Analysis Of Productivity Of Ready Mixed Concrete Using Multiple Regression Analysis And Artificial Neural Network

Abdul Khaliq C. M., #2 Mr.S.Sabarinathan. #1 Construction Engineering And Management. #2 Asst Prof, Department of Civil Engineering, Shree Venkateshwara Hi-Tech Engineering College, Gobichettipalayam

Abstract- With rapid growth in the construction industry, Ready Mix Concrete (RMC) is playing a key role in offering high-quality customized concrete to contractors and builders. Productivity is a vital consideration for companies in the construction industry in terms of survival or growth. The primary goal of this research is to develop a quantitative model (regression model) for predicting the production rate of RMC and its total cost using pump for building construction projects. As stated earlier, the production rate of RMC in construction projects is affected by several factors and the accuracy of estimate could be challenged when effect of multiple factors is considered simultaneously. In this project the variables for predicting production rate of RMC(concreting productivity) using pump and to find total cost of concreting process are examined. The correlation between these variables as independent variables and the production rate variable as dependent variable using correlation analysis is tested. Regression model for RMC productivity and total cost for concrete placement is found. This regression model is compared with Artificial Neural Network (ANN).

INTRODUCTION

The Construction industry of India is an important indicator of the development as it creates investment opportunities across various related sectors. The construction industry is a major contributor towards India’s GDP, both directly and indirectly. It employs 33 million people, and any improvements in the construction sector affect a number of associated industries such as cement, steel, technology, skill-enhancement, etc. USD 1,000 billion investments for infrastructure sector projected in 12th five year plan (2012-17). It is noted that 10% of India’s GDP is based on construction activity.

Concrete is used more than any other man-made material to make dams, parking lots, building structures, roads, pavements, and more. Therefore, to manage a construction project effectively, it is essential to control concrete pouring production rate.

READY MIX CONCRETE

The Ready mix concrete business in India is in its infancy but it is having a steady growth in the last 2 decades. For example, 70% of cement produced in a developed country like Japan is used by Ready Mix concrete business there. In Europe and USA it is about 60%. Here in India Ready Mix concrete business used around just 2% in the beginning of the 90’s and presently the commercial RMC is at 9-10% of total cement production with another 10% estimated to come from project based captive RMC plants totally taking the mechanized RMC Production to 20% of the cement production in India and there is still a lot to catch up in terms of growth and conversion of Site mix Concrete(SMC)to Ready mixed concrete.

The Indian cement industry is the second largest in the world with an installed capacity of 340 million tonnes and the production for the year 2013-14 was around 260 million tonnes and presently the commercial RMC alone consumes around 9-10% of the total cement production and producing approximately 30-32 million cubic meter of commercial readymixed concrete annually.

Captive RMC plants which are set up at project sites in metros and cities have been estimated to produce around another 35 million cubic meter of ready -mixed concrete annually, which in turn taking the total production of mechanized concrete (production of concrete from RMC batching plants) in India to about 65-67 million cubic meter annually. In the developed countries the cement consumption through RMC route is about 70-75% (USA) and 65-70% (Europe and Japan). As a testimony to the growth of RMC industry in India, as per best of the knowledge, currently there are more than 900 commercial RMC plants present and operating in about 95 to 100 cities and towns across India including metros, tier 1 and tier 2 cities and in total there are more than 2600 ready-mixed concrete batching plants in operation in many metros, cities, and various project locations across the country.
Productivity is a vital consideration in the construction industry because improvement in productivity has a direct impact on all other industries and on the national economy. Productivity is also a central determinant of man’s standard of living and plays a crucial role in the national economy of countries because for the economy to improve, the productivity of the various sectors in the economy has to increase. Construction labour productivity is one of the most frequently researched topics because in most countries, labour cost comprises 30 to 50% of the overall project’s cost and thus regarded as a true reflection of the economic success of the operation. Since labour cost represents a considerable proportion of the final cost of the building, labour is confirmed as the most important factor of production. Moreover, because it creates value and sets the general level of productivity, labour productivity is usually adopted as an index for measuring overall productivity while concrete work is an important and fundamental part of modern construction practice common to international construction and can provide a meaningful indication of the comparative performance of contractors since it is essentially a cyclical task similar on all construction sites, regardless of international location.

