in the data frame. And also data cleaning involves splitting the data set into two separate data sets: the first columns as output data set which is CLP and the reaming columns as input data set. The output data set contains the CLP which was collected from the construction sites and converted into the output of the crew performing the concreting activity in cubic meter per hour. Whereas the input data set contains all the inputs or parameters that bring together a certain amount of outputs.

Some features have an order of magnitude larger than others and unlikely these features are significantly more correlated than others to the outputs. Therefore to avoid this over correlation, data scaling was performed in python using the minmax scaler data normalization technique as discussed in section 2.2.1. In this study, the given dataset was scaled between 0.1 and 0.9.

4.5.2. Optimal Data Division

The CLP model was developed on all 114 data instances collected through direct observation. This dataset was divided into training, validation and test data sets for the purpose of accurate modeling and for testing the performance of the model. The best data allocation for this problem is shown in table 4.7. This optimal number of data divisions was obtained by trial and error. Data was divided into different training, validation, and testing data divisions and observed their performance. Therefore the data division shown in the table performs best than other data division with less error and high convergence.

Table 4. 7: Optimal Model Data Division

Type of Dataset	Number of Data Instances	Percentage (%)
Training	74	65
Validation	17	15
Testing	23	20
Total	144	100

4.5.3. ANN Optimal Parameters

Python 3.7 version has been used to develop the ANN model. The researcher was adopted Python for modeling CLP because python is the top best programming language used in 2020. The code used to develop this model was written in the Jupyter notebook and analyzed and modeled by using different Anaconda libraries like Tensorflow, Keras, Scikit learn, Matplotlib and other programing libraries used for mathematical computations and visualizations. Table 4.8 shows the optimal model development parameters. Most of this multi-layer perceptron (MLP) parameters was obtained by trial and error after comparisons of the performance of the model.

Table 4. 8: The Optimal ANN Model Parameters

S/N	Document String Type	Description
1	Hidden layer size	Number of layers and neurons are introduced (1 hidden layer and 2 hidden nods)
2	Activation	Activation used in the hidden layer (Logistic)
3	Maximum iterations	Number of epoch (2000)
4	Solver (Optimizer)	For weight optimization (Adam)
5	Initial learning rate	Controls weights and bias update (0.1)
6	Momentum	For gradient decent update(0.9)
7	Early stopping	Stops training when loss stops decreasing (True)
8	Validation fraction	Set aside data for validation (15%) and also the detail of the parameters used and the steps followed to analyze and model this problem is shown in appendix 11

4.5.4. Effects of Hidden Nodes in Performance of NN’s

After executing the above parameters in Python, simulated outputs have been compiled and accuracy of the model has been determined by calculating Mean Squared Error (MSE), Mean Absolute Error (MAE), and coefficient of determination (R^2) by using the formulas discussed in section 2.8 through Python functions. MLP Regressor ANN mapping set of input data’s to output, the basis for this transformation is the number of nodes and number of hidden layers. Therefore numerous model was developed by varying the number of hidden nodes and hidden layers, the performance results of the numerous models are summarized as shown in table 4.9 and in figure 4.4 and 4.5. The best model was selected on the basis of model performance for the test datasets.

Table 4. 9: Performance Results of One Hidden Layer Model

Neurons	MAE Train		MSE Train		R^2 Train	
	Train	Test	Train	Test	Train	Test
1	0.03253	0.04141	0.00170	0.00457	0.94080	0.90182
2	**0.02051**	**0.03060**	**0.00121**	**0.00316**	**0.96110**	**0.92065**
3	0.02962	0.03561	0.00170	0.00391	0.94105	0.91596
4	0.02136	0.03395	0.00094	0.00407	0.96739	0.91253
5	0.02016	0.03621	0.00088	0.00420	0.96924	0.90972
10	0.02652	0.04498	0.00129	0.00562	0.95500	0.87939
15	0.02652	0.04498	0.00129	0.00562	0.95500	0.87939
20	0.03276	0.04400	0.00234	0.00583	0.91867	0.87482
30	0.08388	0.11183	0.01497	0.02511	0.48165	0.46114

The results in table 4.9 was obtained by selecting the maximum score the developed models shows from two hundred different trainings for each in different number of nodes. Therefore it is seen that the model with 2 hidden nodes can predict CLP with less MAE, and MSE values of **0.03060,** and **0.00316** respectively. The R^2 value for training datasets was **0.9611**, demonstrating that the outputs/predictions are **96%** close to the target values. Whereas the R^2 value for test dataset was **0.92065**, which proofs that the model is able to predict **92%** of future outcomes accurately. Therefore for the building construction projects located in Addis Ababa city, the MLP neural network structure with two hidden nodes shows maximum convergence and least error.

Figure 4.4 and 4.9 display the effects of number of neurons on the values of R^2 and MSE respectively. R^2 values ranges from 96% to 48% for train data set and it ranges from 87% to 46% for test datasets. Whereas MSE values ranges from 0.094% to 1.497% for train data set and it ranges from 0.316% to 2.511% for test datasets. Therefore after comparing the results of R^2 and MSE for the test datasets the model with one hidden layer and two hidden neurons shows maximum accuracy and least errors respectively.

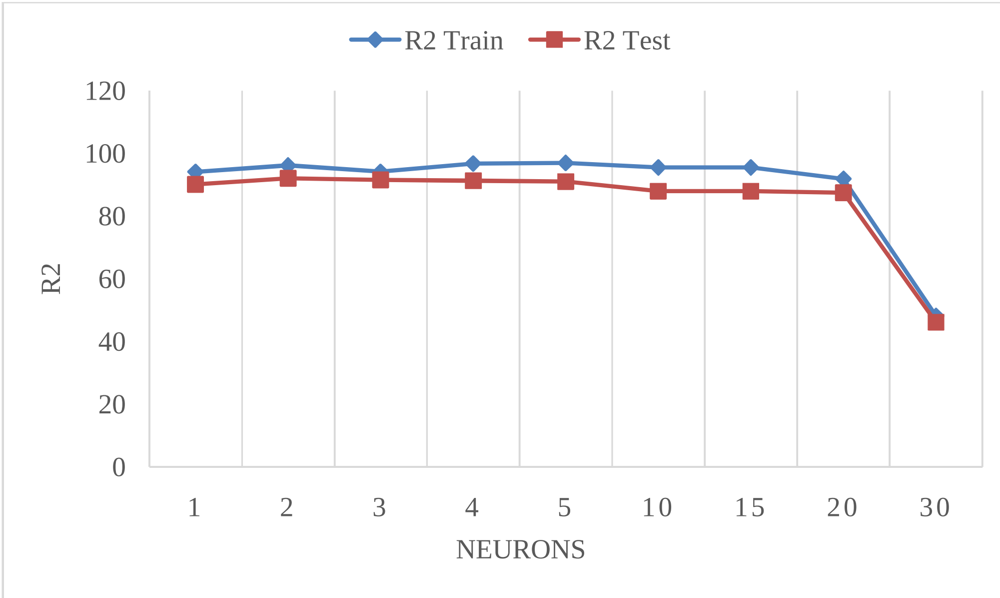

Figure 4. 4: R^2 Values with their Corresponding Neurons

Since the developed model will be used for future CLP rate estimation, the model with high value of R^2 with list error is selected as optimal model to predict future concreting activity rates. It is observed during model training phase that as the number of hidden layers increases the performance of a model will not be improved. Therefore the model with two hidden neuron has a maximum accuracy and least error as compared to other models.

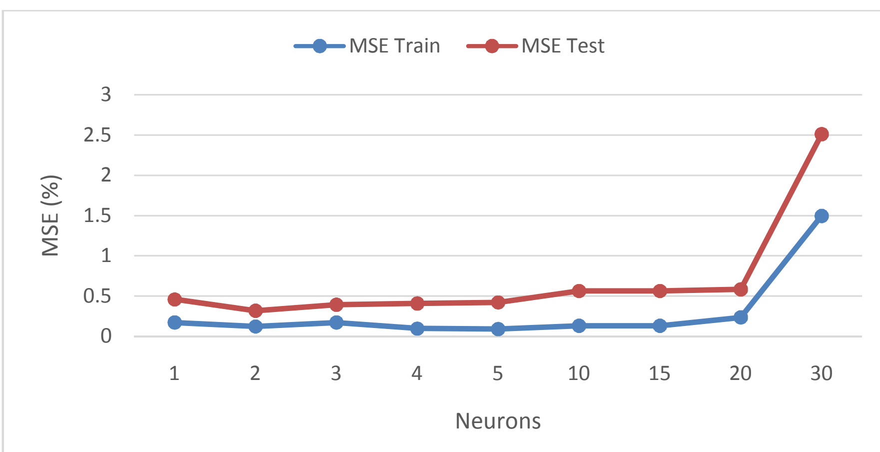

Figure 4. 5: MSE of Different Models with their Corresponding Neurons

ANN is sophisticated method that can predict CLP for building projects of Addis Ababa city with the average accuracy percentage of 92%. This average accuracy percentage was checked by using the 20% data that was left aside for this purpose. The data's used for testing the performance of the model was not introduced during training of the model, this separate data set for training and testing is important to accurately evaluate the performance of the developed model.

