MODELLING CONSTRUCTION LABOUR PRODUCTIVITY FROM LABOUR'S CHARACTERISTICS

MOHAMMED HAMZA MOMADE

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy in (Civil Engineering)

School of Civil Engineering
Faculty of Engineering
Universiti Teknologi Malaysia

JANUARY 2020

DEDICATION

This thesis is dedicated to my father, mother and sister who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to all Telfordians and Toastmasters, who taught me that even the largest task can be accomplished if it is done one step at a time and with passion. Finally, this is dedicated to all those who believe that anything is possible in life with hard work, dedication and faith in the Almighty.

ACKNOWLEDGEMENT

In preparation of this thesis, I was in contact with many people, researchers, academicians, and practitioners. They have contributed towards my understanding and thoughts. In particular, I wish to express my sincere appreciation to my research supervisor, AP Dr Shamsuddin Shahid, for encouragement, guidance, critics and friendship. I am also very thankful to my co-supervisor Professor Ts Dr Rosli Mohd Bin Hainin for his guidance, advice and motivation. Without their continued support and interest, this thesis would not have been the same as presented here. My fellow postgraduate student should also be recognised for their support. My sincere appreciation also extends to all my colleagues and others who have provided assistance at various occasions. Their views and tips are useful indeed. Unfortunately, it is not possible to list all of them in this limited space. I am grateful to all my family members.

ABSTRACT

Labour is a fundamental input to any construction project to achieve the highest level of productivity. Productivity remains as one of the most important ways to measure the overall performance of construction project. Construction productivity is directly related to labour and thus, it is mainly dependent on human effort and performance. Improvement of Construction Labour Productivity (CLP) can directly help to improve the performance of construction companies, become more competitive, besides contributes to national economy. The aim of the research is to develop and introduce a new framework for systematic assessment of the factors influencing construction labour productivity and use the collected data to create models by applying state-of-art techniques and comparing the accuracies in predicting the labour productivity in construction. The scope of the study was limited to Malaysia only. A thorough literature survey was conducted to list the factors related to CLP with different studies throughout the globe. The factors were filtered using two-stage procedures - first the factors were shortlisted based on the relevance of labour and then a survey was conducted among project managers to rank the factors based on the importance of Malaysian context using a 3-point Likert scale on each factor. The ranks of the factors were analysed using statistical tools. The top class factors were identified using Jenks Optimization Techniques. The classified CLP factors were used to design a field survey to collect data from construction workers. Five state-of-arts of models were developed to predict the CLP from the factors including three data mining models, one conventional model and one multi-criteria model. Salary of labour was considered as a proxy to the productivity to develop the models. The performance of the models were assessed using five categorical indices. The results of literature review revealed that a total of 112 factors related to productivity in construction industry have been identified throughout the globe. Ten factors were identified through the analysis of preliminary survey data using different methods. Among them, seven factors were found common for all the methods which were identified as the important CLP factors for Malaysian construction industry. The factors are (1) Lack of Work Experience (2) Job Category (3) Education/Training (4) Nationality (5) Worker Skills (6) Age and (7) Marital Status. The relative performance of different models was compared to identify the best model in term of the rate of accuracy in prediction of labour productivity. Data mining models were found to perform better compared to other models. The Percentage of Correct (PC) for data mining models were found in the range of 0.735-0.835, Probability of Detection (POD) between 0.741 and 0.911, Heidke Skill Score (HSS) between 0.792 and 0.802 and Peirce Skill Score (PSS) in the range of 0.792 to 0.799, while the False Alarm Ratio (FAR) were found in the range of 0.102 to 0.279. The values were found better than that obtained using Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (PC=0.739, POD=0.740, HSS=0.794, PSS=0.725 and FAR=0.256) and much better than that obtained using Linear Regression (LR) (PC=0.577, POD=0.618, HSS=0.533, PSS=0.498 and FAR=0.533). Among the data mining models, Support Vector Machine (SVM) was found to provide the best results in term of all statistical metrics used. The POD for SVM was found above 90% in predicting different categories of productivity. The method discussed in this research can serve as a newly developed framework to predict the level of construction labour productivity for project.