**FACTORS AFFECTING POURING RMC**

Many researchers have already identified, investigated, and recognized the factors affecting RMC, factors affecting the poor productivity of construction building, are lack of skills from the workers, lack of tools/equipment, poor construction methods, poor communication, lack of materials, weather conditions, poor site conditions, and accidents at work sites were among the most important factors affecting productivity. Moreover it is mentioned that the duration of concrete pouring operation depends on the following factors: number of concrete trucks, concrete trucks capacity, and number of batch plants available, batch plant capacity, and distance between the construction site and the concrete batch plant. It is also mentioned that type of operation (construction building element), truck volume (capacity), total operation volume, average inter arrival time based on batch plant location from the site, number of loads in operation, and the workability of the RMC using slump test are essential factors that influence the productivity of RMC operation. In addition it is mentioned that factors such as planning, scheduling, quality control, worker’s ability and skills, motivation, and organization can improve the productivity for construction projects. Data were collected from private construction projects in Kerala. In addition, factors like distance between batching plant and site, site characteristics, weather, truck mixers capacity, and truck mixers availability could be considered to influence the output in concrete operations. The placing method is a major determinant of the speed of placing, but the shape of the pouring and its location are technical factors that also influence productivity. Besides, it is found in their research that quantity, crew size, temperature, overtime, job type, and concrete pump were selected as the factors that may influence productivity for concrete pouring in the construction project.

**CONCRETING PRODUCTIVITY RATES**

Just as flow processes are easily thought of in terms of time, construction operations are easily thought of in terms of productivity rates. Productivity is however usually defined in different ways depending on the purpose of measurement. In construction, trade productivity is ordinarily defined for conceptual and analytical simplification as the ratio of the output in a particular trade related to the tradesman’s inputs and can be expressed in quantitative terms as physical productivity. Two forms of productivity are used in the construction industry:

1. Productivity = output/input or
2. Productivity = input/output.

The first form is widely used in construction and existing literature while the second is often employed for estimating. It is important to specify the input and output to be measured when calculating productivity because there are many inputs to the construction system, such as labour, materials, equipment, tools, capital and design. Also, the conversion process from inputs to outputs associated with construction operations is complex, being influenced by the technology used and by many externalities such as government regulations, weather, unions, economic conditions and management and by various environmental components. Even for an operation like concreting, with well-known equipment and work methods, construction productivity estimation can be challenging owing to the unique work requirements and changeable environment of each construction project as well as the complexity of the influences of job and management.
factors on operational productivity. An accurate estimate of the productivity for in-situ concreting operations is desirable for planning purposes because planning engineers require productivity rates to estimate and schedule pours, resource levels, and accounting control.

Different yardsticks are usually employed for measuring the concreting productivity by giving the placement labour or equipment productivity as the ratio between the quantity of concrete poured to the man hours (mh) or equipment hours (eh) committed by the concreting gang or equipment respectively, the mixer productivity as the ratio between the quantity of concrete poured to the mixer-hours spent on site. Concreting productivity consequently entails relating a single input (worker-hour or equipment-hour) to a single output (concrete volume in m³) and the simple productivity ratio of this input and output is calculated assuming a closed system with all other factors held constant except for the desired input and output (Wang, 1999). The overall productivity for an entire concreting operation, which is the placing rate is thus appropriately measured as the ratio of the quantity of concrete placed to the total time of the operation in m³/hr (Wang, 2001). In this study, the convention of measuring labour productivity as input divided by output or operative hours per unit of work.

