



Review Article

Application Intelligent Predicting Technologies in Construction Productivity

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Abstract: In this paper, it's reviewed the concept and methods of measuring productivity construction and the most important factors affecting on productivity. In addition, the most important applications of techniques (Multiple Linear Regression (MLR), Artificial Neural Network (ANN), and support vector machine techniques (SVM)) in the construction productivity field. Most of the previous studies are interested in identifying the factors affecting the construction productivity so as to achieve control and improve construction productivity and find a mathematical model to estimation construction productivity. Use several techniques to analyze the data of which was used to Identify factors affecting such as (relative importance, quantitative engineering project scope definition, Severity index, sensitivity analysis), and to use them for the development of predictive models such as (Linear Regression, Fuzzy models, Support Vector Machine and Artificial Neural Network).

Keywords: Labor Productivity, Multiple Linear Regressions (MLR), Artificial Neural Network (ANN), Support Vector Machine Techniques (SVMT)

1. Introduction

Construction productivity rates are the origin for estimating costs and time accurately that are necessary to finish a project. Productivity is defined as the ratio of output of quality that is needed with respect to the inputs of a certain production condition. In the construction sector, it is normally acknowledged as work output per man-hours worked. "Enhanced productivity contributes in helping contractors and a project owner in terms of it is considered more profitable and efficient. In addition, it also aids them to accurately estimate bidding for projects (Al-Zwainy et al., 2013)".

Labour productivity is a principal part of information for forecasting and planning a construction project.

The present practice of estimation of labour productivity depends mainly on an individual's experience or available productivity data. A systematic approach has a lack in terms of estimating and measuring labour productivity. Even though

past project data has significant predictive productivity information, a low quality of past data and the lack of a reliable productivity measurement system could reduce a powerful analysis of labour productivity. (Song and AbouRizk, 2008)

2. Research Aim

The aim of this study is exploring the applications of techniques (Multiple Linear Regression (MLR), Artificial Neural Network (ANN), and support vector machine techniques (SVM)) in the construction productivity field.

3. Research Importance

The prediction methods proposed in this research use Multiple Linear Regression Analysis (MLRA), Artificial Neural Network (ANN), and Support Vector Machine

techniques (SVM) methods to provide a forecasting that includes both objective and subjective information. These artificial intelligence techniques either emulate the human ability to learn from past experience and to apply quick solutions to new situations or use analogy-based decisions to propose new solutions. The outcomes expected from this research is presents a useful tool for the estimate engineers who are responsible for predicting construction productivity in their early planning process.

4. Concept of Productivity

Back in 1986, Thomas and Mathews (1986) stated that no standardized productivity definition had been established in the construction industry. It is difficult to define a standard productivity measure because companies use their internal systems which are not standardized. (Hee-Sung, et al., 2005).

In general, consensus is to define productivity as a ratio of output to input. In view of this, two approaches to productivity measurement emerge: total factor productivity where all inputs and outputs are considered; and single factor productivity where a single production factor is taken into consideration. (Smih, 1987).

European Productivity Agency (EPA) has defined productivity as: "Productivity is an attitude of mind. It is the mentality of progress, of the constant improvements of that which exists. It is certainty of being able to do better today than yesterday and continuously. It is the constant adaptation of economic and social life to changing conditions. It is the continual effort to apply new techniques and methods. It is the faith in human progress"

$$\text{Single Resource Productivity} = (\text{Total Output} / (\text{Total Input})) \quad (3)$$

The further suggestion that the economic productivity (in which both input and output are considered in terms of money) is easier to calculate, it is the physical productivity (such as that of labour on concrete works) which enables a manager to control the construction process. (Michael, et al., 2000).

Productivity is estimated at several levels of information for many purposes in construction sector. For instance, it could be estimated to specify industry trends and to create performance evaluations with other industry sections (BFC 2006). The productivity measurement level of any company or project offers external and internal benchmarks for evaluation with project or company standards (Park et al. 2005; Ellis and Lee 2006). For project scheduling and comprehensive estimating, productivity estimated at an activity level. In addition, productivity at the activity level was usually denoted to as labour productivity because the construction activities are generally labour intensive. It determines the input as labour hours and the output as completed quantities (Dozzi and AbouRizk 1993). Hence, productivity is estimated by labour hours per work unit in addition to the other resource inputs for example overhead costs and equipment, generally being linked to labour hours. Predicting and quantifying labour productivity for comprehensive estimating and planning purposes is the emphasis of this research (Song and AbouRizk, 2008).

Humphreys, 1991 defined productivity as the ratio of output to input, and can be defined by the following equations.

$$\text{Productivity Rate} = (\text{Total output}) / (\text{Total work-hours}) \quad (1)$$

Telsang, 2000 defined the productivity "Productivity is a function of providing more and more of everything to more people with less and less consumption of resources".

Productivity could be defined as "a link between time, cost and quality" (Researcher).