ABSTRAK

Tenaga pekerja merupakan input asas kepada projek pembinaan bagi mencapai produktiviti. Produktiviti merupakan cara paling penting untuk mengukur prestasi projek pembinaan. Produktiviti pembinaan berkait dengan sumber tenaga kerja secara langsung bagi menilai prestasi manusia. Penambahbaikan Produktiviti Pekerja Pembinaan (CLP) dapat membantu untuk menambah baik prestasi kerja syarikat pembinaan, menjadikan syarikat pembinaan kita lebih berdaya saing dan mampu menyumbang kepada pembangunan ekonomi negara. Tujuan penyelidikan ini adalah membangunkan dan memperkenalkan rangka kerja baharu dengan menilai faktor yang mempengaruhi produktiviti buruh pembinaan secara sistematik dan membuat model kajian dengan menggunakan teknik moden dan membandingkan ketepatan dan keberkesanan teknik dalam meramalkan produktiviti buruh pembinaan berdasarkan data yang dikumpul. Skop kajian ini hanya meliputi di negara Malaysia sahaja. Kajian literatur yang teliti telah dilakukan dengan menyenaraikan faktor yang berkaitan dengan CLP yang dikenal pasti daripada kajian yang berbeza di seluruh dunia. Faktor tersebut telah ditapis menggunakan prosedur secara dua peringkat: faktor tersebut disenarai pendek berdasarkan kaitannya dengan buruh terlebih dahulu. Kemudian, satu kaji selidik telah dijalankan antara orang berkalangan pengurus projek untuk menentukan faktor berdasarkan kepentingan mereka dalam konteks Malaysia menggunakan skala 3-point Likert bagi setiap faktor. Kedudukan factor tersebut dianalisis dengan menggunakan alat-alat statistik. Faktor berkepenthgan dikenal pasti dengan kaedah Teknik Jenks Optimization. Faktor CLP yang diklasifikasikan telah digunakan beg merancang tinjauan lapangan untuk mengumpulkan data daripada pekerja pembinaan. Lima model telah dibangunkan untuk meramalkan CLP daripada faktor yang diperoleh dengan penggunaan tiga model perlombongan data, satu model konvensional, dan satu model multi-kriteria. Gaji buruh dianggap sebagai proksi untuk produktiviti semasa pembamgvnan model. Prestasi model dinilai dengan menggunakan lima kategori indeks. Hasil daripada kajian literatur, sejumlah 112 faktor yang berkaitan dengan produktiviti dalam industri pembinaan telah dikenal pasti di seluruh dunia. Sepuluh faktor telah dikenal pasti melalui analisis daripada pelbagai kaedah bancian data pada peringkat awal. Tujuh daripada faktor tersebut telah dikenal pasti sebagai faktor CLP yang penting dalam industri pembinaan Malaysia daripada semua kaedah. Antara faktornya ialah (1) Kekurangan Pengalaman Pekerja (2) Kategori Pekerjaan (3) Pendidikan/Latihan (4) Kewarganegaraan (5) Kemahiran Pekerja (6) Umur dan (7) Status Perkahwinan. Prestasi relatif yang dikaji menggunakan model yang lain juga dibandingkan untuk mengenal pasti model yang paling berkesan untuk meramalkan produktiviti pekerja secara tepat. Model perlombongan data telah dikenal pasti sebagai model yang terbaik untuk mengendalikan analisis ini. PC untuk model perlombongan data didapati dalam lingkungan 0.735-0.835, POD di antara 0.741 dan 0.911, HSS di antara 0.792 dan 0.802, dan PSS dalam lingkungan 0.792 hingga 0.799, manakala FAR didapati dalam lingkungan 0.102 hingga 0.279. Hasil daripada kajian melalui kaedah ini didapati adalah lebih baik daripada hasil kajian yang diperoleh daripada penggunaan kardah TOPSIS (PC=0.739, POD=0.740, HSS=0.794, PSS=0.725 and FAR=0.256) dan jauh lebih baik daripada penggunaan kaedah LR (PC=0.577, POD=0.618, HSS=0.533, PSS=0.498 and FAR=0.533). Antara pelbagai model perlombongan data yang digunakan, kaedah SVM didapati memberi hasil kajian yang paling baik dari segi metrik statistik yang diguna pakai. POD bagi kaedah SVM didapati mampu mencapai tahap prestasi lebih daripada 90% dalam ramalan kategori produktiviti yang berlainan. Dengan itu, Metod yang dibahaskan dalam kajian ini dapat menjadi sebagai suatu rangka kerja yang baharu untuk meramalkan tahap produktiviti pekerja pembinaan bagi sesuatu projek pembinaan.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

UTM	-	Universiti Teknologi Malaysia
AHP	-	Analytic Hierarchy Process
TOPSIS	-	The Technique for Order of Preference by Similarity to Ideal Solution
CLP	-	Construction Labour Productivity
SVM	-	Support Vector Machine
RF	-	Random Forest
US	-	United States
GDP	-	Gross Domestic Product
LOP	-	Loss of Productivity
UK	-	United Kingdom
UAE	-	United Arab Emirates
ID	-	Identification
PPE	-	Personal Protection Number
QWL	-	Quality of Working Life
DBOT	-	Design/Build/Operate/Transfer
EPC	-	Turnkey/Engineering, Procurement And Construction
ANN	-	Artificial Neural Network
FL	-	Fuzzy Logic
CART	-	Communication Access Real-Time Translation
SDBC	-	Sum of Squared Deviations Between
SDAM	-	Sum of Squared Deviations from the Array Mean
SDCM	-	Sum of the Squared Deviations from the Class Means
GVF	-	Goodness of Variance Fit
MLR	-	Multiple Linear Regression
SPSS	-	Statistical Packages for Social Sciences
LASSO	-	Least Absolute Shrinkage and Selection Operator.
BA	-	Boruta Algorithm
MZSA	-	Maximum Z Score among Shadow Attributes
GLM	-	Generalized Linear Model

GAM	-	Generalized Additive Models
RSS	-	Residual Sum of Squares
LM	-	Linear Method
ASCE	-	American Society of Civil Engineers
SLFN	-	Single-Hidden Layer Feed forward Neural Network
SRM	-	Structural Risk Minimization
OOB	-	Out of Bag
AHP	-	Analytic Hierarchy Process
MCDM	-	Multiple-Criteria Decision-Making
PIS	-	Positive Ideal Solution
NIS	-	Negative Ideal Solution
FN	-	Number of Instances That Predicted Incorrectly As Gullies
TN	-	Number of Instances That Predicted Correctly as Non-Gullies
FP	-	Number of Instances That Predicted Incorrectly as Non-Gullies
TP	-	Number of Cases That Predicted Correctly as Gullies
PC	-	Percentage of Correct
POD	-	Probability of Detection
HSS	-	Heidke Skill Score
FAR	-	False Alarm Ratio
PSS	-	Peirce Skill Score
CIDB	-	Construction Industry Development Board
RM	-	Ringgit Malaysia

LIST OF SYMBOLS

%	-	Percentage
=	-	Equal Sign
/	-	Slash
K	-	Kernel function
α_i	-	Parameters
b	-	Parameters
N	-	Number of Training Data
x_i	-	Vectors
x	-	Independent Vector
n_1	-	Number of Respondents
X_i	-	Correlation Coefficient
Y	-	Correlation Coefficient
X_j	-	Predictor Set
n	-	Number of Predictors
α	-	Model Parameters
Σ	-	Sigma
β_i	-	Strength of the Influence of X
CLPt	-	Construction labour productivity for the project, t

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Introduction

The productivity of a major industry like construction is of significant importance for the economic growth of a nation (Naoum, 2016). The construction sector not only makes a remarkable contribution to the performance of the overall economy, but it also serves as a significant source of employment (Giang and Pheng, 2011). Labour is a fundamental input to any construction project to achieve the highest level of output in terms of the level of productivity (Hwang and Soh, 2013, Gerek et al., 2015). Labour is part of, but distinct from, other resources, because it has specific characteristics (Kaming et al., 1998). It constitutes the largest portion of the project cost. Studies show that it shares about 20-50% of total project cost (Buchan et al., 1993; Zakeri et al., 1997; Kaming et al., 1998), and therefore the project costs can be reduced significantly by improving labour productivity (Kazaz and Ulubeyli, 2004; Kim et al., 2015). The importance of construction labour productivity (CLP) in success for construction project has been reported in numerous studies (Neelima, 2018; Sweis et al. 2009; Fayek and Tsehayae, 2012; Ma et al., 2016). CLP has been reported as one of the key components and an effective indicator of efficiency in construction industry. It has a direct impact on the competitiveness of small and medium enterprises. Labour will continue to be a key factor for the success of construction projects in future (Tsehayae and Robinson Fayek, 2014). Therefore, improvement of CLP would be a major issue of concern in future as it is now (Attar et al., 2012).