COSTING OF PRODUCTION, DELIVERY OF RMC

RMC refers to concrete that is specifically manufactured for delivery to the customer's construction site by truck-mounted transit mixers in a freshly mixed and plastic or unhardened state. The first ready-mix factory was built in the 1930s, but the industry did not begin to expand significantly until the 1960s, and it has continued to grow since then. RMC can be custom-made to suit different applications and is sold by volume usually expressed in cubic meters. It is sometimes preferred over on-site concrete mixing because of the precision of the mixture and reduced worksite confusion. Other advantages of RMC include elimination of storage space for basic materials at site, less labor, and lower levels of pollution at the site. A disadvantage of RMC is the impact of traveling time on properties of concrete. This time is largely influenced by the distance from plant to site, weight limits of roads and bridges, and traffic conditions. Today, modern additives help elongate the time-span of RMC at added expense. To our knowledge, no research exists that utilizes for measuring placement productivity of RMC.

To estimate the cost of a demanded volume of RMC, it is necessary to cost required materials, labor involved, fuel and maintenance needed, plant and ancillary equipment hired and depreciated, and delivery of RMC to customer site. The proposed cost model divides the cost of RMC into 1) On-floor cost, 2) Cost of delivery: a new model for costing the delivery of RMC is proposed. Hence cost model contains on floor cost and cost of delivery. One floor cost includes all the costs(materials and labour) related to that floor.

OBJECTIVES

The primary goal of this project is to develop a quantitative model (regression model) for predicting the production rate of RMC and its total cost using pump for building construction projects. As stated earlier, the production rate of RMC in construction projects is affected by several factors and the accuracy of estimate could be challenged when effect of multiple factors is considered simultaneously. The increases in the project duration (related to any delays in pouring concrete activity) have negative effects on the project cost, as that time delays usually equal cost over runs. For this reason, developing the regression model to predict production rate of RMC can assist planners and estimators to reduce the effort required to plan the construction operation and to improve the accuracy of production rate estimate to complete a project within budget and schedule.

There are five objectives, which are given below

1. To examine and discover the variables for predicting production rate of RMC (concreting productivity) using pump and to find total cost of concreting process
2. Test the correlation between these variables as independent variables and the production rate variable as dependent variable using correlation analysis
3. To enable site planners to use the model to predict the production rate with reasonable accuracy.
4. Find Regression model for RMC productivity and total cost for concrete placement
5. Compare this regression model with Artificial Neural Network (ANN)

LITERATURE REVIEW

The following literature are studied for the project

Shou Qing Wang, George Ofori and Cheng LianTeo (2001) identified the productivity of RMC placing is of great importance to the productivity improvement of the whole construction industry of each country. They made a study undertaken at the end of 1999 on the productivity and utilization of labor and equipment resources in the placing of in-situ RMC in Singapore. The study involved close observation of 32 pours on building sites, each from its beginning to end. Much detailed productivity information was derived and different concrete placing methods were compared. Factors affecting the RMC placing performance were also studied. Benchmarks, which describe the current state of RMC placing in Singapore were produced not only for measuring progress of RMC placing productivity over time but also formaking comparisons with other large cities.

F. Khademil and K. Behfarnia (2016) studied, two different data-driven models, artificial neural network (ANN) and
multiple linear regression (MLR) models, have been developed to predict the 28 days compressive strength of concrete. Seven different parameters namely 3/4 mm sand, 3/8 mm sand, cement content, gravel, maximums size of aggregate, tensile modulus, and water-cement ratio were considered as input variables. For each set of these input variables, the 28 days compressive strength of concrete were determined. A total number of 140 input-target pairs were gathered, divided into 70%, 15%, and 15% for training, validation, and testing steps in artificial neural network model, respectively, and divided into 85% and 15% for training and testing steps in multiple linear regression model, respectively.

Comparing the testing steps of both of the models, it can be concluded that the artificial neural network model is more capable in predicting the compressive strength of concrete in compare to multiple linear regression model. In other words, multiple linear regression model is better to be used for preliminary mix design of concrete, and artificial neural network model is recommended in the mix design optimization and in the case of higher accuracy requirements.