5. Construction Productivity

The definition of construction productivity is difficult, by using the engineering analogy of efficiency, is defined as: (Michael, et al., 2000)

$$\text{Efficiency} = \text{Output} / \text{Input} \quad (2)$$

The definition appears reasonable until the input is considered when it becomes apparent that one can use many resources such as labour, plant and equipment, materials, management, fuel etc. some of which are very difficult to quantify. Despite the difficulties, this definition is used to gauge the overall productivity of industry or organization productivity defined in this way is called total productivity. At project level however, it is not very useful and and it is more common to consider the productivity of a subgroup of the inputs and outputs. For example, the productivity measures of a single resources such as labour (partial productivity is the equivalent when more than one but not all the aspects are included). Thus:

6. Productivity Measuring

In broad terms, productivity measures can be classified either as single-factor productivity measures (relating a measure of output to a single measure of input) or as multi-factor productivity measures (relating a measure of output to several inputs) (OECD, 2001).

Because the measured of productivity is vary, so there is no single measure of productivity, (OECD, 2001). Productivity considered by a construction organization in terms of, for example, the cost of placing a cubic meter of concrete, or the time taken to lay a given number of bricks. Productivity measures do not deal adequately with the impact of technological change, or with factor substitution, where capital and equipment may be substituted for labour.

Governments and policy makers measure the relationship between inputs and outputs either as Labour Productivity (LP) (measured either as gross output or value-added per worker, or gross output or value-added per hour) or as Total Factor Productivity (TFP) (measured as gross output or value-added per unit of inputs - with construction sector inputs generally being labour, materials, equipment, energy and capital) (HM Treasury, 2000; Oglesby, et al. 1989). A third type of

productivity measure commonly used in US industry is the Total Productivity (TP), described by Oglesby, et al. (1989) as a project-specific model that is the ratio between outputs measured in a physical unit. TFP is widely recognized as a superior indicator to LP in the evaluation of efficiency in the use of resources in the construction sector (Grupp and Maital, 2003; Zhi et al., 2003).

Always there is a misunderstanding about productivity in the minds of the workforce. To the workers, higher productivity means higher workload, higher efforts, and more profits to owners, and unemployment and threat to job security, but these are not correct observations (Telsang, 2000).

7. Factors Influencing Productivity

The factors influencing productivity have been the subject of inquiry by many researchers. In order to improve productivity, a study of the factors affecting it, whether positively or negatively, is necessary. Making use of those factors that positively affect productivity and eliminating (or controlling) factors that have a negative effect, will ultimately improve productivity. If all factors influencing productivity known, it will also be possible to forecast productivity (Lema, 1995). There is two categories of factors that influencing productivity as shown in figure (1) (Telsang, 2000), as following:

- a) Controllable Factors (Internal Factors).
- b) Non-controllable Factors (External Factors).

7.1. Controllable Factors (Internal Factors)

Some of factors explained as shown in figure 1, as follow:

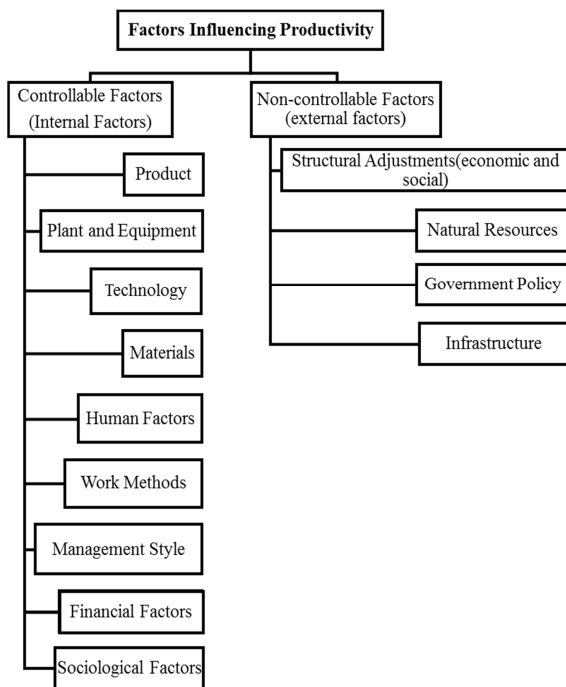


Figure 1. Factors Influencing Productivity (Telsang, 2000).

- 1) Product Factors: Productivity means the extent to which

the product meets the output requirements. Product is judged by its usefulness. The benefit factor of a product can be enhanced by increasing the benefit at the same cost or by reducing cost enhancing for the same benefit (Telsang, 2000).

- 2) Plant and Equipment Factors: Equipment shortage refers to frequent breakdown of major equipment, shortage of spare parts, improper service and maintenance, slack use of machinery or deliberate sabotage by operators. This problem causes major idle time since employed workers are unable to progress their work due to material transportation problems (Zakeri et al., 1996). Productivity can be increased by paying proper attention to utilization, age, modernization, cost, and investment, etc. (Telsang, 2000).
- 3) Technology Factors: Technology utilization impacts productivity in a number of ways. Historical changes in construction equipment have resulted in sustained improvements in task level labour productivity (Allison, et al., 2009). Innovative and technology improve productivity to greater extent. Automation and information technology helps to achieve improvements in material handling, storage, communication system and quality control. The various aspects of technological factors considered according to (Telsang, 2000) are:
 - a) Size and capacity of the plant.
 - b) Timely supply and quality of inputs.
 - c) Production planning and control.
 - d) Repairs and maintenance.
 - e) Waste reduction.
 - f) Efficient material handling system.
- 4) Material Factors: Lack of material is the most critical factor causing low productivity. Lack of material refers to the problems encountered due to inaccessibility of items or excessive time expended to acquire them. Because of this, workers are often idle waiting for materials. Construction activities are interdependent; the site management should plan to ensure that the critical materials are available at site all the time. Sometimes, the non-availability of materials was caused by negligence and sabotage. For instances, during bad economic times, the project manager may purposely delay the work progress to prolong the contract period especially those employed on a contract basis (Abdul Kadir et al, 2005),
- 5) Other Factors: Moreover, there are other factors such as human factors, Work methods, and Management style.