There are many challenges facing the construction industry, but one of the most significant is low levels of productivity (Jarkas and Bitar 2011). Construction industries in many countries across the world are greatly concerned about low level of productivity (Lim and Alum 1995; Egan 1998; Thomas and Sudhakumar 2013; Ayele and Fayek 2019). There is nothing as dangerous to an economy as a decrease in productivity because it creates inflationary pressure, social conflict and mutual suspicion (Drucker 2012; Dixit et al. 2019; Shoar and Banaitis 2019). By acknowledging the factors that cause low levels of construction labour productivity, project managers can address the problems at an early stage, thus minimise the time and cost overruns (Kaming et al. 1997; Kaming et al. 1998; Abdul Kadir et al. 2005; Palikhe et al. 2019; Seddeeq et al. 2019). CLP significantly influences the profitability of construction companies; however, CLP exhibits the highest variability among project resources and thus is a major source of project risk (Tsehayae 2015). Labour in projects is also the most difficult element to define, manage and quantify on their impact. In this sense, it still remains important to determine the factors affecting labour-productivity to manage labour-forces effectively (Kazaz and Acıkara 2015).

CLP has been identified as one of the major factors related to project delay and loss of finance. Hence, slight advancement in the level of CLP on construction projects will enhance the contractor’s profit and serve the national economy (Abdel-Razek and Abdel-Hamid, 2007). The evaluation of CLP rates and identification of factors affecting CLP are critical in project control and improvement of productivity in construction. CLP is the dominating aspect in the construction industry as it encourages cost savings and effective utilization of resources (Alaghbari et al., 2019). It is a key element in determining the success and failure of any construction project (Golnaraghi et al., 2019). This is the main reason why CLP related research has benefited from a lot of attention in the industry/academia in past and recent years (Abraham, 2005; Moselhi et al., 2005; Muqeem et al., 2012; Gundecha, 2013; Gupta and Kansal, 2014; Gerek et al., 2015; Tsehayae and Fayek, 2016; Parthasarathy et al., 2018; Hamza et al 2019).

Understanding critical factors that affect CLP can help to develop strategies to reduce inefficiencies and to more effectively manage construction labour forces. This will not only improve the project performance of construction companies, but also make them more competitive and consequently increase the chances of survival within this highly competitive sector (Wilcox et al. 2000; Ailabouni et al. 2007; Robles et al. 2014; Langmade 2017). The factors related to CLP can be used for the development of CLP models for estimation and prediction of CLP from different factors (Kim et al., 2015; Ma et al., 2016; Tsehayae and Fayek, 2018). The CLP prediction models can be used in construction planning and scheduling and eventually in improvement of CLP. Besides, the models are often used as an effective tool in the estimation and monitoring of manpower and equipment resources in construction (Parthasarathy et al., 2018).

Hypothetically, the equation of productivity is the output of production per unit of input. At the industrial level, the equation of productivity remains the same as the ratio between total product output and total input resource from an economic perspective (Hanna et al., 2005, Ayele and Fayek, 2019). The composition of personnel in construction projects and its connection to various networks make CLP very difficult to measure and understand the concept of productivity and find the correct correlation (Bernstein, 2003). The construction projects even of identical type and nature carry an uncommon site, design methods, which makes the assessment of CLP very difficult to measure. Productivity models are even more problematic and laborious to create, especially due to its dependency on various environmental, physical, economic, social and behavioural factors. In addition, to date, there has been no line drawn on the correct interpretation and meaning of work activities nor a standard productivity measurement system (Park et al., 2005). Hence, identification of productivity factors and modelling of productivity in construction is a major challenge in the construction industry. A number of studies have been conducted in recent years where different methodologies have been used for assessment of different aspects of construction productions and influential factors responsible for productivity in different socio-economic contexts have been identified (Wilcox et al. 2000; Ailabouni et al. 2007; Robles et al. 2014; Langmade 2017; Afolabi et al. 2018; Ohueri et al. 2018; Momade 2019; Alaghbari et al. 2019; Palikhe et al. 2019). The CLP models can be used for forecasting activity durations and thus, project scheduling. It can help in efficient planning and management of construction project in order to improve overall productivity of project.

1.2 Problem Statement

Application of computer in construction has increased rapidly with the increase of computational capacity and ability to solve construction-related challenges. Considering productivity as the major challenge in construction, sufficient advancements have also been achieved in computational modelling of construction productivity. Different methods in including fuzzy logic, neural network, etc. have been used for modelling labour productivity from various productivity-related factors. However, choice of appropriate modelling tools and selection of labour-related factors remain major challenges (Portas and AbouRizk, 1997; Tsehayae and Fayek, 2016; Golnaraghi et al., 2019; Shoar and Banaitis, 2019). There are many influential factors that determine labour productivity in the construction sector. The factors may change depending on market conditions, social context and geographical location of the construction project. Therefore, labour productivity factors should be linked to the surrounding environment. Screening out the factors based on their relevance and significance according to location and socio-economic context is often disputable. A systematic framework for the selection of appropriate factors relevant to labour productivity is therefore sought.

A large number of factors related to labour are responsible for productivity. A parsimonious system should be able to predict productivity from a minimum number of factors. Therefore, identification of most influencing factors from the whole set of labour factors responsible for productivity is a challenging task. The approach generally used are highly subjective and biased to human judgement. Therefore, finding factors that most suitable for the development of a good production model remains a challenge in construction productivity modelling. There is a need to explore a new method for the identification of the optimum number of factors which can avoid subjectivity in the selection of factors.

The major goal in any construction project is to improve productivity. A CLP model can help to stimulate the productivity from labour characteristics to optimize the work schedule and maximize the benefit. Researchers to date have used different forms of linear regression-based models which are not able to capture the non-linear relationship between labour related factors and productivity. Non-linear models can be used for better simulation of construction labour productivity from labour related factors. However, the relationship between the labour factors with productivity is often highly complex which emphasizes the need for exploration of a new method for the improvement of the performance of CLP models.