The minimum error observed for the optimal model was obtained after performing numerous trial and error by varying the number of neurons in the hidden layer and the number of forward and backward iterations or epochs. Therefore the minimum error was achieved with two hidden neurons and 1000 number of epochs as shown in figure 4.6

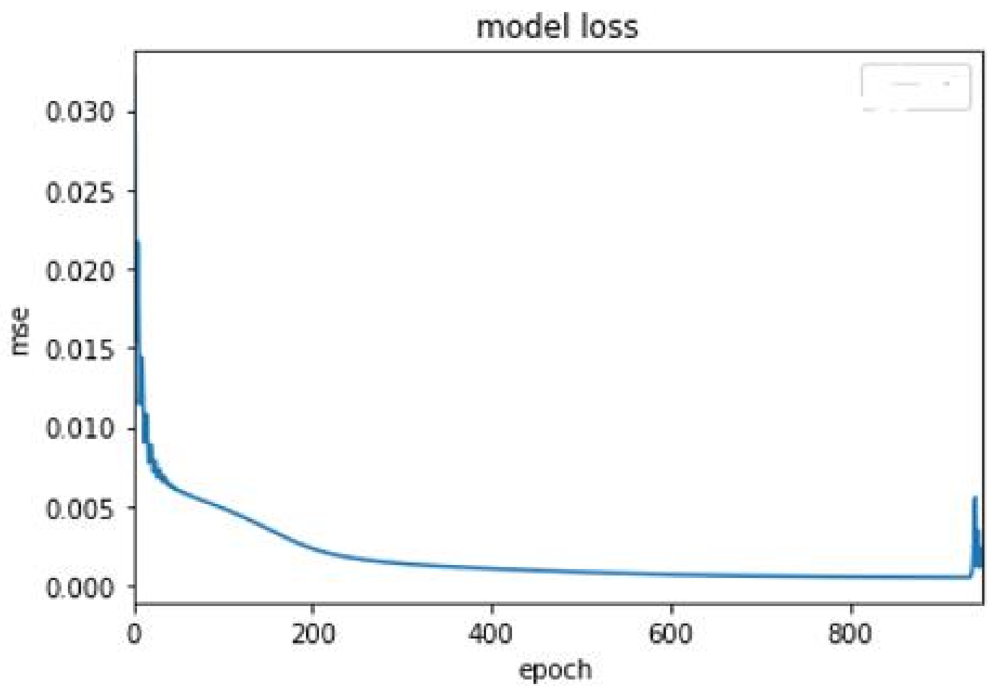

Figure 4. 6: Training Mean Squared Error

The scatter plot in figure 4.7 shows the true and predicted values of productivity for the test dataset of 23 data samples that was selected and set aside for this purpose. The figure shows a good agreement between predicted and actual productivity values drawn in 45 degree line. From the graph we can conclude that the predicted productivity/machine guess values of productivity is approximately similar to actual values of productivity and the points observed around the 45-degree line shows reasonable concentration of the predicted values of productivity. Therefore the developed ANN model have a higher capability to predict CLP of concreting activity.

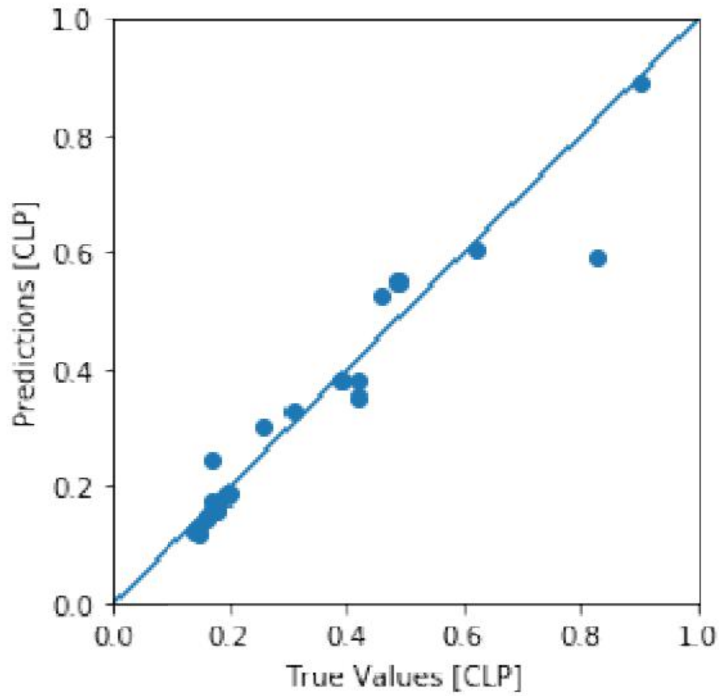

Figure 4. 7: Scattered Plot of Predicted and Actual Rates

4.6. Equation of the ANN model

The equation of ANN gives the value of an output node as a function of the values at the input nodes, bias and connection weights. The connection weights and biases which are used for the final modeling are obtained from the optimal ANN models. The results of weights and biases for the optimal model is summarized in table 4.10. Therefore the coefficients and intercepts can be translated into formulas or mathematical models.

The CLP of concreting activity can be mathematically expressed using the connection weights and biases for the optimal model which are listed in table 4.10 as follows:

X1 = (X1*W11 + X2*W12 + X3*W13 + X4*W14 + X5*W15 + X6*W16 + X7*W17 + X8*W18 + X9*W19 + X10*W110 + X11*W111 + BH1)……………………………. (1)

X2 = (X1*W21 + X2*W22 + X3*W23 + X4*W24 + X5*W25 + X6*W26 + X7*W27 + X8*W28 + X9*W29 + X10*W210 + X11*W211 + BH2)……………………………. (2)

But it should be noted that before adopting equation 1 and 2 for estimation of CLP rates all the input values should be scaled between 0.1 to 0.9 ranges using minmax scaler formulas as discussed in section 2.3.1. The maximum and minimum values that are required to use the minmax formula can be obtained from table 4.5.

Table 4. 10: Optimal Model Weights and Biases

Weights between input nodes and hidden node 1	Weights between input nodes and hidden node 2	Hidden Biases	Hidden to output weights	Output bias
W11= -0.80771825	W21= -1.29754431	BH1 =	W11H0=	B01=
W12= 0.145702103	W22= -2.42387211	0.358	-0.6679519	1.955
W13= -0.528524606	W23= 2.26612486	34581	W12HO=	71816
W14= 0.201301486	W24= 2.74387717	BH2 =	-1.62451474	
W15= 0.132271702	W25= -0.026419671	-1.508		
W16= 0.0334985595	W26= -0.00353481671	88807		
W17= -0.0949299372	W27= 0.00908773745			
W18= -0.282357359	W28= 0.336306823			
W19= 0.103049981	W29= 0.588741942			
W110= -0.214612051	W210= 2.39695108			
W111= -1.21460908	W211= 10.5258561			

Then the values of “X1” and “X2” should be pass through sigmoid activation function as shown in equation 3 bellow. If the values of “X1” and “X2” fails to pass through the sigmoid functions the non-linear relationship between the input and output variables can’t be established and the model performance can be affected. It is also a standard practice in ANN modeling to pass the values of “X1” and “X2” through the activation function.

$X1H = 1 / (1+e^{-x1})$ and $X2H = 1 / (1+e^{-x2})$…………………………………….. (3)

Next the values of X1H and X2H should be multiplied with the corresponding weights:

O = ((X1H*W11HO) + (X2H*W12HO) + BO1)

Finally the value of O which represents the scaled value of output should be converted into the unscaled predicted value of output using minmax scaler formula.

To avoid the manual computation of CLP rate using this long formula and also to avoid estimation mistakes the researcher built the required equation model using Excel programmed sheet. To apply and predict CLP for concreting activity only input data is required, so that the programmed Excel sheet automatically predict the CLP rate. The programmed Excel sheet format is attached here in appendix 12.