7.2. External Factors (Uncontrollable Factors)

There are two main factor group were explained as follow: (Telsang, 2000)

- 1) Structural Adjustment: It includes both economic and social changes. Economic changes that influence significantly are:
 - a) Shift in employment from agriculture to manufacturing industry,
 - b) Important of technology,
 - c) Industrial competitiveness.

- 2) Natural Resource: Manpower, land and raw materials are vital to the productivity improvement. (Telsang, 2000). There is also another external factor, which is Government and infrastructure.

8. Applications Productivity in Construction Sector

Below review some of the previous studies about applications about construction productivity in construction sector:

Rojas and Aramvarekul (2003) conducted a study to investigate labour productivity drivers and productivity in the US construction sector. They made surveying for different projects (e.g. contractor, consultant, owner etc.). In this study, it was concluded that the worker management skills and manpower matters are the two core enhancement drivers.

Graham and Smith (2004) collected historical productivity data concerning the concrete supply and in situ distribution for the reason of deriving a forecasting model by using Case Based Reasoning (CBR) principles.

Chan and Kaka (2007) studied the factors of construction productivity in the United Kingdom by conducting a survey based on questionnaire aimed at both blue collar workers and white-collar managers. In addition, in-depth interviews were combined for this purpose.

Song and AbouRizk (2005) used past data to quantitatively forecast productivity by developing an empirical framework (Quantitative Engineering Project Scope Definition (QEPSD)). These data include complexity (e.g. fittings number) and steel drafting building elements' type (e.g. beams, columns) with the work hours that is resulted.

Dai et al. (2009) took a "bottom-up" approach by examining the craft workers' perceptions in the US regarding the relative impact of 83 productivity factors (e.g. behavioral issues, safety, project management, communication skills) through a series of focus groups sessions.

Choi et al. (2012) Finding, The poor working environment is an indirect hindrance for the productivity in construction context as well, because it prevents the industry from attracting productive and qualified human resources.

Ulubeyli, Kazaz and Er. (2014) studied factors effect on productivity among members of the construction workforce in Turkey. A survey of 82 construction firms in Turkey undertaken using a questionnaire of 54 questions directed to managers, engineers, architects, and other technical staff. Using the results of the survey, economic and socio-psychological factors that affect labour performance evaluated and discussed in detail. The results show that monetary factors remain pre-eminent in influencing productivity, but that socio psychological factors appear to be of increasing importance in this developing economy.

Hickson and Ellis (2014) this study highlights the factors affecting labour productivity of the Construction industry in Trinidad and Tobago. A questionnaire used to gather the relevant data from members of the Trinidad and Tobago

Contractors Association. It involved ranking 42 predefined factors divided into 4 categories: Management; Technological; Human/Labour and External. The Relative Importance of Indices (RII) was determined and the factors ranked. Top factors effect on construction labour productivity in Trinidad and Tobago are ten: the lack of labour supervision, unrealistic scheduling and expectation of labour performance, shortage of experienced labour, construction manager's lack of leadership skills, skillset of labour, delay in responding to requests for information, payment delay, communication problems between site management and labour, rain, late arrival, early quitting, and frequent unscheduled breaks. The research has direct benefits to key stakeholders in the construction industry.

Thomas and Sudhakumar (2014) designed a questionnaire survey of project managers, site engineers, supervisors and craftsmen, in the state of Kerala in India, to identify the factors influencing construction labour productivity. The top five factors identified as having a significant impact on productivity: (1) timely availability of materials at the worksite, (2) delayed material delivery by the supplier, (3) strikes called by political parties, (4) frequent revisions of drawings/design, resulting in additional work/rework and (5) timely availability of drawings at the worksite. The findings provide a better understanding of the factors influencing productivity in the Indian context and will aid construction practitioners in making effective plans for productivity improvement.

9. Applications (MLR, ANN and SVM) in Construction Productivity

Below review some of the previous studies that have used modern technologies in the development of production models in construction sector:

9.1. Applications for Multiple Linear Regression (MLR) in Construction Productivity

Dawood S. (2002) measured the standard productivity of reinforcement concrete building structure and, using Linear Regression (LR) technique to forecasting construction productivity. Moreover, data are collected using direct work study measurement method (work sampling and time study) of work study techniques, through carried out observing (221) samples a span of 10 months for forms and reinforcement of column and slab work including different private and socialist sector in construction of Iraq projects.

Thomas (2009) implemented statistical analysis methods to conduct cause-effect analysis on historical cumulative productivity measurements, so as to evaluate the significance of the learning curve effects on construction operations.