There are many CLP models available which can be used for prediction of labour productivity. The performance of the CLP model depends on the distribution and variability of labour-related factors used for the development of CLP model. Thus, the performance of the CLP model varies widely for different sets of data. This indicates the necessity of assessment of the comparative performance of different CLP models to identify the best model for the reliable prediction of productivity. Besides, the performance evaluation of CLP models should be based on different characteristics such as reliability and precision in prediction for a perfect measure of model performance for predicting productivity. This emphasizes the need for comparative evaluation of different state-of-art CLP model using robust performance evaluation metrics for the selection of the best model to be proposed for use in the construction industry.

1.3 Aim & Research Objectives

The aim of the research is to introduce a new framework for systematic assessment of the factors influencing construction labour productivity and use the collected data to create models by applying state-of-art techniques and compare their accuracies in predicting labour productivity in construction. The research objectives are stated as follows:

(a) To develop a systematic framework for the selection of construction labour productivity factors by linking market conditions, social context and geographical location

(b) To apply robust statistical approaches for prioritization of construction labour productivity factors according to their importance

(c) To construct data-driven models for prediction of labour productivity in construction projects

(d) To review the performance of productivity models and identify the best approach for labour productivity modelling to be used in the construction industry for management

1.4 Scope of the Study

Initial identification of the factors which influence labour productivity was conducted through a critical analysis of literature. Data was collected through an opinion survey using a Likert Scale. The survey questionnaire was designed to calculate the effectiveness of the factors which have been identified on the topic of labour productivity for the construction industry. The questionnaire was designed in both spoken languages: English and Bahasa Malay. The survey was conducted among people working in construction project management and construction workers. The opinion data of project managers was collected to understand their perception of labour productivity. On the other hand, data was also collected through interview of construction site workers including both foreign and local to capture their views. Foreign labour from Indonesia & Bangladesh (constitute the majority of foreign construction workers in Malaysian construction projects) and local Malaysian workers involved in residential and factory projects were interviewed.

There are many methods used for modelling of CLP using influencing labour related factors. Most of the researchers in the past have used one or two models at most for CLP prediction. In the present study, five state-of-arts of models were developed to predict the CLP from the factors including three data mining models namely, Artificial Neural Network (ANN), Random Forest (RF), Support Vector Machine (SVM), one conventional model known as generalized Linear Regression (LR), and one multi-criteria model called the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS).

1.5 Significance of the Study

Labour is the major driving force in any construction project. It also shares the major cost of a construction project. The CLP prediction model developed in this study can be used for the scheduling and management of a construction project to improve the overall productivity of the construction project.

Understanding critical factors that affect labour productivity can help to develop strategies to reduce inefficiencies and to manage construction labour force more effectively. The outcome can help practitioners to develop a wider and deeper perspective of the factors influencing the productivity of operatives and to provide guidance to construction project managers for the efficient utilization of the labour force.

By understanding the influential CLP factors in the region, the factors identified can be used for the selection of labour to improve the productivity of the projects in Malaysia and in other geographical regions.

The methodology proposed in this study can serve as a framework for future studies in other geographical regions for more accurate identification of CLP factors. The methodology adopted can also serve to compare the results of the past studies in other countries by researchers.

Machine learning tools can make a great contribution in solving complex problems in civil engineering. In the last decade, the application of artificial intelligence and predictive models serve as a practical, feasible and quick tool in solving engineering problems. By applying machine learning tools in modelling and prediction, it can assist to reduce the time, manpower, and materials, resulting in a lower cost for the work done.

This study can be used, not only by academics, who are interested in the effect of the subject matter on the application of machine learning tools in construction but also by both local and international industry practitioners, who may be further keen to further understand and explore the applications of AI tools in the field. The study can help researchers and practitioners develop machine learning tools which can improve the performance and accuracy in prediction and modelling in different aspects.

REFERENCES

ABDEL-RAZEK, R. H. & ABDEL-HAMID, M. 2007. Labor productivity: Benchmarking and variability in Egyptian projects. *International Journal of Project Management,* 25, 189-197.

ABDUL-AZIZ, A.-R. 2001. Foreign workers and labour segmentation in Malaysia's construction industry. *Construction Management & Economics,* 19, 789-798.

ABDUL-AZIZ, A.-R. & KASSIM, P. J. 2011. Objectives, success and failure factors of housing public–private partnerships in Malaysia. *Habitat International,* 35, 150-157.

ABDUL KADIR, M., LEE, W., JAAFAR, M., SAPUAN, S. & ALI, A. 2005. Factors affecting construction labour productivity for Malaysian residential projects. *Structural survey,* 23, 42-54.

ABRAHAM, A. 2005. Adaptation of fuzzy inference system using neural learning. *Fuzzy systems engineering.* Springer.

ADAMU, K., DZASU, W., HARUNA, A. & BALLA, S. 2011. Labor productivity constraints in the Nigerian construction industry. *Continental Journal of Environmental Design and Management,* 1, 9-13.

AFOLABI, A., OJELABI, R. A., OMUH, I., TUNJI-OLAYENI, P. & ADEYEMI, M. 2018. Critical success factors influencing productivity of construction artisans in the building industry. *International Journal of Mechanical Engineering and Technology (IJMET),* 9, 858-867.

AILABOUNI, N., GIDADO, K. & PAINTING, N. Factors affecting employee productivity in the UAE construction industry. Proceeding Conference for Postgraduate Researchers of the Built and Natural Environment (PRoBE), 2007. 33-46.

AL-SHARIF, F. & KAKA, A. PFI/PPP topic coverage in construction journals. Proc., 20th Annual ARCOM Conf, 2004. 711-719.

AL-ZWAINY, F. M. S., ABDULMAJEED, M. H. & ALJUMAILY, H. S. M. 2013. Using multivariable linear regression technique for modeling productivity construction in Iraq. *Open Journal of Civil Engineering,* 3, 127-135.

ALAGHBARI, W., AL-SAKKAF, A. A. & SULTAN, B. 2019. Factors affecting construction labour productivity in Yemen. *International Journal of Construction Management,* 19, 79-91.

ALINAITWE, H. M., MWAKALI, J. A. & HANSSON, B. 2007. Factors affecting the productivity of building craftsmen-studies of Uganda. *Journal of Civil Engineering and Management,* 13, 169-176.