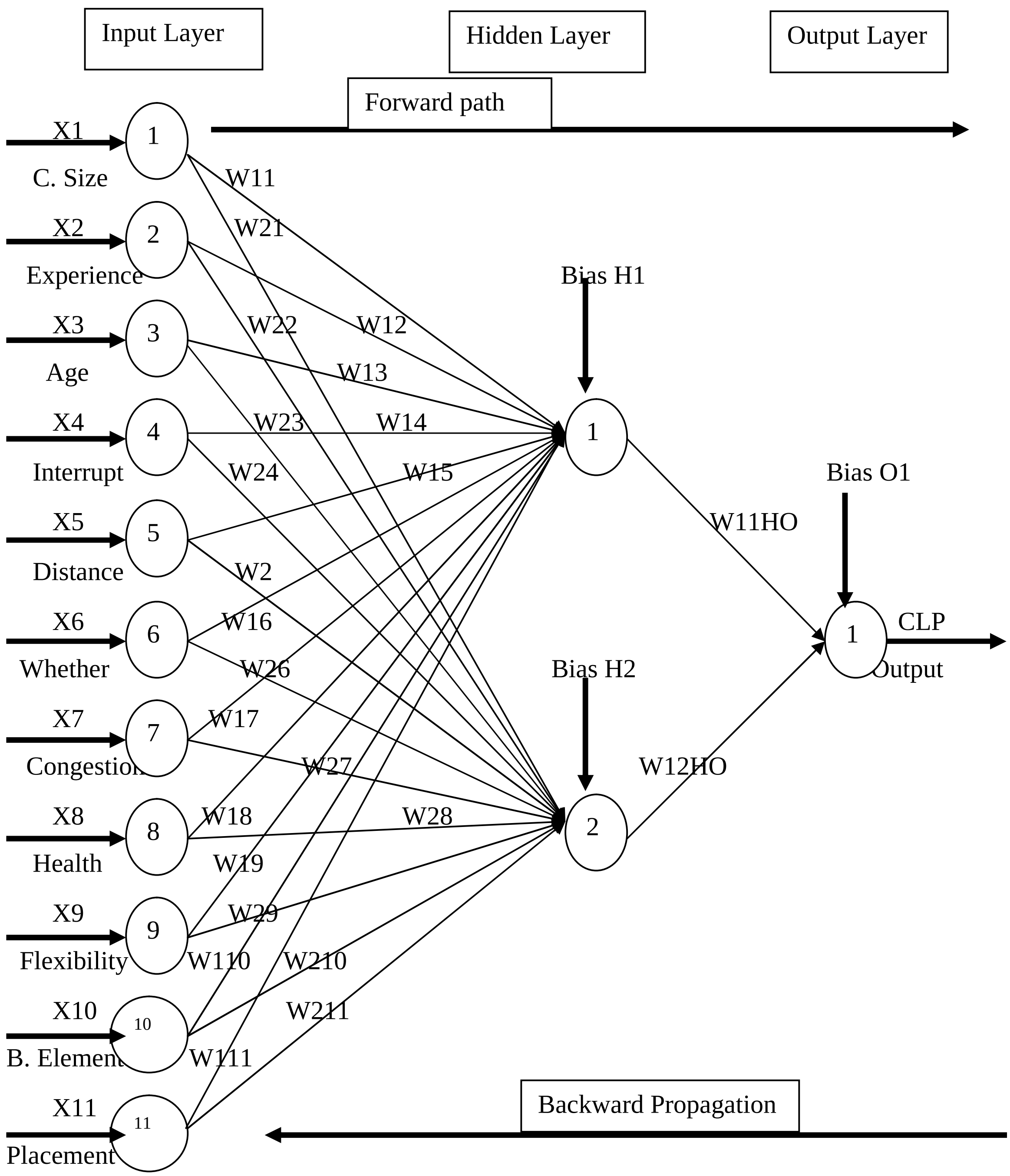

Figure 4. 8: Architecture of Optimal Model (Researcher Design)

From figure 4.8 it is clearly shown that the optimal model architecture have 11 input nodes, 2 hidden nodes, and 1 output node (11-2-1 node structure). This optimal model is a multilayer structure because it consists three layers: input, hidden, and output layers. The optimal model was developed after 1000 times of forward and backward paths. During the forward path the network arbitrarily assigns numerical values to the weights and biases based on the data's feed to the network, then the network compares the predicted values with actual values to calculate the error. Taking this error the network propagates backward to adjust these weights and biases so that after 1000 iterations the model generates optimal values for weights and biases which can represent the data which was feed to the network. From the developed models the optimal model was the model with least mean squared error and high coefficient of determination value which was obtained after numerous trial and errors.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

The eleven most critical influencing parameters that can influence the construction labor productivity were identified and classified into five objective variables; crew size, distance from mixing place to final casting place, crew experience, level of interruption and disruption, and age of workers. Whereas the health status of workers, weather conditions, congested work areas, placement techniques, and crew flexibility are the six subjective variables.

From descriptive statistical analysis results, the experience of the crew, age of workers, and placement techniques are the top three influencing factors that are highly correlated with CLP with R values of 0.5681, 0.5349, and -0.5227. during execution of concreting activity as; the health status of workers getting bad, the place of performing the task becomes more congested, the distance of final placement of concrete from the mixing place gets longer, the number of workers performing the task in question decreases, the willingness of the crew to perform other members task decreases, the weather condition becomes adverse, and interruption levels of workers during construction increases results in a decrease in crew production rate of concreting activity. Therefore, bearing in mind these results construction stakeholders are expected to give due attention to enhance productivity and profitability of the company.

The final optimal model have eleven variables in input layer, one hidden layer with two nodes and one node in the output layer which shows the optimal structure of the productivity of concreting activity in Addis Ababa city. This structure was practically enough for developing optimal model using some sort of neural network parameters. To ensure accuracy of the model and enhances model performance collected data have been systematically divided in to training, validation, and testing dataset, with 65%, 15% and 20% of proportions respectively.

ANN model was developed based on the 114 datasets which were collected from Addis Ababa building projects. The developed model has the ability to predict CLP rate of concreting activity with 92% of coefficient of determination and 0.316% of MSE for testing data set. This result shows that the developed model have higher capability to predict CLP with acceptable range of errors.

Construction stakeholders can easily use the programmed Excel sheet to predict CLP of concreting activity for their future projects. Therefore, developing a construction labor productivity estimation model using ANN’s for concreting activity, which was the general objective of this study is successfully achieved.

5.2. Recommendations

The findings evolved from the analysis and discussion of this study have resulted in the following recommendations:

- ✓ The strength of the relationship between CLP and its critical influencing parameters identified through R values should be considered by project stakeholders in their concreting activity building projects. It is therefore strongly recommended to improve this strength of relationship by proper planning and management of the influencing factors at the site.
- ✓ Other models should be developed for different construction activities such as formwork, plastering, painting, floor finishing, reinforcement, excavation works and other construction works which can have a strong capability to estimate or predict the production rate using artificial neural networks.
- ✓ Different private and government-owned companies and associations are recommended to establish a productivity database for their executed projects so that researchers will found it simpler to develop a model for the productivity estimation process.
- ✓ To improve efficiency and accuracy of estimation for future projects contractors are greatly encouraged keeping historical data of productivity in finished projects. Therefore, this improved efficiency and accuracy of contractors in the estimation of production rates will enhance their profitability and success in the construction industry.
- ✓ The government of Ethiopia as well as other stakeholders in the construction industry should develop CLP estimation models for all construction activities so that they can estimate the rate with high level of accuracy.

5.3. Recommendations for Further Research

Although several issues emerged during the course of the investigation, this study was confined to the stipulated aspects. However, there are critical aspects for further study if one is interested to develop a CLP model for projects success, competitiveness, and profitability.

For further research, the following aspects could be explored:

- ✓ A wider geographical location can be chosen so that a numerous number of construction projects considered to establish the CLP model in the wider context.
- ✓ Further research is needed to investigate the numerous potential influencing factors of CLP which ranges from international to project level.
- ✓ Further research and investigation is also needed to develop a CLP model for other activities of building projects.
- ✓ This type of models should be developed by researchers for all construction types so that the construction industries profitability could enhanced.
- ✓ Further research can also be done using other programming languages or other methods of modeling, so that the best technique could be selected.