Al-Zwainy et al. (2013) carried out a study to develop a model for marble finishing works of floors in construction productivity forecasting by using Linear Regression technique. One model developed depended on 100 set of data collected in Iraq for different types of projects such as residential, commercial and educational projects. These are used in

developed the model and evaluated. Ten influencing factors are utilized for productivity forecasting by MLR model, and they include age, experience, number of the assist labour, and height of the floor, size of the marbles tiles, security conditions, and health status for the work team, weather conditions, site condition, and availability of construction materials. One model built for the prediction of the productivity of marble finishing works for floors. It 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%.

Al-Zwainy and Neran (2016) carried out a study to development a mathematical model for predicting the cost of the communication towers projects. Multifactor linear regression technique is developed and used for predication of the cost of communication towers projects in Iraq. Seven effectiveness factors are used for cost forecasting by MLR model, they involve Security Conditions, Tower Types, Experience of Contractor, Foundation Types, Tower High, Main Cable and Site Area. It was found that Multifactor linear regression has the flexibility to foretell the cost with an excellent degree of accuracy 90.1%, mean absolute percentage error 9.891% and coefficient of correlation (R) was 98.6%.

Tsehayae and Fayek (2016) carried out a study to development the system model parameters comprising factors and practices and work sampling proportions (WSPs) were identified from literature. Field data were collected from 11 projects over a span of 29 months. Activity models based on the relationship between construction labour productivity (CLP) and WSPs were created, and their validity was tested using regression analysis for eight activities in the concreting, electrical and shutdown categories. The proposed system model was developed for concreting activity using the key influencing parameters in conjunction with WSPs. The results of the regression analysis indicate that WSPs, like direct work, are not significantly correlated to CLP and fails to explain its variance. Evaluation of the system model approach for the concreting activity showed improved CLP prediction as compared to existing approaches.

9.2. Applications Artificial Neural Networks (ANN) in Construction Productivity

Moselhi et al (2005) introduced a new neural network model for quantifying the impact of change orders on construction productivity. The study is based on a comprehensive literature review and a field investigation of projects constructed in Canada and the USA. The field investigation was carried out over a 6-month period and encompassed 33 actual cases of work packages and contracts. Factors contributing to the adverse effects of change orders on labour productivity are identified and a model presented earlier is expanded to account primarily for the timing of change orders, among other factors. The developed models, as well as four models developed by others, have been incorporated in a prototype software system to estimate the loss of labour productivity due to change orders. A numerical

example is presented to demonstrate the use of the developed model, and illustrate its capabilities.

Ezeldin and Sharara (2006) developed CLP prediction models for forms assembly, steel fixing, and concrete pouring activities using feed-forward back-propagation neural networks, and indicated that the concrete pouring CLP model was the least accurate one as compared to others.

Song and AbouRizk (2008) investigated a way to estimate construction productivity by gathering past project data. In this study, productivity models using historical data were developed. They used steel drafting and fabrication productivities as a sample in their models by using techniques such as discrete-event simulation and artificial neural network. These productivity models were developed and validated using actual data gathered from a steel fabrication company.

Al-Zwainy et al. (2012) developed a model to estimation of the productivity of construction projects. 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%.

Mady M. (2013) developed an artificial neural networks model for giving an expert opinion to predict the production rate for slabs works. This model consists of input layer with 11 neurons, 2 hidden layer with 6, 4 neurons for first and second layer respectively by Neurosolution software version 5.07 was used to build up the models. The best model was obtained through the traditional trial and error process.

Heravi and Eslamdoost (2015) studied labour productivity of concreting work for gas, steam, and combined cycle power plant construction projects using neural networks.

Khaleel T. (2015) developed a model to prediction the cost of expressway project. The data used in this model was collected from Stat Commission for Roads and Bridges in Iraq. It was found that ANNs have the ability to predict the Total Cost for expressway project with a good degree of accuracy of the coefficient of correlation (R) was 90.0%, and average accuracy percentage 89%.

9.3. Applications Support Vector Machine (SVM) in Construction Sector

Yan and Shi (2010) was the student worker to investigate the use of SVM to predict elastic modulus of high and normal strength of concrete. The elastic modulus predicted by SVM was compared with the experimental data and those from other prediction models (ANN and RA). SVM verified good performance and proven to be better than other models (ANN and RA).

Mahfouz (2012) The researcher used the technique SVM development model productivity estimate steel structure and found that the use of Naive Bayes (NB) model is the most suited among the developed ones, for it has attained the highest performance measures which, Prediction Accuracy of 71%, average recall of 64%, average precision of 59, and average F-Measure of 61%.

Petruseva et al. (2013) this study presented a forecasting model for construction time, using support vector machine

(SVM) – recently one of the most accurate predictive models. First, a linear regression model has been applied to the data for 75 objects, using Bromilow’s “time cost” model. After that a support vector machine model to the same data was applied and significant improvement of the accuracy of the prediction was obtained.

Mirahadi and Zayed (2016) this research proposed a hybrid intelligent model to enhance the accuracy of productivity estimation for construction operations. The proposed framework has modeled the effect of the qualitative as well as quantitative variables on construction productivity and optimized the dynamic structure of the model according to the inherent characteristics of the data. For this purpose, a modified version of a Neural Network Driven Fuzzy Reasoning (NNDFR) structure was developed.