ALSUGAIR, A. M. & AL-QUDRAH, A. A. 1998. Artificial neural network approach for pavement maintenance. *Journal of computing in civil engineering,* 12, 249-255.

ALUMBUGU, P. O., SAIDU, I., GULMA, A. S. A., OLA-AWO, W. A., ABDULAZEEZ, A. & SULEIMAN, B. 2014. An analysis of relationship between working height and productivity of masonry workers on site. *Civil and Environmental Research,* 6, 72-80.

AMEH, O. J. & OSEGBO, E. E. 2011. Study of relationship between time overrun and productivity on construction sites. *International Journal of Construction Supply Chain Management,* 1, 56-67.

AMLASHI, A. T., ABDOLLAHI, S. M., GOODARZI, S. & GHANIZADEH, A. R. 2019. Soft computing based formulations for slump, compressive strength, and elastic modulus of bentonite plastic concrete. *Journal of Cleaner Production,* 230**,** 1197-1216.

ANTUNES, R. & GONZALEZ, V. 2015. A production model for construction: A theoretical framework. *Buildings,* 5**,** 209-228.

ARDITI, D. & TOKDEMIR, O. B. 1999. Comparison of case-based reasoning and artificial neural networks. *Journal of computing in civil engineering,* 13**,** 162-169.

ASGHARPOUR, M. 1999. MADM decision-making. *Tehran: Tehran University*.

ATTAR, A., GUPTA, A. & DESAI, D. 2012. A study of various factors affecting labour productivity and methods to improve it. *IOSR Journal of Mechanical and Civil Engineering,* 1**,** 11-14.

AYELE, S. & FAYEK, A. R. 2019. A framework for total productivity measurement of industrial construction projects. *Canadian Journal of Civil Engineering,* 46**,** 195-206.

AZMAN, M. A., HON, C. K., SKITMORE, M., LEE, B. L. & XIA, B. 2019. A Meta-frontier method of decomposing long-term construction productivity components and technological gaps at the firm level: evidence from Malaysia. *Construction Management and Economics,* 37**,** 72-88.

BABBIE, E. & RUBIN, A. 1989. Research methods for social work. *Belmonr, CA: Wadsworth*.

BARG, J. E., RUPARATHNA, R., MENDIS, D. & HEWAGE, K. N. 2014. Motivating workers in construction. *Journal of Construction Engineering,* 2014.

BASKORO, L. S., HARA, Y. & OTSUJI, Y. 2019. Labor Productivity and Foreign Direct Investment in the Indonesian Manufacturing Sector. *Signifikan: Jurnal Ilmu Ekonomi,* 8.

BATHRELLOS, G. D., SKILODIMOU, H. D., CHOUSIANITIS, K., YOUSSEF, A. M. & PRADHAN, B. 2017. Suitability estimation for urban development using multi-hazard assessment map. *Science of the Total Environment,* 575**,** 119-134.

BEKR, G. A. 2017. Study of Significant Factors Affecting Labor Productivity at Construction Sites in Jordan: Site Survey. *GSTF Journal of Engineering Technology (JET),* 4.

BERNOLD, L. E. & ABOURIZK, S. M. 2010. *Managing performance in construction*, John Wiley & Sons.

BERNSTEIN, H. M. 2003. Measuring Productivity. *Civil Engineering*.

BERNSTEIN, J. 2018. Productivity and wages: What's the connection?

BIANCHINI, F. & HEWAGE, K. 2012. How "green" are the green roofs? Lifecycle analysis of green roof materials. *Building and environment,* 48**,** 57-65.

BINGLEY, P. & ERIKSSON, T. 2000. *Pay spread and skewness, employee effort and firm productivity*, Department of Economics, Faculty of Business Administration, Aarhus School ….

BORCHERDING, J. D. 1977. What Is the Construction Foreman Really Like—. *Journal of the Construction Division,* 103**,** 71-85.

BOUSSABAINE, A. & DUFF, A. R. 1996. An expert-simulation system for construction productivity forecasting: Conformation method used to illustrate the uncertainty associated with expert's knowledge. *Building Research and Information,* 24**,** 279-286.

BREIMAN, L. 2001. Random forests. *Machine learning,* 45**,** 5-32.

BREIMAN, L., FRIEDMAN, J., STONE, C. J. & OLSHEN, R. A. 1984. *Classification and regression trees*, CRC press.
BRUNIES, R. & EMIR, Z. 2001. Calculating loss of productivity due to overtime using published charts—Fact or fiction. *The Revay Report,* 20**,** 1-7.
CARD, D. 1999. The causal effect of education on earnings. *Handbook of labor economics*. Elsevier.
CHAN, P. W. & KAKA, A. 2007. Productivity improvements: understand the workforce perceptions of productivity first. *Personnel Review,* 36**,** 564-584.
CHIA, F. C., SKITMORE, M., RUNESON, G. & BRIDGE, A. 2012. *An analysis of construction productivity in Malaysia*.
CHILD, D. 1990. *The essentials of factor analysis*, Cassell Educational.
CHOUDHRY, R. M. 2017. Achieving safety and productivity in construction projects. *Journal of Civil Engineering and Management,* 23**,** 311-318.
COLLIS, J. & HUSSEY, R. 2013. *Business research: A practical guide for undergraduate and postgraduate students*, Macmillan International Higher Education.
COOPER, D. F. 2005. *Project risk management guidelines: managing risk in large projects and complex procurements*, John Wiley & Sons, Inc.
CORTES, C. & VAPNIK, V. 1995. Support-vector networks. *Machine learning,* 20**,** 273-297.
COUNCIL, N. R. 2009. *Advancing the competitiveness and efficiency of the US construction industry*, National Academies Press.
CRESWELL, J. W. & CRESWELL, J. D. 2017. *Research design: Qualitative, quantitative, and mixed methods approaches*, Sage publications.
DAI, J. & GOODRUM, P. M. 2010. Differences in perspectives regarding labor productivity between Spanish-and English-speaking craft workers. *Journal of Construction Engineering and Management,* 137**,** 689-697.
DAI, J., GOODRUM, P. M. & MALONEY, W. F. 2009. Construction craft workers' perceptions of the factors affecting their productivity. *Journal of Construction Engineering and Management,* 135**,** 217-226.
DAMAŠEVIČIUS, R. 2010. Structural analysis of regulatory DNA sequences using grammar inference and support vector machine. *Neurocomputing,* 73**,** 633-638.
DAVIES, P. H. 2001. Spies as informants: triangulation and the interpretation of elite interview data in the study of the intelligence and security services. *Politics,* 21**,** 73-80.
DEVADASON, E. S. & MENG, C. W. 2014. Policies and laws regulating migrant workers in Malaysia: A critical appraisal. *Journal of Contemporary Asia,* 44**,** 19-35.
DIXIT, S., MANDAL, S. N., THANIKAL, J. V. & SAURABH, K. 2019. Evolution of studies in construction productivity: A systematic literature review (2006–2017). *Ain Shams Engineering Journal*.
DIXIT, S., PANDEY, A. K., MANDAL, S. N. & BANSAL, S. 2017. A study of enabling factors affecting construction productivity: Indian scnerio. *International Journal of Civil Engineering & Technology,* 8**,** 741-758.
DOLAGE, D. & CHAN, P. 2013. Productivity in Construction-A Critical Review of Research. *Engineer: Journal of the Institution of Engineers, Sri Lanka,* 46.
DOLOI, H., SAWHNEY, A., IYER, K. & RENTALA, S. 2012. Analysing factors affecting delays in Indian construction projects. *International journal of project management,* 30**,** 479-489.
DRUCKER, P. 2012. *Managing in turbulent times*, Routledge.