VinayChandwani, Vinay AgrawalI, Ravindra Nagar1, SarbjeetSingh (2015), identified that RMC is manufactured at a plant and transported to the construction site, loss of workability is of prime concern due to the considerable time interval between mixing and placing of concrete. Workability of concrete is measured using a slump test to evaluate the life of the concrete during its transportation phase and the uniformity of the concrete from batch to batch. The proportions of cement, fly ash, coarse aggregates, fine aggregates, water, and admixtures in the concrete govern its workability or slump value. In this study, an Artificial Neural Networks (ANNs) learning from past examples gathered from a RMC plant were used to model the functional relationship between the input parameters and the slump value of concrete. The ANN model provided promising results compared to first-order and second-order regression techniques for modeling the unknown and complex relationships exhibited by the design mix proportions and the slump of concrete. The neural network synaptic weights that control the learning mechanism of ANN were further used to compute the percentage of relative importance of each constituent of RMC on the slump value, providing insight into the composite nature of concrete. The technique presented in the study will enable technical staff to quickly estimate the slump of RMC based on its design mix constituents without having to perform multiple design mix trials in order to achieve a customized slump value.

Faiq Mohammed Sarhan Al-Zwainy (2013) studied at developing construction productivity estimating model for marble finishing works of floors using Multivariable Linear Regression technique (MLR). The model was developed based on 100 set of data collected in Iraq for different types of projects such as residential, commercial and educational projects. Which these are used in developing the model and evaluating its performance. Ten influencing factors are utilized for productivity forecasting by MLR model, and they include age, experience, number of the assist labor, height of the floor, size of the marbles tiles, security conditions, health status for the work team, weather conditions, site condition, and availability of construction materials. One model was built for the prediction of the productivity of marble finishing works for floors. It was found that MLR have the ability to predict the productivity for finishing works with excellent degree of accuracy of the coefficient of correlation (R) 90.6%, and average accuracy percentage of 96.3%. This indicates that the relationship between the independent and independent variables of the developed models is good and the predicted values from a forecast model fit with the real-life data.

A. Samer Ezeldin1 and Lokman M. Sharara(2006) identified that to overcome the variability and the impact of subjective factors on the cost of concrete-related activities in developing countries, neural networks can offer a guiding tool. In this study, three neural networks were developed to estimate the productivity, withina developing market, for formwork assembly, steel fixing, and concrete pouring activities. Eighteen experts working in six projects were carefully selected to gather the data for the neural networks. Ninety-two data surveys were obtained and processed for use by the neural networks. Commercial software was used to perform the neural network calculations. The processed data were used to develop, train, and test the neural networks. The results of the developed framework of neural networks indicate adequate convergence and relatively strong generalization capabilities. When used to perform a sensitivity analysis on the input factors influencing the productivity of concreting activities, the framework has demonstrated a good potential in identifying trends of such factors.

VinayChandwani , VinayAgrawal, RavindraNagar (2014) explores the usefulness of hybridizing two distinct nature inspired computational intelligencc technologies viz., Artificial Neural Networks (ANN) and Genetic Algorithms (GA) for modeling slump of Ready Mix Concrete (RMC) based on its design mix constituents viz., cement, fly ash, sand, coarse aggregates, admixture and water-binder ratio. The methodology utilizes the universal function approximation ability of ANN for imbibing the subtle relationships between the input and output variables and the stochastic search ability of GA for evolving the initial optimal weights and biases of the ANN to minimize the probability of neural network getting trapped at local minima and slowly converging to global optimum.

M. F. M. Zain, Suhad M. Abd, K. Sopian, M. Jamil, Che- Ani A.I(2005) proposed a new mathematical models and developed using non-linear regression equation for the prediction of concrete compressive strength at different ages. The variables used in the prediction models were from the knowledge of the mix itself, i.e. mix proportion elements. According to the analysis the models provide good estimation of compressive strength and yielded good correlations with the
data used in this study. The correlation coefficients were 0.995 and 0.994 for the prediction of 7 and 28 days compressive strength respectively. Moreover, the proposed models proved to be significant tool in prediction compressive strength of different concretes in spite of variations in the results.