10. Conclusion

To find out the characteristics and advantages of the current study, the researcher summarized all the previous studies then reviewed the most important differences between past studies.

Table (1) illustrated the Summary of applications (MLR, ANN and SVM) in construction productivity through the data collection methods, used techniques, and results. This table can explain the main points of interest in the construction productivity study:

There is several methods data collection of construction productivity study from them: (Questionnaire, Data based, Interviews, historical data and Work-study). Use several techniques to analyses the data of which was used to:

- Identify factors affecting such as (relative importance, quantitative engineering project scope definition, Severity index, sensitivity analysis).
- To use them for the development of predictive models such as (Linear Regression, Fuzzy models, Support Vector Machine and Artificial Neural Network).

Most of the previous studies are interested in identifying the factors affecting the construction productivity so as to achieve:

- Control and Improve construction productivity and
- Find a mathematical model to estimation construction productivity.

Table 1. Past Studies about the Construction Productivity.

No	Researcher	DATE	Collection data methods	Techniques
1	Dawood S. RESULTS: Through the findings of carried out observing (221) samples of forms and reinforcement for column and slab work including different private and socialist sector in construction of Iraq projects.	2002	Work Sampling And Time Study	Linear Regression
2	Rojas and Aramvarekul RESULTS: These results suggest that respondents consider the improvement of labour productivity within their reach and control rather than determined by external conditions.	2003	Questionnaire	Relative Importance
3	Graham and Smith RESULTS: The model was found to provide more precise and consistent estimates than the planner, with 90% of the estimates being within a 10% relative error of the observed value. However, Case-Based Estimator (CBE) did not perform as accurately when estimating operations which were thought to occur only rarely (outliers).	2004	Data based	Decision Tree
4	Song and Abou Rizk RESULTS: Actual data was analysed and used to demonstrate the benefits of historical data prepared using quantitative engineering project scope definition (QEPSD) for project scope definition. It was found that the new method led to increased utilization of previously untapped values in historical data, improving the accuracy of project scope definition, and productivity modelling. The study concludes with a discussion of the potential benefits of adopting the QEPSD method, and its implications upon various project management functions.	2005	Historical Data	QEPSD
5	Moselhi et al. RESULTS: The developed model, as well as four models developed by others, has been incorporated in a prototype software system to estimate the loss of labour productivity due to change orders.	2005	Work study	Neural Network
6	Ezeldin and Sharara RESULTS: 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.	2006	Work study	Neural Networks And Sensitivity Analysis
7	Chan and Kaka RESULTS: The study found distinct differences between the two groups, with white - collar managers being more concerned with resource planning issues and the blue - collar workers placing more value on the utilisation of resources. Furthermore, the site observations demonstrated that integrating these differences through employee involvement could lead to productivity improvements.	2007	Interviews And Questionnaire	-
8	Song and AbouRizk RESULTS: The collected productivity information were accustomed develop labour productivity models victimization such techniques as artificial neural network and discrete-event simulation. These productivity models were developed and valid victimization actual information collected from a steel fabrication company.	2008	Historical Data	Neural Network And Discrete Event Simulation
9	Thomas RESULTS: It is shown using an actual project, how cumulative data gives a distorted view of performance. It is suggested that in some instances, a learning curve is a sign of a poorly managed project.	2009	Historical Data	Learning Curve
10	Yan and Shi RESULTS: SVM verified good presentation and proven to be enhanced than other mod-els (ANN and RA).	2010	Data Based	SVM,ANN & LR