DURDYEV, S. & ISMAIL, S. 2019. Offsite Manufacturing in the Construction Industry for Productivity Improvement. *Engineering Management Journal*, 1-12.

DURDYEV, S., ISMAIL, S. & BAKAR, N. A. 2012. Factors causing cost overruns in construction of residential projects: case study of Turkey. *International Journal of Science and Management,* 1, 3-12.

DURDYEV, S. & MBACHU, J. 2011. On-site labour productivity of New Zealand construction industry: Key constraints and improvement measures. *Construction Economics and Building,* 11, 18-33.

DURDYEV, S. & MBACHU, J. 2018. Key constraints to labour productivity in residential building projects: Evidence from Cambodia. *International Journal of Construction Management,* 18, 385-393.

EGAN, J. 1998. Rethinking construction, construction task force report for department of the environment, transport and the regions. *Ed: HMSO, London.*

EL-HENDAWY, S., AL-SUHAIBANI, N., ELSAYED, S., REFAY, Y., ALOTAIBI, M., DEWIR, Y. H., HASSAN, W. & SCHMIDHALTER, U. 2019. Combining biophysical parameters, spectral indices and multivariate hyperspectral models for estimating yield and water productivity of spring wheat across different agronomic practices. *PloS one,* 14, e0212294.

ENSHASSI, A., MOHAMED, S., MUSTAFA, Z. A. & MAYER, P. E. 2007. Factors affecting labour productivity in building projects in the Gaza Strip. *Journal of civil engineering and management,* 13, 245-254.

EZELDIN, A. S. & SHARARA, L. M. 2006. Neural networks for estimating the productivity of concreting activities. *Journal of construction engineering and management,* 132, 650-656.

FAYEK, A. R. & ODUBA, A. 2005. Predicting industrial construction labor productivity using fuzzy expert systems. *Journal of construction engineering and management,* 131, 938-941.

FELLOWS, R. F. & LIU, A. M. 2015. *Research methods for construction*, John Wiley & Sons.

FIELD, A. 2013. *Discovering statistics using IBM SPSS statistics*, sage.

FINKE, M. R. 1996. Claims for construction productivity losses. *Pub. Cont. LJ,* 26, 311.

FORD, M. 2006. After Nunukan: the regulation of Indonesian migration to Malaysia. *Mobility, labour migration and border controls in Asia.* Springer.

FREEMAN, R. 2008. Labour productivity indicators. Comparison of two OECD databases, productivity differentials and the Balassa-Samuelson effect. *Retrieved from OECD Statistics Directorate Web site: http://www. oecd. org/dataoecd/57/15/41354425. pdf*

GEREK, I. H., ERDIS, E., MISTIKOGLU, G. & USMEN, M. 2015. Modelling masonry crew productivity using two artificial neural network techniques. *Journal of Civil Engineering and Management,* 21, 231-238.

GHODDOUSI, P. & HOSSEINI, M. R. 2012. A survey of the factors affecting the productivity of construction projects in Iran. *Technological and economic development of economy,* 18, 99-116.

GHOSH, S. & KATKAR, S. 2012. Modeling uncertainty resulting from multiple downscaling methods in assessing hydrological impacts of climate change. *Water resources management,* 26, 3559-3579.

GHOSH, S. & MUJUMDAR, P. P. 2008. Statistical downscaling of GCM simulations to streamflow using relevance vector machine. *Advances in water resources,* 31, 132-146.
GIANG, D. T. & PHENG, L. S. 2011. Role of construction in economic development: Review of key concepts in the past 40 years. *Habitat international,* 35, 118-125.
GOLNARAGHI, S., ZANGENEHMADAR, Z., MOSELHI, O. & ALKASS, S. 2019. Application of Artificial Neural Network (s) in Predicting Formwork Labour Productivity. *Advances in Civil Engineering,* 2019.
GOODRUM, P. M., ZHAI, D. & YASIN, M. F. 2009. Relationship between changes in material technology and construction productivity. *Journal of Construction Engineering and Management,* 135, 278-287.
GREEN, B. 2016. Productivity in construction: creating a framework for the industry to thrive. *Published by the Chartered Institute of Building (CIOB).*
GRIEGO, R. & LEITE, F. 2016. Premature Construction Start Interruptions: How Awareness Could Prevent Disputes and Litigations. *Journal of Legal Affairs and Dispute Resolution in Engineering and Construction,* 9, 04516016.
GUNDECHA, M. 2012. Study of Factors Affecting Labor Productivity at a building construction Project in the USA. *Master of Science, North Dakota State University Of Agriculture and Applied Science.*
GUNDECHA, M. M. 2013. Study of factors affecting labor productivity at a building construction project in the usa: web survey.
GUPTA, B. 1975. Labour incentive in India of iron and steel industry. *Research Abstract Quarterly*, 171-176.
GUPTA, V. & KANSAL, R. 2014. Improvement of construction labor productivity in Chambal Region. *International Journal of Research in Engineering and Technology,* 3, 34-37.
HAIR, J. F., ANDERSON, R. E., TATHAM, R. L. & BLACK, W. C. 1998. Multivariate data analysis. 1998. *Upper Saddle River.*
HALLIGAN, D. W., DEMSETZ, L. A., BROWN, J. D. & PACE, C. B. 1994. Action-response model and loss of productivity in construction. *Journal of Construction Engineering and Management,* 120, 47-64.
HAMOUDA, H. & ABU-SHAABAN, N. 2015. Enhancing Labour Productivity within Construction Industry through Analytical Hierarchy Process, the Case of Gaza Strip. *Universal Journal of Management,* 3, 329-336.
HANCHER, D. E. & ABD-ELKHALEK, H. A. 1998. The effect of hot weather on construction labor productivity and costs. *Cost Engineering,* 40, 32.
HANNA, A. S., CHANG, C.-K., SULLIVAN, K. T. & LACKNEY, J. A. 2008. Impact of shift work on labor productivity for labor intensive contractor. *Journal of construction engineering and management,* 134, 197-204.
HANNA, A. S., TAYLOR, C. S. & SULLIVAN, K. T. 2005. Impact of extended overtime on construction labor productivity. *Journal of construction engineering and management,* 131, 734-739.
HASAN, A., BAROUDI, B., ELMUALIM, A. & RAMEEZDEEN, R. 2018. Factors affecting construction productivity: a 30 year systematic review. *Engineering, Construction and Architectural Management,* 25, 916-937.
HASTIE, T. & TIBSHIRANI, R. 1990. Exploring the nature of covariate effects in the proportional hazards model. *Biometrics*, 1005-1016.