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APPENDIX

Appendix 1: Literature Summary of Key Input Parameters Influencing CLP

Name of authors	Title	Country	Year of publication	Modeling techniques	Identified factors
SasanGolnaraghi, Zahra Zangenehmadar, Osama Moselhi, and Sabah Alkass	Application of Artificial Neural Network(s) in Predicting Formwork Labour Productivity	Canada	2019	ANN using MATLAB 2017a	Temperature, humidity, wind speed, precipitation, gang size, labor percentage, work type, floor height, and work method.
Faiq Mohammed Sarhan AL-Zwainy , Hatem A. Rasheed and Huda Farhan Ibraheem	Development of construction productivity Estimation model using artificial neural network For finishing works for floors with marble	Iraq	2012	ANN using Neuframe 4 program	Objective Variables ✓ Age ✓ Experience ✓ Number of labor ✓ Height of the floor ✓ Size of the marble tile Subjective variables ✓ Security conditions ✓ Health status of work team ✓ Weather condition ✓ Site condition ✓ Availability of construction materials
Sana Muqeem, MohdFaris Khamidi, Arazi B. Idrus, and Saiful Bin Zakaria	Prediction modeling of construction labor production rates using Artificial Neural Network	Malaysia	2011	ANN using MATLAB Version 7.04	✓ Weather ✓ Lack of availability of material and equipment ✓ Location of project ✓ Site conditions ✓ Number of workers

Sana Muqeem, AraziIdrus, M. FarisKhamidi, Jale Bin Ahmad, and Saiful Bin Zakaria	Construction labor production rates modeling using Artificial neural network	Malaysia	2011	ANN using MATLAB version 7.8.0	✓ Weather ✓ Availability of material and equipment ✓ Location of project ✓ Site conditions ✓ Number of workers
Emad Elwakil, Tarek Zayed, and Tarek Attia	Construction productivity model using the fuzzy approach	Vancouver, British Columbia	2015	Using different equations	✓ Temperature ºC ✓ Humidity (%) ✓ Precipitation ✓ Wind Speed (km/h) ✓ Floor height ✓ Work type ✓ Gang Size (workers) ✓ Labor Percent (%) ✓ Time(min)
Faiq Mohammed Sarhan Al-Zwainy, Mohammed HashimAbdulmajeed, and HadiSalih MijwelAljumaily	Using multivariable linear regression technique for modeling productivity construction in Iraq	Iraq	2013	MLR using SPSS v-19	Objective Variables ✓ Age ✓ Experience ✓ Number of labor ✓ Height of the floor ✓ Size of the marble tile Subjective variables ✓ Security conditions ✓ Health status of work team ✓ Weather condition ✓ Site condition ✓ Availability of construction materials
Abraham AssefaTsehayae	Developing and optimizing context-specific and universal construction	Canada	2015	Fuzzy inference system	Activity level parameters ✓ Labour and crew ✓ Materials and Consumables ✓ Equipment and tools ✓ Task property ✓ Location property

	labour productivity models				✓ Foreman ✓ Engineering and instructions. Project level parameters Organization level parameters National level parameters Global level parameters
Gafel Kareem Aswed	Productivity estimation model for a bricklayer in construction projects using neural network	Iraq	2016	Neuro Solutions version 6.0.0	✓ Age ✓ Experience ✓ Gang health ✓ Gang Number ✓ Weather ✓ Wages ✓ Site condition ✓ Material availability ✓ Wall length ✓ Wall thickness ✓ Wall height ✓ Mortar type ✓ Security in site

Appendix 2: Study Information Sheet

My name is ______________________________. I belong to the research team studying the Development of Construction Labour Productivity Model Using Artificial Neural Networks for Building Projects in Jimma Town. This research is being conducted by a master student (**Dawit Benti**) at Jimma University, Jimma Institute of Technology, Department of Construction Engineering and Management.

The objective of this study is to develop a model using Artificial Neural Networks for estimating the labor productivity of building projects. I kindly ask you to participate in this study and give me a genuine answer to my quires. Your participation in this study is greatly helpful in **identifying the most critical factor or parameter which can affect construction labor productivity of concreting activity.** I hope I have clarified the purpose of the study. If you have any question you can contact me through my phone number **+251911291561** or email: dawitbenti@yahoo.com

The questions listed in the next page describes the factors or parameters that can ***affect labor productivity of*** ***concreting*** **activity** for building construction projects. All information provided in this research will be treated with strict confidentiality and allowed to serve only for the purpose of the research under consideration. I sincerely thank you for your earnest cooperation in advance.

Appendix 3: Questionnaire

Type of organization/company you are involving:

Contractor	
Consultant	
Client	

Please rate the following productivity influencing factors **according to its priority level for contribution in <u>labor</u> productivity of <u>concreting activity</u>** by circling the appropriate number based on the guide below:

(1)	Unimportant
(2)	Moderately Important
(3)	No Idea
(4)	Very Important
(5)	Extremely Important

No.	Factors affecting the productivity of **concreting activity**	(1)	(2)	(3)	(4)	(5)
A.	**Objective (Quantitative) factors**					
1	Crew Size (number of workers)	1	2	3	4	5
2	Crew experience (seniority)[1]	1	2	3	4	5
3	Age of workers	1	2	3	4	5
4	Average wind speed	1	2	3	4	5
5	Number of consecutive days worked	1	2	3	4	5
6	Number of languages spoken	1	2	3	4	5
7	Number of craftsperson technical training	1	2	3	4	5
8	Level of overtime	1	2	3	4	5
9	Level of interruption and disruption	1	2	3	4	5
10	Foreman experience	1	2	3	4	5
11	Distance to temporary material storage to casting place	1	2	3	4	5
12	Space of casting (volume of work)	1	2	3	4	5
13	Other factors? Please describe…					

[1]Tsehayae A. A. (2005). Developing and Optimizing Context-Specific and Universal Construction Labour Productivity Models. A thesis submitted in partial fulfillment of the requirements for the degree of doctor of philosophy. The University of Alberta.

No.	Factors affecting the productivity of **concreting activity**	(1)	(2)	(3)	(4)	(5)
B.	**Subjective (Qualitative) factors**					
1	Weather condition (comfort level)[2]	1	2	3	4	5
2	Location of project	1	2	3	4	5
3	Comfortability of materials storage for work	1	2	3	4	5
4	Scaffold requirement	1	2	3	4	5
5	Skill level of labour	1	2	3	4	5
6	Congested work area (arrangement of false work)	1	2	3	4	5
7	Communication problems with workers	1	2	3	4	5
8	Alcoholism	1	2	3	4	5
9	Disruption of power/water supplies	1	2	3	4	5
10	Health status of workers	1	2	3	4	5
11	Extent and quality of supervision	1	2	3	4	5
12	Safety requirements	1	2	3	4	5
13	Quality requirements	1	2	3	4	5
14	Crew flexibility (crew willingness in performing other members task)[3]	1	2	3	4	5
15	Building element (footing, grade beam, column, slab…)	1	2	3	4	5
16	Cover from weather effect	1	2	3	4	5
17	Working condition (noise)	1	2	3	4	5
18	Placement technique (Pump, Crane, bucket, direct chute…)	1	2	3	4	5
19	Other factors? Please describe…					

[2]Sana Muqeem, AraziIdrus, M. FarisKhamidi, Jale Bin Ahmad, Saiful Bin Zakaria (2011) Construction labor production rates modeling using the artificial neural network, Journal of Information Technology in Construction (ITcon), Vol. 16, pg. 713-726,

[3]Molleman, E., and van den Beukel, A. (2007). “Worker flexibility and its perceived contribution to performance: The moderating role of task characteristics.” Human Factors Ergonomics in Manuf. Servi. Industries, 17(2), 117-135.

THANK YOU FOR YOUR COOPERATION!!

Appendix 4: Amharic Version of Study Information Sheet

ስለ ጥናቱ ጠቅላላ መረጃ

ስሜ____ ይባላል፡፡ እኔ በአዲስ አበባ ከተማ የህንጻ ፕሮጀክቶች አርቴፊሻል ኒዉራል ኔትወርክን በመጠቀም የግንባታ ሰራተኞችን ምርታማነት ሞዴል የማበልጸግ ጥናት ላይ ከተሰማሩ አጥኚ ቡድን አንዱ ነኝ፡፡ ጥናቱን የሚያጠናዉ በጅማ ዩኒቨርስቲ፣ ጅማ ቴክኖሎጂ ተቋም፣ ግንባታ ምእንድስና እና አስተዳደር ትምህርት ክፍል ማስተርስ ዲግሪ ተመራቂ ተማሪ (ዳዊት በንቲ) ነዉ፡፡

የዚህ ጥናት አላማ የህንጻ ፕሮጀክቶችን እርቴፊሻል ኒዉራል ኔትወርክን በመጠቀም የግንባታ ሰራተኞችን ምርታማነት ሞዴል ማበልጸግ ነዉ፡፡ የሚጠየቁትን ጥያቄ ትክክለኛ ነዉ ብለዉ የሚያምኑትን መልስ ይመልሱልኝ ዘንድ በትህትና እጠይቃለሁኝ፡፡ **እርሶም በዚህ ጥናት ላይ ተሳታፊ በመሆኖ የአርማታ ስራ ምርታመነት ላይ ከፍተኛ አሰተዋዕጾ ያላቸዉን አንኳር ነጥቦች እለያቸዉ ዘንድ ይረዳኛል**፡፡ የጥናቱን ዓላማ ከሞላ ጎደል ገልጫለሁኝ ብዬ አስባለሁ፡፡ ምንም አይነት ጥያቄ ካልዎት በአድራሻየ: ስልክ ቁጥር+**251911291561** አልያም ኢ-ሜይል dawitbenti@yahoo.com ልታገኙኝ ትችላላቹ