Emad Abd-El Hamied El-Maghraby (2014) presented and discussed a new model for predicting the production rate of PRMC using tower cranes by using the multiple linear regression analysis. The researcher developed the regression model by identifying 36 factors affecting PRMC using tower cranes. The researcher used correlation analysis to identify the most independent variables correlated to the dependent variable (production rate). The validation exercise demonstrated that the model derived for estimating pouring concrete production rate produces good results when comparing with the actual pouring concrete production rate.

Faig Mohammed Sarhan AL-Zwainy, Hatem A. Rasheed and Huda Farhan Ibrahim (2015) noted that the quality of construction management depends on accurate estimation of the construction productivity. In this paper, Multi-layer perceptron trainings using the back-propagation algorithm neural network is formulated and presented for estimation of the productivity of construction projects. Data used in the study are for residential, commercial and educational projects from different part from Iraq. These are used in training the model and evaluating its performance. Ten influencing factors are utilized for productivity forecasting by ANN model, they include age, experience, number of the assist labor, height of the floor, size of the marbles tiles, security conditions, health status for the work team, weather conditions, site condition, and availability of construction materials. One model was built for the prediction the productivity of marble finishing works for floors. It was found that ANNs have the ability to predict the productivity for finishing works with a very good degree of accuracy of the coefficient of correlation (R) was 89.55%, and average accuracy percentage of 90.9%.

Prof. Dr. Mohammed Mansour Kadhum Eng. Ahmed Abdulrazzaq Hussein Agha (2016) focused on development a model to predict the ultimate load carrying capacity of Reactive Powder Concrete (RPC) columns. Two different statistical methods regression techniques (RT) and the artificial neural network (ANN) methods were used for determining the RPC columns ultimate load carrying capacity. The data collected from three experimental studies the first used to develop the model and the other two used as a casestudy. Experimental results used as input data to develop prediction models. Two different techniques adopted to develop the models the first was Artificial Neural Network (ANN) and the second was multi linear regression techniques (RT). The models use to predict the ultimate load carrying capacity of RPC columns. To predict the ultimate load carrying capacity of RPC columns four input parameters were identified cross-section, micro steel fiber volume fraction content, compressive strength and main steel reinforcement area. Both models build with assistance of MATLAB software. The results exhibit that the cross section area has most significant effect on ultimate load carrying capacity.

Rifat Sonmez (1996) conducted research to date on construction labor productivity usually has focused on the effect of a single factor while neglecting the effects of the other factors. Factor model was the only model that focused on quantification of the effect of multiple factors. It was suggested that the factor modeling methodology which was developed for masonry construction could also be used for other tasks. However the factor modeling methodology had several limitations. The modeling methodology defined in this study for productivity modeling of labor intensive construction tasks, is an improvement over the factor modeling methodology in the way it addresses the following three issues. Use of neural networks for construction labor productivity was also explored in this study. Neural networks with their mapping capabilities helped the overall modeling process. Neural networks have shown potential to identify the effects of the factors, especially when interactions and non-linear relations were present.

Olatunde Olaoluwa (2015) developed a regression model to assess factors affecting labour productivity. According to him Concrete placement by crane and skip is the least labour intensive and yields the most efficient productivity rate while concrete placement using dumper is the next most labour productive placement method, and although restricted to column/wall foundations and ground floor beams and slabs, is the most popular of the mechanized methods, being used in about 50% of the building sites. Dumper are used for massive concrete foundation slabs and walkways including lawn verges in public space landscaping, running through and connecting different playfields within large sports complexes and stadia. They can travel across almost any terrain where soft, sandy composition of the ground prevents the use of conventional trucks and enable concrete to be placed efficiently over large areas while monitoring quality control. Dumper also have the advantage of travelling at speeds up to 30 km/hr with high manoeuvrability where access may be limited working with either forward tipping or effective placement on either side, which is very useful for foundation trench filling and concreting storm water drains. In Nigeria, dumpers have become a favourite for Contractors who have found it to be the ideal solution for job-site construction and in situ concrete laying on small and medium concreting projects because they cannot afford pumps and cranes.