HASTIE, T., TIBSHIRANI, R., FRIEDMAN, J. & FRANKLIN, J. 2005. The elements of statistical learning: data mining, inference and prediction. *The Mathematical Intelligencer,* 27, 83-85.
HAZELTINE, C. S. 1976. Motivation of construction workers. *Journal of the Construction Division,* 102.
HECKMAN, J. J. 2013. The viability of the welfare state. *Global Perspectives on the Rule of Law.* Routledge-Cavendish.
HENG, A. B., CHEOLSUNG, P., HAOMING, L., THANGAVELU, S. M. & WONG, J. 2006. The impact of structured training on workers' employability and productivity. *Centre for Applied and Policy Economics, Paper.*
HERBSMAN, Z. & ELLIS, R. 1990. Research of factors influencing construction productivity. *Construction Management and Economics,* 8, 49-61.
HESSAMI, M., GACHON, P., OUARDA, T. B. & ST-HILAIRE, A. 2008. Automated regression-based statistical downscaling tool. *Environmental Modelling & Software,* 23, 813-834.
HEWAGE, K. N. & RUWANPURA, J. Y. 2006. Carpentry workers issues and efficiencies related to construction productivity in commercial construction projects in Alberta. *Canadian Journal of Civil Engineering,* 33, 1075-1089.
HICKSON, B. G. & ELLIS, L. A. 2014. Factors affecting construction labour productivity in Trinidad and Tobago. *The Journal of the Association of Professional engineers of Trinidad and Tobago,* 42, 4-11.
HIYASSAT, M. A., HIYARI, M. A. & SWEIS, G. J. 2016. Factors affecting construction labour productivity: a case study of Jordan. *International Journal of Construction Management,* 16, 138-149.
HOERL, A. E. & KENNARD, R. W. 1970. Ridge regression: Biased estimation for nonorthogonal problems. *Technometrics,* 12, 55-67.
HONG, Y., CHAN, D. W., CHAN, A. P. & YEUNG, J. F. 2011. Critical analysis of partnering research trend in construction journals. *Journal of management in engineering,* 28, 82-95.
HUIZINGA, F. H. & BROER, P. 2004. *Wage moderation and labour productivity,* CPB Netherlands Bureau for Economic Policy Analysis.
HWANG, B.-G. & SOH, C. K. 2013. Trade-level productivity measurement: Critical challenges and solutions. *Journal of Construction Engineering and Management,* 139, 04013013.
HWANG, B.-G., ZHAO, X. & TOH, L. P. 2014. Risk management in small construction projects in Singapore: Status, barriers and impact. *International Journal of Project Management,* 32, 116-124.
HWANG, C.-L. & YOON, K. 1981. Methods for multiple attribute decision making. *Multiple attribute decision making.* Springer.
IBARRA BERASTEGUI, G., SÁENZ AGUIRRE, J., EZCURRA TALEGÓN, A., ELÍAS SAENZ, A. J. & DÍAZ DE ARGANDOÑA GONZÁLEZ, J. 2011. Downscaling of surface moisture flux and precipitation in the Ebro Valley (Spain) using analogues and analogues followed by random forests and multiple linear regression.
IBBS, W. 2012. Construction change: Likelihood, severity, and impact on productivity. *Journal of Legal Affairs and Dispute Resolution in Engineering and Construction,* 4, 67-73.
IBBS, W. & SUN, X. 2017. Weather's Effect on Construction Labor Productivity. *Journal of Legal Affairs and Dispute Resolution in Engineering and Construction,* 9, 04517002.

IFEDILI, C. J. 2013. EFFECTIVE SUPERVISION OF NIGERIAN UNIVERSITY WORKERS–A TASK FOR MODERN ADMINISTRATORS. *European Journal of Business and Social Sciences,* 2, 24-32.

JANG, H., KIM, K., KIM, J. & KIM, J. 2011. Labour productivity model for reinforced concrete construction projects. *Construction Innovation,* 11, 92-113.

JARKAS, A. M., AL BALUSHI, R. A. & RAVEENDRANATH, P. 2015. Determinants of construction labour productivity in Oman. *International Journal of Construction Management,* 15, 332-344.

JARKAS, A. M. & BITAR, C. G. 2011. Factors affecting construction labor productivity in Kuwait. *Journal of construction engineering and management,* 138, 811-820.

JARKAS, A. M. & HAUPT, T. C. 2015. Major construction risk factors considered by general contractors in Qatar. *Journal of Engineering, Design and Technology,* 13, 165-194.

JARKAS, A. M. & RADOSAVLJEVIC, M. 2012. Motivational factors impacting the productivity of construction master craftsmen in Kuwait. *Journal of Management in Engineering,* 29, 446-454.