No	Researcher	DATE	Collection data methods	Techniques
11	Mahfouz RESULTS: For it has attained the highest performance measures which, Prediction Accuracy of 71%, average recall of 64%, average precision of 59, and average F-Measure of 61%.	2012	Historical Data	SVM
12	Dai et al. RESULTS: The findings show that craft workers do have a good understanding of the factors affecting their daily productivity, and most of the adversarial factors affecting productivity can be addressed by site management teams. Factors involving tools and consumables, materials, engineering drawing management and construction equipment were identified as having the greatest impact on productivity from the craft workers' perspective. These findings will be beneficial for engaging craft workers in productivity improvement and improving the efficiency of construction jobsites.	2012	Interviews	-
13	Choi et al. RESULTS: The results of a non-linear regression analysis based on the comprehensive US Economic Census data show that the construction industry's sub-sectors with the highest productivity are the most profitable with regard to the gross margins that they are able to generate. This study and its model will help decision makers better assess macroeconomic performance and conduct trend analysis of the construction industry to serve as a basis for developing strategic roadmap for the future	2012	Data Based	Regression Analysis
14	Al-Zwainy RESULTS: 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%.	2012	Work Study	Neural Network
15	Al-Zwainy et al. RESULTS: 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%.	2012	Direct Observation Method	Neural Network
16	Mady, M. RESULTS: Development model to predict the production rate for slabs works. This model consists of input layer with 11 neurons, 2 hidden layer with 6, 4 neurons for first and second layer respectively by Neurosolution was used to build up the models. The best model was obtained through the traditional trial and error process.	2013	Work Study	Neural Network
17	Al-Zwainy et al., RESULTS: 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%.	2013	Work Study	Linear Regression
18	Petruseva et al., RESULTS: First, conventional linear regression model has been applied to the data using the well-known "time cost" model, and after that, the predictive model with SVM was build and applied to the same data. The results show that the predicting with SVM was significantly more accurate.	2013	Questionnaires And Interviews	SVM and LR
19	Ulubeyli, Kazaz and Er RESULTS: The results were evaluated by one sample t-test, and hence, today's situation of the construction industry in Turkey regarding labor productivity was displayed by a statistical analysis that compares man-day values in theory and in Practice.	2014	Questionnaire	Statistical Analysis
20	Hickson and Ellis RESULTS: The relative importance of indices (RII) was determined and the factors were ranked. The top ten factors affecting construction labour productivity in Trinidad and Tobago. Recommendations have been made in the study to address these factors.	2014	Questionnaire	Relative Importance
21	Thomas and Sudhakumar The findings provide a better understanding of the factors influencing productivity in the Indian context and will aid construction practitioners in making effective plans for productivity improvement.	2014	Questionnaire	Severity Index
22	Al-Zwainy F. M. RESULTS: The main objective of this research is to development a mathematical model for predicating the construction productivity of floor using artificial neural perceptron network ANP. One model was built for the prediction the total productivity of building project. Information on the relative importance of the factors affecting the above productivity parameters predictions were presented and practical equations for the predictions of the above construction productivity were developed.. It was found that ANPNs have the ability to predict the Total productivity for finishing works for building project with a good degree of accuracy of the coefficient of correlation (R) was 96.2%, and average accuracy percentage of 96.4%	2014	Form Measurement Of Work	Neural Network
23	Heravi and Eslamdoost RESULTS: The results proved a better prediction performance for Bayesian regularization than early stoping. To demonstrate the prediction performance of the presented models, the developed models are implemented at two real power plant construction projects. Moreover, in order to extract the influence rate of each factor on the predictive behavior of the neural network models and to identify the most influential factors a sensitivity analysis is conducted.	2015	Work Study	Neural Network
24	Khaleel T. RESULTS: It was found that ANNs have the ability to predict the Total Cost for expressway project with a good degree of accuracy of the coefficient of correlation (R) was 90.0%, and average accuracy percentage 89%.	2015	Work Study	Neural Network
25	Sherekar and Tatikonda RESULTS: The result indicated that the three important factors affecting on labor productivity of small construction projects in Pune are Renumeration, drug use, Ignore Safety Precautions. and in large construction projects top three factors are job satisfaction, level of training and work planning scheduling.	2016	Questionnaire	Analytic Hierarchy Process

No	Researcher	DATE	Collection data methods	Techniques
26	Al-Zwainy and Neran RESULTS: It was found that MLR has the flexibility to foretell the cost with an excellent degree of accuracy AA% was 90.1%, MAPE was 9.891% and R was 98.6%.	2016	Questionnaire	Linear Regression
27	Tsehayae and Fayek RESULTS: The results of the regression analysis indicate that WSPs, like direct work, are not significantly correlated to CLP and fail to explain its variance. Evaluation of the system model approach for the concreting activity showed improved CLP prediction as compared to existing approaches.	2016	Work Sampling	Linear Regression
28	Mirahadi and Zayed RESULTS: The developed model helps researchers and practitioners use historical data to forecast the productivity of construction operations with a level of accuracy greater than what could be offered by traditional techniques.	2016	Historical Data	Fuzzy Models and Ann
29	Saja H. Rasool and, Faiq M. S. Al-Zwainy RESULTS: One model was built for the prediction the labor productivity rates for brickwork item. The data used in this model was collected from construction project in Iraq. It was found that Multiple Linear Regression (MLR) have the ability to predict the construction productivity for brickworks with a good degree of accuracy of the coefficient of correlation (R) was 87.28%, and average accuracy percentage of 92.5%. In the second part of this research was development another mathematical model for the same variables using Logistic Regression Technique (LRT). Results of the study showed that the use of a binary logistic regression gave a logical response results are consistent with the studied case with a moderate degree of average accuracy percentage of 95.8%. the application of Logistic Regression Technique, as a modern technique, in Iraqi construction project is necessary to ensure successful management,	2016	Historical Data	Logistic and Multiple Regression Approaches