በሚቀጥለዉ ገጽ ላይ የተዘረዘሩት ጥያቄዎች **ለህንጻ ግንባታ የአርማታ ስራ ምርታማነት ምክንያት አልያም አስተዋፅጾ ሊኖራቸዉ ይችላሉ**፡፡ ይህን መጠይቅ ሲሞሉ የመረጃዎ ሚስጥር ሙሉ በሙሉ የተጠበቀና የሚያገለግለዉም ለጥናት ብቻ ነዉ፡፡ ለሚያሳዩኝ መልካም ትብብር በቅድሚያ ላመሰግን እወዳለሁኝ፡፡

Appendix 5: Amharic Version of Questionnaire

የሚሰሩበት ድርጅት

ስራ ተቋራጭ	
አማካሪ	
ባለቤት	

አባክዎን ከዚህ በታች ለተዘረዘሩት <u>**የአማታ ስራ የሰራተኞች ምርታማነት**</u> **ላይ አስታዋፅዖ ላላቸዉ ነጥቦች** በተሰጡት የመመዘኛ መስፈርት መሰረት ደረጃ ይስጡ::

(1)	አያስፈልግም
(2)	እንብዛም አያስፈልግም
(3)	አስፈለጊ ነዉ
(4)	በጣም አሰፈላጊ ነዉ
(5)	አጅግ በጣም አሰፈላጊ ነዉ

ተቁ	**ለአርማታ ስራ ምርታማነት አስተዋጾዎ (ሚና) ያላቸዉ ነጥቦች**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
ሀ	**በቁጥር ሊገለጹ የሚቺሉ አስተዋጾዎች**					
1	የሰራተኞች ብዛት	1	2	3	4	5
2	የሰራተኞች ልምድ	1	2	3	4	5
3	የሰራተኞች ዕድሜ	1	2	3	4	5
4	አማካኝ የንፋስ ፍጥነት	1	2	3	4	5
5	ተከታታይ የስራ ቀናት ብዛት	1	2	3	4	5
6	ለስራ ሚጠቀሙበት የቋንቋ ብዛት	1	2	3	4	5
7	ሞያዊ ስልጠና የተከታተሉ የሰራተኞች ብዛት	1	2	3	4	5
8	የትርፍ ጊዜ ስራ መጠን	1	2	3	4	5
9	ስራ የሚያቋርጡበት አልያም የሚረበሹበት መጠን	1	2	3	4	5
10	የግንባታ ሰራተኛ አለቃ (foreman) ልምድ	1	2	3	4	5
11	በጊዜያዊ ዕቃ ማከማቻ (መጋዝንና) የስራዉ ስፍራ ማሀል ያለዉ ርቀት	1	2	3	4	5
12	የስራዉ መጠን	1	2	3	4	5
13	ሌሎች ካሉ ይዘርዝሩ					

ለ	**በቁጥር ሊገለጹ የማይቺሉ አስተዋጾዎች**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
1	የአየር ንብረት ሁኔታ	1	2	3	4	5
2	የስራዉ ቦታ (ስፍራ)	1	2	3	4	5
3	የዕቃዎች ማከማቻ ቦታ ለስራዎች አመቺ መሆን	1	2	3	4	5
4	የመወጣጫ አስፈላጊነት	1	2	3	4	5
5	የሰራተኛዉ የችሎታ መጠን	1	2	3	4	5
6	የተጨናነቀ የስራ ስፍራ	1	2	3	4	5
7	የሰራተኞች የመግባባት ችግር	1	2	3	4	5
8	አልኮል ተጠቃሚነት	1	2	3	4	5
9	የዉኃ አልያም የመበራት መቆራረጥ ችግር	1	2	3	4	5
10	የሰራተኞች የጤና ሁኔታ	1	2	3	4	5
11	የቁጥጥር መጠንና ጥራት	1	2	3	4	5
12	የደህንነት አስፈላጊነት	1	2	3	4	5
13	የጥራት አስፈላጊነት	1	2	3	4	5
14	የሰራተኞች የሌላዉንም ስራ የመስራት ፍላጎት	1	2	3	4	5
15	የግንባታዉ ክፍል (footing, grade beam, column, slab)	1	2	3	4	5
16	ከአየር ንብረት ሁኔታ ከለላ	1	2	3	4	5
17	የስራ ሁኔታ (ጫጫታ)	1	2	3	4	5
18	የአሞላል ዘዴ (ፓምፕ፣ክሬይን፣ሰንኬሎ፣ማንሸራተቻ)	1	2	3	4	5
19	ሌሎች ካሉ ይዘርዝሩ					

ስለተባበሩኝ አመሰግናለሁ!!

Appendix 6: Summery of Questionnaire Response and Relative Importance Index

Summary of Questionnaire Response and Relative Importance Index										
Questions	EI (n1)	VI (n2)	NI (n3)	MI (n4)	U (n5)	Highest (A)	Total (N)	RII (PI)	Rank	RII (%)
Question 1	18	14	0	0	0	5	32	0.913	1	91.25
Question 2	16	11	0	5	0	5	32	0.838	6	83.75
Question 3	15	7	0	10	0	5	32	0.769	11	76.875
Question 4	0	8	4	13	7	4	32	0.508	28	50.78125
Question 5	4	7	0	16	5	5	32	0.531	24	53.125
Question 6	2	11	0	11	8	5	32	0.525	26	52.5
Question 7	1	9	0	11	11	5	32	0.463	30	46.25
Question 8	7	8	0	10	7	5	32	0.588	16	58.75
Question 9	13	11	0	8	0	5	32	0.781	10	78.125
Question 10	2	9	0	15	6	5	32	0.513	27	51.25
Question 11	18	11	0	3	0	5	32	0.875	3	87.5
Question 12	5	8	0	16	3	5	32	0.575	18	57.5
Question 13	17	12	0	3	0	5	32	0.869	4	86.875
Question 14	0	10	0	9	13	4	32	0.555	20	55.46875
Question 15	2	9	0	12	9	5	32	0.494	29	49.375
Question 16	4	12	0	14	2	5	32	0.613	14	61.25
Question 17	3	13	0	15	1	5	32	0.613	14	61.25
Question 18	17	9	0	5	1	5	32	0.825	7	82.5
Question 19	3	14	0	13	2	5	32	0.619	12	61.875
Question 20	6	6	0	11	9	5	32	0.531	24	53.125
Question 21	3	11	0	16	2	5	32	0.581	17	58.125
Question 22	18	12	0	2	0	5	32	0.888	2	88.75
Question 23	2	10	0	19	1	5	32	0.556	19	55.625
Question 24	6	11	0	10	5	5	32	0.619	12	61.875
Question 25	0	10	0	9	13	4	32	0.555	20	55.46875
Question 26	15	11	0	4	2	5	32	0.806	9	80.625
Question 27	17	11	0	4	0	5	32	0.856	5	85.625
Question 28	3	9	0	15	5	5	32	0.538	22	53.75
Question 29	3	9	0	15	5	5	32	0.538	22	53.75
Question 30	13	14	0	5	0	5	32	0.819	8	81.875

Appendix 7: Quantification of Input Parameters

SN.	Parameter	Description	Measurement scale (unit)	Data source
A.	**Objective (Quantitative) factors**			
1	Crew Size	The total number of the crew performing the actual task	Integer	DC
2	Crew experience	The average years of experience of the crew members on concreting activity	Real number	F+CM
3	Age of workers	Average age of workers performing the actual work in years.	Real number	F+CM
4	Average wind speed	Refers to the recorded daily average wind speed	Real number (km/hr)	DC
5	Number of consecutive days worked	Number of consecutive days worked without week rests	Integer	F
6	Number of languages spoken	Total number of the language spoken by the crew performing the actual task	Integer	DC
7	Number of craftsperson technical training	All technical training, including apprentice training which may be useful to perform the task	Integer	F+CM
8	Level of overtime	The level of overtime is used to measure long-term physical fatigue.	Integer (Total overtime per week, hrs.)	F
9	Level of interruption and disruption	The time lost and delay events caused due to several reasons, which may disrupt the crew from performing the assigned tasks.	Integer (total minutes spent)	DC
10	Foreman experience	The foreman experience in terms of the year in industry, after becoming a foreman.	Real number (years of experience)	F
11	Distance to temporary	The average distance between materials stored	Integer (average distance of all ingredients)	DC

	material storage to casting place	on-site and final casting place.		
12	Space of casting (volume of work)	The total volume of work performed or concrete casted	Integer (volume in M^3)	DC
B.	**Subjective (Qualitative) factors**			
1	Whether condition	The atmospheric weather condition of the site during performing the required task	1-4 pre-determined rating shown below 1- Sunny 2- Moderately sunny 3- Moderately rainy 4- Rainy	DC
2	Location of project	Refers to the place where the project is executed	1-4 pre-determined rating shown below 1- In Jimma 2- Near Jimma (< 10kms.) 3- Between 10kms and 50kms 4- > 50kms from Jimma	DC
3	Comfortability of materials storage for work	Self-explanatory	1-4 pre-determined rating shown below 1- Extremely comfortable 2- Comfortable 3- Moderately comfortable 4- Not comfortable	DC
4	Scaffold requirement	Self-explanatory	1-4 pre-determined rating shown below 1- >3m required 2- Between 2 and 3m required 3- <2m required 4- Not required	DC
5	Skill level of labor	The overall skill of labors to perform the task	1-4 pre-determined rating shown below 1- Very good 2- Adequate 3- Inadequate 4- Poor	DC+ F
6	Congested work area	Arrangement of falsework and ease of the site to perform the task in question	1-4 pre-determined rating shown below 1- Completely uncongested 2- Somewhat congested	DC