This study examines labour productivity in concrete placement by dumpers to provide additional knowledge and insights into concrete production and placement in Nigeria and enhance the use of dumpers for concrete placement and in the construction industry generally. The factors with an impact on concreting...
productivity are first identified by a review of relevant literature.

Song and AbouRizk (2008) have successfully applied ANN and discrete-event simulation in developing a labour productivity model for steel drafting and shop fabrication activities. They found ANN to be effective in modelling individual activities that have complex detailed operations and a complex mapping relationship between productivity and influencing factors.

Ezeldin and Sharara (2006) designed a framework using neural networks to predict the productivity of forms assembly, steel fixing, and concrete pouring while incorporating both quantitative and qualitative factors. The results show that the networks adequately converged and have reasonable generalizing capabilities.

Dunlop and Smith [2003] mentioned that in concrete operations, unanticipated conditions and actions can result in a loss of productivity, factors like distance between batching plant and site, site characteristics, weather, truck mixers capacity, and truck mixers availability could be considered to influence the output in concrete operations. The factors were identified and classified into six groups: 1) Crane movements, which include: hoisting height, angular movement, and radial movement, 2) crane capacity, 3) skill of operators, 4) nature of load, which include weight, length, area similarly, hoisting orientation, 5) location of load include, loading point, unloading point, and 6) weather. He also reported the use of multiple linear regression to determine the statistical relationship between actual productivity and the explanatory variables like number of truck mixers used, type of pour, average volume of concrete, etc for concreting via a pump. He also implemented a stepwise procedure, which allows the regression model to be iteratively redefined until only the explanatory variables that are statistically significant remained in the model. The regression analysis methodology used, on the other hand, was backward elimination, stepwise regression beginning with a full set of explanatory variables or factors that were identified to account for much of the variability in concreting operations.

Ameh and Odusami (2002), the output of the construction industry is about 3-8% of the Gross Domestic Product (GDP) in most countries. Construction traditionally contributes to a country’s total employment figures and the nation’s revenue as a whole. In the US, construction accounts for 14% of the gross national product (GNP) and about 8% of total employment. The construction industry is reported to be the largest Nigerian industry, employing a good proportion of the work force and controlling over 50% of GNP. Productivity is a vital consideration in the construction industry because improvement in productivity has a direct impact on all other industries and on the national economy. Productivity is also a central determinant of man’s standard of living and plays a crucial role in the national economy of countries because for the economy to improve, the productivity of the various sectors in the economy has to increase production.

AbouRizk et al. (2001) discussed an approach based on ANNs that enables an estimator to produce accurate labour production rates (labour/unit) for industrial construction tasks such as welding and pipe installation. The model was composed of a two-stage ANN, which was used to predict an efficiency multiplier (an index) based on input factors identified by the user.

Wang (1999), submit that it is important to specify the input and output to be measured when calculating productivity because there are many inputs to the construction system, such as labour, materials, equipment, tools, capital and design. Also, the conversion process from inputs to outputs associated with construction operations is complex, being influenced by the technology used and by many externalities such as government regulations, weather, unions, economic conditions and management and by various environmental components. Even for an operation like concreting, with well-known equipment and work methods, construction productivity estimation can be challenging owing to the unique work requirements and changeable environment of each construction project as well as the complexity of the influences of job and management factors on operational productivity.