References

- [1] Abdul Kadir, M., Lee, W., Jaafar, M., Sapuan, S. and Ali, A. (2005). "Factors Affecting Construction Labour Productivity for Malaysian Residential Projects". *Structural Survey*. 2005. Vol. 23, no. 1, p. 42-54. DOI 10.1108/02630800510586907. Emerald.
- [2] Allison, L. Huang; Robert, E. Chapman; and David T. Butry, (2009), "Metrics and Tools for Measuring Construction Productivity, Technical and Empirical Considerations", *US Department of Commerce, National Institute of Standards and Technology*.
- [3] Al-Zwainy, F. M., (2012). "the use of Artificial Neural Networks for Productivity Estimation of Finishing Stone Works for Building Projects". *Journal of Engineering and Development*, Vol. 16, no. 2, pp. 42-60.
- [4] Al-Zwainy, F. M., Hatem A Rasheed, Huda F Ibraheem, (2012). "Development of the Construction Productivity Estimation Model Using Artificial Neural Network for Finishing Works For Floors With Marble". *ARNP Journal of Engineering and Applied Sciences*. Vol. 7, No. 6, pp. 714-722.
- [5] Al-Zwainy, F. M., Abdulmajeed, M. and Aljumaily, H. (2013). "Using Multivariable Linear Regression Technique for Modeling Productivity Construction in Iraq". *Open Journal of Civil Engineering*. Vol. 03, no. 03, pp. 127-135. DOI 10.4236/ojce.2013.33015. Scientific Research Publishing, Inc.
- [6] Al-Zwainy, F. M., (2014). "Development of the Mathematical Model for Predicating the Construction Productivity in IRAQ Using the Artificial Neural Perceptron Network". *Journal of Engineering and Development*, Vol.18, no. 2, pp. 1-21.
- [7] Al-Zwainy F. and Neran T. Hadhal (2016). "Building a Mathematical Model for Predicting the Cost of the Communication Towers Projects Using Multifactor Linear Regression Technique". *International Journal of Construction Engineering and Management*, Vol. 05, no. 1, pp 25-29.
- [8] Al-Zwainy F. and Saja H. Rasool (2016). "Estimating Productivity of Brickwork item using Logistic and Multiple Regression Approaches". *Scholars Journal of Engineering and Technology (SJET)*, Vol. 04, No. 5, pp 234-243.
- [9] Building Futures Council, BFC (2006) "Measuring productivity and Evaluating Innovation in the U.S. construction industry", *Building Futures. Council, Alexandria, Va.*
- [10] Chan, P. and Kaka, A. (2007) "Productivity Improvements: Understand the Workforce Perceptions of Productivity First" *Personnel Review*. Vol. 36, no. 4, p p. 564-584. DOI 10.1108/00483480710752803. Emerald.
- [11] Choi, K., Haque, M., Lee, H., Cho, Y. and Kwak, Y. (2012) "Macroeconomic Labour Productivity and Its Impact on Firm's Profitability", *Journal of the Operational Research Society*, Vol. 64, no. 8, pp. 1258-1268. DOI 10.1057/jors.2012.157. Springer Nature.
- [12] Dawood, S. (2002) "Standard Productivity of Labor in The Implementation Of Reinforced Concrete Structures of the Buildings and the Factors Influencing Them", *a thesis submitted to the Civil Engineering Department Project Management, University of Technology – Iraq, MSc.*
- [13] Dai, J., Goodrum, P. M. and Maloney, W. F. (2009) "Construction Craft Workers' Perceptions of the Factors Affecting their Productivity". *Journal of Construction Engineering and Management*. Vol. 135, no. 3, pp. 217-226. DOI 10.1061/(asce)0733-9364(2009)135:3(217). American Society of Civil Engineers (ASCE).
- [14] Dozzi, S. P., and AbouRizk, S. M. (1993) "Productivity in Construction", *Ottawa, ON: Institute for Research in Construction, National Research Council.*
- [15] Ellis, R. D., and Lee, S. (2006) "Measuring Project Level Productivity on Transportation Projects", *Journal of Construction Engineering and Management*. Vol. 132, no. 3, p. 314-320. DOI 10.1061/(asce)0733-9364(2006)132:3(314). American Society of Civil Engineers (ASCE).
- [16] Ezeldin, A. and Sharara, L. (2006) "Neural Networks for Estimating the Productivity of Concreting Activities", *Journal of Construction Engineering and Management*, 132(6), pp. 650-656.
- [17] Graham, D. and Smith, S. (2004) "Estimating the Productivity of Cyclic Construction Operations Using Case-Based Reasoning". *Advanced Engineering Informatics*. Vol. 18, no. 1, p. 17-28. DOI 10.1016/j.aei.2004.03.001. Elsevier BV.