			3- congested 4- uncongested	
7	Communication problems within workers	Problems observed due to lack of communication skill of labors during performing the task	1-4 pre-determined rating shown below 1- Completely free 2- Somewhat free 3- Free 4- Not free	DC+F
8	Alcoholism	Drunk in the workplace and prohibiting the execution of the task.	1-4 pre-determined rating shown below 1- Completely free 2- Somewhat free 3- Free 4- Not free	DC+F
9	Disruption of power/water supplies	Delay events caused due to power/water shortages on site	1-4 pre-determined rating shown below 1- Completely free 2- Somewhat free 3- Free 4- Not free	DC
10	Health status of workers	Health status of workers during the execution of the task	1-4 pre-determined rating shown below 1- Very good 2- Good 3- Moderate 4- Bad	DC
11	Extent and quality of supervision	Supervision skill of the foreman in terms of the orientation of crew members	1-4 pre-determined rating shown below 1- Very good 2- Adequate 3- Inadequate 4- Poor	DC
12	Safety requirements	Availability of personal protective equipment's for crews performing the task	1-4 pre-determined rating shown below 1- Completely available 2- Somewhat available 3- Available 4- Not available	DC
13	Quality requirements	Availability of quality detail quality requirements in the specification	1-4 pre-determined rating shown below 1- Completely available 2- Somewhat available 3- Available	

			4- Not available	
14	Crew flexibility	Crew willingness in performing other members task	1-4 pre-determined rating shown below 1- Completely willing 2- Willing 3- Somewhat willing 4- Completely unwilling	DC
15	Building element	Footing, grade beam, column, slab…	1-4 pre-determined rating shown below 1- Slab 2- Beam 3- Column 4- Septic tank	DC
16	Cover from weather effect	Cover of the workplace from weather effect	1-4 pre-determined rating shown below 1- Yes 2- No	DC
17	Working condition	Level of noise created by equipment's and nearby environment	1-4 pre-determined rating shown below 1- Very high noise 2- Somewhat noisy 3- Normal noise 4- Very normal noise	DC
18	Placement technique	Pump, Crane, bucket, direct chute…	1-4 pre-determined rating shown below 1- Pump 2- Winch 3- Direct chute 4- Bucket	DC

Appendix 8: Productivity Data Collection Form

Number=_______			Objective Variables				
Total time used using the stopwatch	Quantity produced in m^3 (cast)	Productivity in m^3/hr = (quantity produced)/(Total time used)	Crew size in number (number of workers)	Crew experience in years (Average)	Age of workers in years (Average)	Level of interruption in minutes (Total time spent)	Distance to temporary material storage in meter (Average)
T=	Q=	P=Q/T	N=	1___2___ 3___4___ 5___6___ 7___8___ 9___10___ 11___12___ 13___14___ 15___16___ 17___8___ 19___20___ 21___22___ 23___24___ 25___26___ Average=	1___2___ 3___4___ 5___6___ 7___8___ 9___10___ 11___12___ 13___14___ 15___16___ 17___8___ 19___20___ 21___22___ 23___24___ 25___26___ Average=	1______ 2______ 3______ 4______ 5______ 6______ 7______ Total=	D=

Subjective Variables

Whether condition	Congested work area	Health status of workers	Crew flexibility	Building element	Placement technique
1- Sunny 2- Moderately sunny 3- Moderately rainy 4- Rainy	1- Completely uncongested 2- Somewhat congested 3- congested 4- uncongested	1- Very good 2- Good 3- Moderate 4- Bad	1- Completely willing 2- Willing 3- Somewhat willing 4- Completely unwilling	1- Slab 2- Beam 3- Column 4- Septic tank	1- Pump 2- Winch + Bucket 3- Direct chute 4- Bucket + Pump

Appendix 9: Tabulated Site Productivity Data for CLP

ID	CLP	Crew Size	Crew Experience	Age	Interruption level	Distance	Whether	Congested Area	Health Status	Crew Flexibility	Building Element	Placement Techniques
1	1.49	9	3.22	22.88	27	7.5	1	1	1	2	1	2
2	2.33	9	3.22	22.88	2	10.5	1	1	1	2	1	2
3	2.1	9	3.22	22.88	0	15.9	1	1	1	2	1	2
4	2.25	9	3.22	22.88	0	14.3	1	1	1	2	1	2
5	1.47	9	3.22	22.88	18	16.3	1	1	1	2	1	2
6	2.26	8	3	24.63	0.5	18	2	2	2	1	1	2
7	1.45	8	3	24.63	6	17.6	2	2	2	1	1	2
8	2.25	8	3	24.63	0	19.2	2	2	2	1	1	2
9	1.83	8	3	24.63	8	20.1	2	2	2	1	1	2
10	2.2	8	3	24.63	0	16.8	2	2	2	1	1	2
11	20	10	9.9	31.8	0	35	2	2	1	3	2	1
12	20	10	9.9	31.8	0	33.5	2	2	1	3	2	1
13	16.66	9	9	29	3	29.2	2	2	1	3	2	1
14	18.18	7	7.43	27.14	1	24.8	2	2	1	3	2	1
15	17.02	6	8.5	24.16	0	16.2	2	2	1	3	2	1
16	7.5	8	10	34	30	33.3	2	2	1	1	2	1
17	9.8	8	10	34	13	22.1	2	2	1	1	2	1
18	8.47	8	10	34	20	32.2	2	2	1	1	2	1
19	7.27	8	10	34	42	39.8	2	2	1	1	2	1
20	13.21	8	10	34	10	21.1	2	2	1	1	2	1
21	3.78	10	4.2	27.2	86	32.2	4	2	2	2	2	1
22	6.17	10	4.2	27.2	32	12.6	3	2	2	2	2	1
23	9.23	10	4.2	27.2	18	16.8	3	2	2	2	2	1
24	8.14	10	4.2	27.2	26.5	28.5	2	3	2	2	2	1
25	7.53	10	4.2	27.2	31.06	38	2	3	2	2	2	1
26	14.28	9	4.78	26.88	4.28	13.8	1	2	2	2	2	1

27	13.16	9	4.78	26.88	6.24	14.3	1	3	2	2	2	1
28	10.15	9	4.78	26.88	18.8	38	1	3	2	2	2	1
29	17.1	9	4.78	26.88	3.36	13	1	2	2	2	2	1
30	13.04	9	4.78	26.88	8.48	18.6	1	3	2	2	2	1
31	3.19	11	5.55	29.09	8.4	30.1	1	1	1	2	1	4
32	2.7	11	3	24.82	1.36	36.8	1	1	1	2	1	4
33	2.64	11	3	24.82	1	29.3	1	2	1	2	1	4
34	2.03	11	3	24.82	21	42.6	3	1	1	2	1	4
35	2.5	11	3	24.82	2	46.3	1	2	1	2	1	4
36	2.82	8	4.12	27.63	26	39.3	3	2	2	2	1	4
37	2.85	8	4.12	27.63	0	24.5	1	1	2	1	1	4
38	2.04	8	4.12	27.63	9	25.5	1	1	2	2	1	4
39	2.14	8	4.12	27.63	11	29.2	3	2	2	2	1	4
40	2.1	9	3.44	26.5	1	39.8	2	2	2	2	1	2
41	1.44	9	3.44	26.5	15	42.8	2	2	2	2	1	2
42	0.87	9	3.44	26.5	41.3	45.1	4	2	2	2	1	2
43	1.95	9	3.44	26.5	0	45.3	2	2	2	3	1	2
44	1.88	9	3.44	26.5	0	46.6	2	2	2	3	1	2
45	0.93	8	4.87	26.12	48	49.8	4	1	1	2	1	2
46	1.71	8	4.87	26.12	12	46.3	3	1	1	2	1	2
47	2.06	8	4.87	26.12	0	38.8	3	1	1	2	1	2
48	1.83	8	4.87	26.12	0	35.4	3	1	1	2	1	2
49	1.47	9	3.84	24.77	7.13	24	1	1	2	3	3	2
50	1.88	9	3.89	24.77	0.5	28	1	1	2	3	3	2
51	0.83	9	3.89	24.77	6	32	1	1	2	3	3	2
52	1.47	9	3.89	24.77	9	36.1	1	1	2	3	3	2
53	1.93	9	3.89	24.77	1	35.4	2	1	2	2	3	2
54	1.51	9	3.89	24.77	3	38.2	2	2	2	2	3	2
55	1.1	9	3.89	24.77	12	42	2	2	2	2	3	2
56	0.83	9	3.89	24.77	18	41.5	2	1	2	2	3	2
57	0.87	9	3.89	24.77	12	29.8	3	1	2	3	3	2
58	1.29	9	3.89	24.77	2	36	3	2	2	3	3	2