Li, H., Chen, L. Y., and Love, P. E. D. (1999), prepared a literature review, in which they established that professional subjective judgment and regression analysis were the two main techniques utilized for predicting the seismic retrofit construction cost. The study presented in this paper aims at predicting this cost by employing the advanced modelling technique known as the artificial neural network (ANN) methodology. Using this methodology, a series of nonparametric ANN models were developed based on significant predictors of the net construction cost (NCC). Nonparametric RCE models were developed by means of the ANN methodology. Using the paradigms most utilized in the ANN methodology, a new two-phase development procedure was proposed for the successful development of ANN models. A number of equations were examined in this study for the purpose of initializing the number of hidden neurons. Of the equations examined, the equation proposed with the involvement of the number of training data set within its formulation was found to be of great use for the aforementioned purpose.

Sonmez and Rowings (1998) presented a methodology based on regression and neural network modelling techniques for quantitative evaluation of the impact of multiple factors on productivity. The methodology was applied to develop productivity models for pouring concrete, concrete formwork, and concrete finishing tasks, using data compiled from eight building projects RRR works covered 72 projects with the use of four variables (Country’s gross national income (GNI) per capita, climate, Transparency international corruption
perceptions index (TICPI), and percent of local bidders), and the coefficient of correlation was 0.708 after 1,250 epochs.

Anson and Wang [1998] mentioned that concrete placing productivity was influenced by many factors; the placing method is a major determinant of the speed of placing, but the shape of the pouring and its location are technical factors that also influence productivity. Besides he found in their research that quantity, crew size, temperature, overtime, job type, and concrete pump were selected as the factors that may influence productivity for concrete pouring in the construction projects.

Kaming, et. al, (1997) Chan explains since labour cost represents a considerable proportion of the final cost of the building, labour is confirmed as the most important factor of production. Moreover, because it creates value and sets the general level of productivity, labour productivity is usually adopted as an index for measuring overall productivity while concrete work is an important and fundamental part of modern construction practice common to international construction and can provide a meaningful indication of the comparative performance of contractors since it is essentially a cyclical task similar on all construction sites, regardless of international location.

Portas and AbouRizk (1997) developed a neural network model to estimate the construction productivity for the concrete formwork elements (i.e., slabs, walls, and columns). They investigated a number of alternative neural network structures, and the adapted one was a three-layered network with a fuzzy output structure, which provided the most suitable model since much of the input was subjective.

Moselhi et al. (1991) described neural network architectures and their potential applications in construction engineering and management. They introduced neural networks as a promising management tool that can enhance current automation efforts in the construction industry. He provided a discourse on the understanding, usage, and potential for application of ANNs within civil engineering. They first presented a graphical interpretation of the way in which ANNs operate and then demonstrated the ways in which different types of civil engineering problems can be tackled using ANNSiranian construction productivity.

Onitiri (1983) submits that the major reason for the Japanese dominance of the international world market today is their exemplary high level of productivity, arguing that other developing countries like Hong Kong, Singapore, the Philippines, India, Mexico and Brazil have similarly made inroads into the industrial market because of their consciousness and commitment to a high level of productivity borne out of a disciplined application of technical knowledge been used as a new information management tool

**CONCLUSION**

This paper has presented and discussed a new model for predicting the production rate of RMC by using the multiple linear regression analysis and artificial neural network for assessing total cost of RMC placement in the concrete placement operations. 25 factors has been considered for concreting productivity and 12 factors has been considered for developing labour productivity. The correlation analysis to identify the most independent variables correlated to the dependent variable (production rate). It has been noted that number of vibrators used, concreting location, weather conditions, concreting element, height of concreting, degree of supervision, number of workers per crew size of pouring, duration labour skill in steel erecting, carpenter performance on foam work etc place major role in achieving productivity. The procedures for Multiple regression analysis and Artificial Neural Analysis are briefly explained in this project.

**4.1 WORK SCHEDULE FOR PHASE II**

The detailed field study of RMC concreting operation is to be studied. The data collected should be analyses and results are to be interpreted. Correlation and regression analysis of slab, beam and columns are to be done. Regression model of the beam , slab and column to be made. The analysis also to be done using Artificial Neuron networks and comparison is made with Regression models

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