- [18] Park, Hee-Sung, Thomas, Stephen R. and Tucker, Richard L., (2005), "Benchmarking of Construction Productivity". *Journal of Construction Engineering and Management*. 2005. Vol. 131, no. 7, p. 772-778. DOI 10.1061/(asce)07339364(2005)131:7(772). American Society of Civil Engineers (ASCE)
- [19] Heravi, G. and Eslamdoost, E. (2015) "Applying Artificial Neural Networks for Measuring and Predicting Construction-Labor Productivity", *Journal of Construction Engineering and Management*. 2015. Vol. 141, no. 10, pp. 04015032,1-11. DOI 10.1061/(asce)co.1943-7862.0001006. American Society of Civil Engineers (ASCE)
- [20] Hickson, B. and Ellis, L. (2014) "Factors affecting Construction Labour Productivity in Trinidad and Tobago" *The Journal of the Association of Professional engineers of Trinidad and Tobago* Vol. 42, no 1, pp 4-11.
- [21] HM Treasury. (2000). "Productivity in the UK: The Evidence and the Government's Approach" Published: November 2000. Available from: http://webarchive.nationalarchives.gov.uk/+/http://www.hmtreasury.gov.uk/ent_prodevi_index.htm
- [22] Humphreys, K. Kenneth, (1984), "Project and Cost Engineers' Handbook", book 2nd ed, Marcel Dekker, Inc., New York.
- [23] Humphreys, Kenneth King, 1991, "Jelen's Cost and Optimization Engineering". book 3rd ed, New York: McGraw-Hill.
- [24] Khaleel T., (2015) "Development of the Artificial Neural Network Model for Prediction of Iraqi Expressways Construction Cost", *International Journal of Civil Engineering and Technology*, Vol.6.no10, pp. 62-76.
- [25] Lema, N. M. (1995) "Construction of Labour Productivity Modeling", *University of Dar Elsalaam. Journal of Project Management*, Vol. 16, no. 2, pp. 107-113
- [26] Mady, M. (2013) "Prediction Model of Construction Labor Production Rates in Gaza Strip using Artificial Neural Networks", a thesis submitted to the Civil Engineering Department Project Management, The Islamic University – Gaza, MSc, pp. 9-11.
- [27] Mahfouz T. (2012). "A Productivity Decision Support System For Construction Projects Through Machine Learning (ML)" *Proceedings of the CIB W78 2012: 29th International Conference –Beirut, Lebanon, 17-19 October*.
- [28] Michael, J. M., and Sami, Q., (2000), "System Thinking and Construction Productivity", *Joint research between Civil engineering, University of Nottingham U. K. Department of Civil Engineering and Architecture of University Bahrain*.
- [29] Mirahadi F. and Zayed T. (2016). "Simulation-Based Construction Productivity Forecast Using Neural-Network-Driven Fuzzy Reasoning" *Automation in Construction*. Vol. 65, p. 102-115. DOI10.1016/j.autcon.2015.12.021. Elsevier BV.
- [30] Moselhi, Osama, Assem, Ihab and El-Rayes, Khaled, 2005, "Change Orders Impact on Labor Productivity". *Journal of Construction Engineering and Management*. 2005. Vol. 131, no. 3, p. 354-359. DOI 10.1061/(asce)0733-9364(2005)131:3(354). American Society of Civil Engineers (ASCE)
- [31] OECD. (2001), "Measurement of Aggregate and Industry-Level Productivity Growth", *In Measuring productivity, OECD manual*.
- [32] Oglesby, C. H., Parker, H. W. and Howell, G. A. (1989) "Productivity Improvement in Construction". *Book, New York: McGraw-Hill*.
- [33] Park, H., Thomas, S. R., and Tucker, R. L. (2005) "Benchmarking of Construction Productivity." *Journal of Construction Engineering and Management*. 2005. Vol. 131, no. 7, p. 772-778. DOI 10.1061/(asce)0733-9364(2005)131:7(772). American Society of Civil Engineers (ASCE).
- [34] Petrusseva, S., Zileska, V. and Zujo, V. (2013) "Predicting construction project Duration With Support Vector Machine". *International Journal of Research in Engineering and Technology*. Vol. 02, no. 11, p. 12-24. DOI 10.15623/ijret.2013.0211003. eSAT Publishing House.
- [35] Rojas, E. M. and Aramvareekul, P. (2003) "Labor Productivity Drivers and Opportunities in the Construction Industry". *Journal of Management in Engineering*. Vol. 19, no. 2, p. 78-82. DOI 10.1061/(asce)0742-597x(2003)19:2 (78). American Society of Civil Engineers (ASCE)
- [36] Smith, A. (1987), "Measuring on Site Production". Transaction of the American Association of Cost Engineers, 311t annual meeting, Atlanta, U.S.A.
- [37] Song, L. and AbouRizk, S. (2008) "Measuring and Modeling Labor Productivity Using Historical Data". *Journal of Construction Engineering and Management*. 2008. Vol. 134, no. 10, p. 786-794. DOI 10.1061/(asce)0733-9364(2008)134:10(786). American Society of Civil Engineers (ASCE).
- [38] Telsang M., (2000) "Industrial Engineering and Production Management", S. Chand & Company LTD. Ram Nager, New Delhi.
- [39] Thomas, A. and Sudhakumar, J. (2014) "Factors Influencing Construction Labour Productivity: An Indian Case Study". *Journal of Construction in Developing Countries*, 19 (1), pp. 53–68.
- [40] Thomas, H. R. (2009) "Construction learning Curves". *Practice Periodical on Structural Design and Construction*, 14 (1), 14-20.
- [41] Tsehayae, Abraham Assefa and Fayek, Aminah Robinson, 2016, "System Model for Analyzing Construction Labour Productivity". *Construction Innovation*. 2016. Vol. 16, no. 2, p. 203-228. DOI 10.1108/ci-07-2015-0040. Emerald.
- [42] Ulubeyli, S., Kazaz, A. and Er, B. (2014) "Planning Engineers' Estimates on Labor Productivity: Theory and Practice", *Procedia - Social and Behavioral Sciences*, 119, pp. 12-19.
- [43] Yan, K. and Shi, C. (2010) "Prediction of Elastic Modulus of Normal and High Strength Concrete By Support Vector Machine", *Construction and Building Materials, Science Direct, Elsevier*, 24(8), pp. 1479-1485.
- [44] Zakeri, M., Olomolaige, P. O., Holt, G. D., and Harris, F. C. (1996), "A Survey of Construction on Iranian Construction Operative's Productivity" *Construction Management and Economic*, Vol. 14, pp. 417-26.

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