59	0.34	9	3.89	24.77	43	38	3	2	2	3	3	2
60	8.18	7	10.4	32.4	0	32.1	1	2	2	3	3	1
61	3.7	7	10.4	32.4	3.5	34.3	1	2	2	3	3	1
62	7.58	7	10.4	32.4	0	26.2	1	3	2	3	3	1
63	5.03	7	10.4	32.4	2.4	29	1	3	2	3	3	1
64	7.66	7	10.4	32.4	0	41.1	1	3	2	3	3	1
65	5.11	7	10.4	32.4	2.3	38.3	1	2	2	3	3	1
66	8.13	7	10.4	32.4	0	38.9	1	2	2	3	3	1
67	4.15	7	10.4	32.4	8.2	43.4	1	3	2	3	3	1
68	5.4	7	10.4	32.4	4.6	45.5	1	3	2	3	3	1
69	8.18	7	10.4	32.4	0	43.6	1	2	2	3	3	1
70	1.31	8	2	22	2	15.2	1	3	1	1	2	2
71	1.26	8	2	22	2.8	18.8	1	3	1	1	2	2
72	1.29	8	2	22	3.2	20.3	1	3	1	1	2	2
73	1.32	8	2	22	1.8	22.7	1	3	1	1	2	2
74	1.33	8	2	22	1	24.1	1	3	1	1	2	2
75	1.36	8	2	22	2.2	28.2	1	3	1	1	2	2
76	1.37	9	3.22	22.67	3	38.7	2	2	2	2	2	2
77	1.53	9	3.22	22.67	0	39.9	2	2	2	2	2	2
78	1.35	9	3.22	22.67	4	42	2	2	2	2	2	2
79	1.32	9	3.22	22.67	6	43.8	2	2	2	2	2	2
80	1.58	9	3.22	22.67	0	45.2	2	2	2	2	2	2
81	1.55	9	3.22	22.67	1	47.8	2	2	2	2	2	2
82	1.38	7	8.143	28.71	2	12	1	3	2	3	2	2
83	1.55	7	8.143	28.71	0	14.7	1	1	2	2	2	2
84	1.56	7	8.143	28.71	0	16.2	1	1	2	2	2	2
85	1.53	7	8.143	28.71	0	19.8	1	1	2	2	2	2
86	1.39	7	8.143	28.71	1	21.1	1	2	2	3	2	2
87	2.66	8	4.62	25.5	0	18.2	2	3	2	1	1	4
88	2.73	8	4.62	25.5	0.5	22.3	2	2	2	1	1	4
89	2.23	8	4.62	25.5	8	23.8	3	2	2	2	1	4
90	2.33	8	4.62	25.5	4.6	24.1	3	2	2	2	1	4

91	2.71	8	4.62	25.5	0	26.4	2	2	2	1	1	4
92	2.57	8	4.62	25.5	0.99	22.3	1	2	2	1	1	4
93	0.68	9	2.89	22.44	56.3	32.2	4	2	2	3	1	4
94	2.28	9	2.89	22.44	3	38.6	3	2	2	3	1	4
95	2.61	9	2.89	22.44	0	36.3	2	2	2	2	1	4
96	2.65	9	2.89	22.44	0	39.2	2	3	2	2	1	4
97	1.08	8	3.87	24	8.3	28.3	1	2	1	1	3	4
98	1.93	8	3.87	24	0	29.8	2	1	1	1	3	4
99	2.1	8	3.87	24	6.4	33.3	1	2	1	1	3	4
100	2	8	3.87	24	0	34.8	2	1	1	1	3	4
101	1.85	8	3.87	24	2.9	35.1	1	2	1	1	3	4
102	1.86	8	3.87	24	10	37.2	2	2	1	1	3	4
103	1.92	9	2.89	22.33	0	15.9	2	2	2	1	3	2
104	0.62	9	2.89	22.33	30.3	17.6	1	2	2	3	3	2
105	1.89	9	2.89	22.33	2.1	19.2	2	1	2	1	3	2
106	1.85	9	2.89	22.33	0	22.1	2	1	2	1	3	2
107	1.78	9	2.89	22.33	0	24	2	2	2	1	3	2
108	1.6	9	2.89	22.33	1.6	25.8	1	3	2	2	3	2
109	8.25	7	6.57	27.7	0	26.2	2	1	1	1	3	1
110	5.35	7	6.57	27.7	2	30.2	1	1	1	1	3	1
111	6.96	7	6.57	27.7	0	34.2	1	1	1	1	3	1
112	8.03	7	6.57	27.7	0	35.6	2	2	1	1	3	1
113	6.96	7	6.57	27.7	1.2	37.4	3	2	1	2	3	1
114	5.49	7	6.57	27.7	3	38.2	3	2	1	2	3	1

Appendix 10: Correlation coefficient of the Dataset

	CLP	Crew Size	Crew Experience	Age	Interruption level	Distance	Whether	Congested Area	Health Status	Crew Flexibility	Building Element	Placement Techniques
CLP	1.000000	0.115993	0.568120	0.534865	-0.057284	-0.120075	-0.074829	-0.194435	-0.198416	-0.091195	0.126592	-0.522719
Crew Size	0.115993	1.000000	-0.347708	-0.165055	0.312474	0.125781	0.118961	-0.026481	0.094087	0.394141	-0.132728	0.015194
Crew Experience	0.568120	0.347708	1.000000	0.019498	0.059103	0.104292	0.170118	0.108299	0.062923	0.037603	0.330210	0.500260
Age	0.534865	-0.165055	0.919498	1.000000	0.081448	0.159922	-0.086516	-0.104308	-0.004247	0.001517	0.184824	-0.458273
Interruption level	-0.057284	0.312474	-0.059103	0.081448	1.000000	0.136746	0.506895	-0.011414	0.042392	0.170061	-0.108032	-0.078589
Distance	-0.120075	0.125781	0.104292	0.159922	0.136746	1.000000	0.317672	0.147011	0.024867	0.246104	0.119887	0.052604
Whether	-0.074829	0.118961	-0.170118	-0.086516	0.506895	0.317672	1.000000	0.015741	0.062325	0.054796	-0.246302	0.100001
Congested Area	-0.194435	-0.026481	-0.108299	-0.104300	-0.011414	0.147011	0.015741	1.000000	0.172981	0.049754	0.016390	-0.033296
Health Status	-0.198416	0.094087	-0.062923	-0.004247	0.042392	0.024867	0.062325	0.172981	1.000000	0.320574	0.052408	-0.014110
Crew Flexibility	-0.091195	0.394141	-0.037603	0.001517	0.170061	0.246104	0.054796	0.049754	0.320574	1.000000	-0.137717	0.105519
Building Element	0.126592	-0.132728	0.330210	0.184824	-0.108032	0.119887	-0.246302	0.016390	0.052408	-0.137717	1.000000	-0.414276
Placement Techniques	-0.522719	0.015194	-0.500260	-0.458273	-0.078589	0.052604	0.100001	-0.033296	-0.014110	0.105519	-0.414276	1.000000

Appendix 11: CLP Modeling Procedures in Python

```
#load the data into pandas
econ_df = pd.read_csv('davemodel.csv',dtype = np.float32)
econ_df
```

...

```
#set the data type of the data frame
econ_df = econ_df.astype(np.float32)
```

```
desc_df = econ_df.describe()
desc_df = desc_df.transpose()
desc_df
```

...

```
#scaling the data: converting the data into a common scale:X_scaled =(X-Xmin)/(Xmax-Xmin)*(max-min) +min
scaler = MinMaxScaler(feature_range=(0.1, 0.9))
econ_df = scaler.fit_transform(econ_df)
econ_df = pd.DataFrame(econ_df, columns = ['CLP', 'Crew Size','Crew Experience','Age','Interruption level','Distance',
                                          'Whether','Congested Area','Health Status','Crew Flexibility','Building Element',
                                          'Placement Techniques'])
display (econ_df)
```

...

```
econ_df = econ_df.astype(np.float32)
econ_df.dtypes
```

...

```
#print out correlation matrix of data frame
corr = econ_df.corr()
#display it
display(corr)
```

```
#plot heatmap
sns.heatmap(corr, xticklabels = corr.columns, yticklabels = corr.columns, cmap ="RdBu")
```

...

```
# split the data into inputs and outputs
X = econ_df.drop(columns=['CLP'])
y = econ_df['CLP']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
```

```
#create a model
nn=MLPRegressor(hidden_layer_sizes=(3,),activation='logistic',max_iter=2000,solver='adam',learning_rate_init=0.1,
                early_stopping=True,validation_fraction=0.15,verbose=False, )
history = nn.fit(X_train, y_train, )
print("Train_score: {0:2f}%".
      format(nn.score(X_train,y_train)*100))
print("val_score: {0:2f}%".
      format(nn.score(X_test,y_test)*100))
```

...

```
mae_train=metrics.mean_absolute_error(y_train, nn.predict(X_train))
mse_train=metrics.mean_squared_error(y_train, nn.predict(X_train))
rsq_train=metrics.r2_score(y_train, nn.predict(X_train))
print(mae_train, mse_train, rsq_train)
```

...

```
mae_test=metrics.mean_absolute_error(y_test, nn.predict(X_test))
mse_test=metrics.mean_squared_error(y_test, nn.predict(X_test))
rsq_test=metrics.r2_score(y_test, nn.predict(X_test))
print (mae_test, mse_test, rsq_test)
```

```
print('coefficients: ', nn.coefs_)
```

...

```
print('intercepts: ', nn.intercepts_)
```

...

```
Y_pred = nn.predict(X_test, )
arrayY_pred= np.array(Y_pred, dtype=np.float32)
arrayY_pred
```

...

```
arrayy_test= np.array(y_test, dtype=np.float32)
arrayy_test
```

...

```
#Comparison of predicted and observed Productivity

a = plt.axes(aspect='equal')
plt.scatter(y_test, Y_pred)
plt.xlabel('True Values [CLP]')
plt.ylabel('Predictions [CLP]')
lims = [0, 1]
plt.xlim(lims)
plt.ylim(lims)
_ = plt.plot(lims, lims)
```

...

```
pd.DataFrame(nn.loss_curve_).plot()
plt.title('model loss')
plt.ylabel('mse')
plt.xlabel('epoch')
```

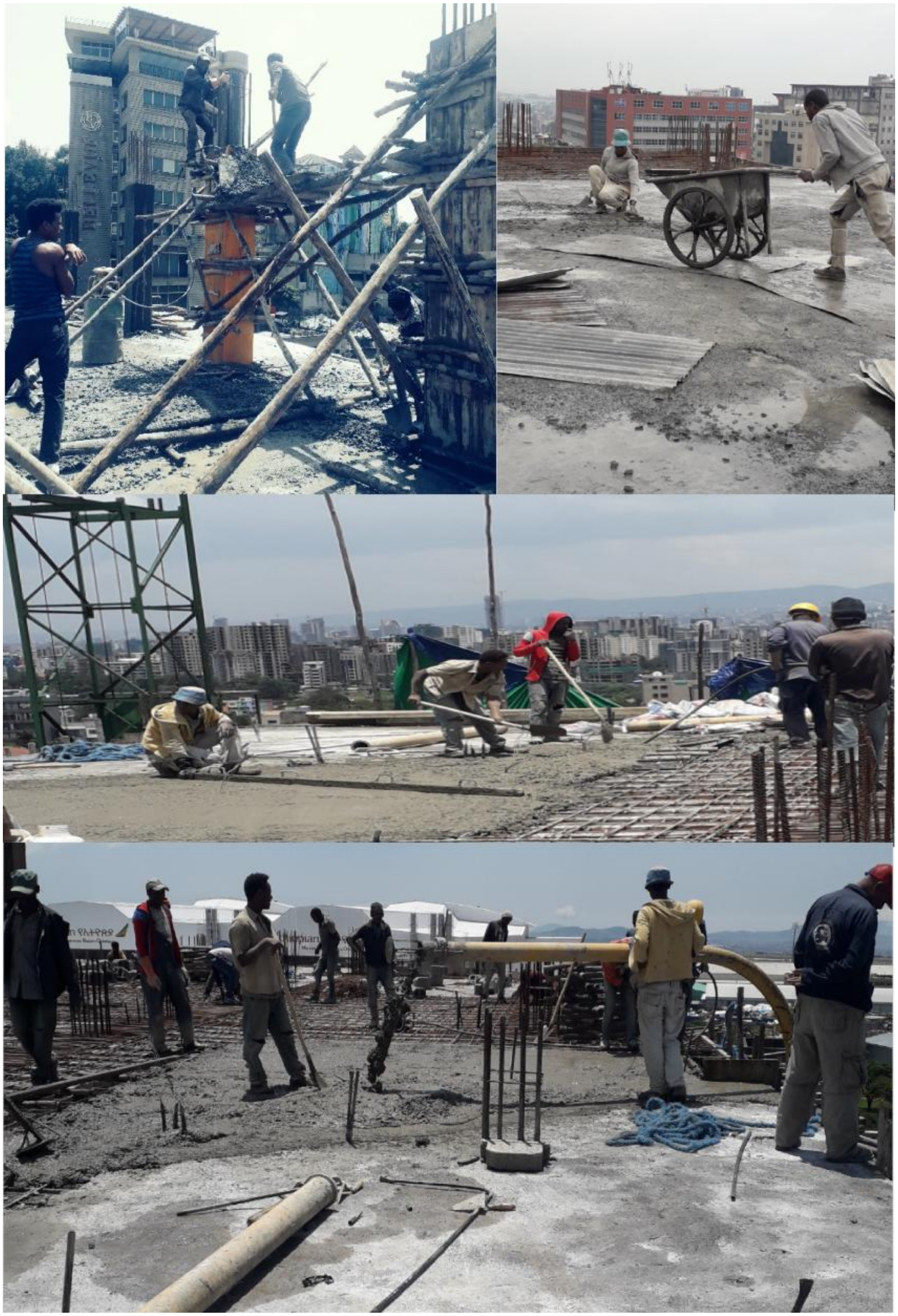
...

```
nn.predict([[]])
```

Appendix 12: Programmed Productivity Estimator Excel Sheet

Input Parameters	Xmax value	Xmin value	Scaler min range	Scaler max range	Input (X)	Xi = X scaled	From optimal nn model(weight b/n hidden node 1 and inputs)	From optimal nn model(weight b/n hidden node 2 and inputs)	From optimal nn model(Hidden bias)	∑Wi*Xi + b	Exponential (e^-x)	activation function (1/(1+e^-x))	From optimal nn model(weight b/n hidden nodes and output)	From optimal nn model(output bias)	Scaled output value(Y_scaled)	yscaled-min	ymax-ymin	max-min	Output CLP(m3/hr)
crew size	11	6	0.1	0.9	8	0.42	-8.08E-01	-1.30E+00	0.3583	-0.42051	1.522736	0.3963951	-0.6679519	1.956	0.4144	0.314399	19.66	0.8	7.82636
Crew Experience	10.4	2	0.1	0.9	6.57	0.535238	1.46E-01	-2.42E+00	-1.509	1.299801	0.272586	0.78580147	-1.6245147						
Age	34	22	0.1	0.9	27.7	0.48	-5.29E-01	2.27E+00											
Interruption Level	86	0	0.1	0.9	0	0.1	2.01E-01	2.74E+00											
Distance	49.7	7.5	0.1	0.9	35.6	0.632701	1.32E-01	-2.64E-02											
Whether	4	1	0.1	0.9	2	0.366667	3.35E-02	-3.53E-03											
Congested area	3	1	0.1	0.9	2	0.5	-9.49E-02	9.09E-03											
Health Status	2	1	0.1	0.9	1	0.1	-2.82E-01	3.36E-01											
Crew Flexibility	3	1	0.1	0.9	1	0.1	1.03E-01	5.89E-01											
Building Element	3	1	0.1	0.9	3	0.9	-2.15E-01	2.40E+00											
Placement technique	4	1	0.1	0.9	1	0.1	-1.21E+00	1.05E+01											
Output																			
CLP	20	0.34	0.1	0.9															

Appendix 13: Photos Taken During Data Collecting Phase




Candy
CAMERA