JAYAWARDANE, A. & GUNAWARDENA, N. 1998. Construction workers in developing countries: a case study of Sri Lanka. *Construction Management & Economics,* 16, 521-530.

JENKS, G. F. 1967. The data model concept in statistical mapping. *International yearbook of cartography,* 7, 186-190.

JENNINGS, G. 2001. *Tourism research,* John Wiley and sons Australia, Ltd.

JEONG, D. I., ST-HILAIRE, A., OUARDA, T. B. & GACHON, P. 2012. Multisite statistical downscaling model for daily precipitation combined by multivariate multiple linear regression and stochastic weather generator. *Climatic Change,* 114, 567-591.

KAMING, P. F., HOLT, G. D., KOMETA, S. T. & OLOMOLAIYE, P. O. 1998. Severity diagnosis of productivity problems—a reliability analysis. *International Journal of Project Management,* 16, 107-113.

KAMING, P. F., OLOMOLAIYE, P. O., HOLT, G. D. & HARRIS, F. C. 1997. Factors influencing construction time and cost overruns on high-rise projects in Indonesia. *Construction Management & Economics,* 15, 83-94.

KARIMI, H., TAYLOR, T. R. & GOODRUM, P. M. 2017. Analysis of the impact of craft labour availability on North American construction project productivity and schedule performance. *Construction Management and Economics,* 35, 368-380.

KAUHANEN, A. & MALIRANTA, M. 2019. The Roles of Job and Worker Restructuring in Aggregate Wage Growth Dynamics 1. *Review of Income and Wealth,* 65, 99-118.

KAUR, A. 2014. Managing labour migration in Malaysia: Guest worker programs and the regularisation of irregular labour migrants as a policy instrument. *Asian Studies Review,* 38, 345-366.

KAZAZ, A. & ACıKARA, T. 2015. Comparison of labor productivity perspectives of project managers and craft workers in Turkish construction industry. *Procedia Computer Science,* 64, 491-496.

KAZAZ, A., MANISALI, E. & ULUBEYLI, S. 2008. Effect of basic motivational factors on construction workforce productivity in Turkey. *Journal of civil engineering and management,* 14, 95-106.

KAZMI, S. W. 2007. Vocational education and skills development: A case of Pakistan. *SAARC Journal of Human Resource Development,* 3, 105-117.
KE, Y., WANG, S., CHAN, A. P. & CHEUNG, E. 2009. Research trend of public-private partnership in construction journals. *Journal of Construction Engineering and Management,* 135, 1076-1086.
KIM, J.-O. & MUELLER, C. W. 1978. *Factor analysis: Statistical methods and practical issues*, Sage.
KINNEAR, P. R. & GRAY, C. D. 1999. *SPSS for Windows made simple*, Taylor & Francis.
KLEIN, N. 2012. *Real wage, labor productivity, and employment trends in South Africa: A closer look*, International Monetary Fund.
KOVACH, K. A. 1987. What motivates employees? Workers and supervisors give different answers. *Business Horizons,* 30, 58-65.
LABARRE, P., EL-ADAWAY, I. & EID, M. The Potential of Construction Project Benchmarking in the Vicksburg District of the US Army Corps of Engineers. Construction Research Congress 2014: Construction in a Global Network, 2014. 1626-1635.
LANGMADE, L. 2017. *Productivity in the Construction Industry Is Declining — Here's How Mobile Can Help [Infographic]* [Online]. https://blog.plangrid.com/2017/11/productivity-construction-industry-declining-heres-mobile-can-help-infographic/: Lynn Langmade Blog. Available: https://blog.plangrid.com/2017/11/productivity-construction-industry-declining-heres-mobile-can-help-infographic/ [Accessed 10 November 2018 2018].
LEARY, M. R. 2004. Introduction to behavioral research methods. *Strategies,* 16, 19.
LEMA, N. M. 1996. *Construction labour productivity analysis and benchmarking: the case of Tanzania.* © Ninatubu Mbora Lema.
LESSING, B., THURNELL, D. & DURDYEV, S. 2017. Main factors causing delays in large construction projects: Evidence from New Zealand.
LI, X., CHOW, K. H., ZHU, Y. & LIN, Y. 2016. Evaluating the impacts of high-temperature outdoor working environments on construction labor productivity in China: A case study of rebar workers. *Building and Environment,* 95, 42-52.
LIBERDA, M., RUWANPURA, J. & JERGEAS, G. Construction productivity improvement: A study of human, management and external issues. Construction Research Congress: Wind of Change: Integration and Innovation, 2003. 1-8.
LIM, E. C. & ALUM, J. 1995. Construction productivity: issues encountered by contractors in Singapore. *International journal of project management,* 13, 51-58.
LIMA, A. R., CANNON, A. J. & HSIEH, W. W. Downscaling temperature and precipitation using support vector regression with evolutionary strategy. Neural Networks (IJCNN), The 2012 International Joint Conference on, 10-15 June 2012 2012. 1-8.
LIPMAN, M. 1987. Critical thinking: What can it be? *Analytic Teaching,* 8.
LOOSEMORE, M. 2014. Improving construction productivity: a subcontractor's perspective. *Engineering, Construction and Architectural Management,* 21, 245-260.
LOWE, J. G. 1987. The measurement of productivity in the construction industry. *Construction management and economics,* 5, 101-113.

MADI, I. 2003. Essential factors affecting accuracy of cost estimation of building contractors. *Unpublished MSc thesis, Islamic University–Gaza, Palestine*.
MAIA, A. G. & SAKAMOTO, A. 2018. Does wage reflect labor productivity? A comparison between Brazil and the United States. *Brazilian Journal of Political Economy,* 38, 629-649.
MAJID, M. A. & MCCAFFER, R. 1997. ASSESSMENT OF WORK PERFORMANCE OF MAINTENANCE CONTRACTORS IN SAUDI ARABIA. DISCUSSION. *Journal of management in Engineering,* 13.
MAKULSAWATUDOM, A., EMSLEY, M. & SINTHAWANARONG, K. 2004. Critical factors influencing construction productivity in Thailand. *The journal of KMITNB,* 14, 1-6.
MALLEY, J., MUSCATELLI, A. & WOITEK, U. 2003. Some new international comparisons of productivity performance at the sectoral level. *Journal of the Royal Statistical Society: Series A (Statistics in Society),* 166, 85-104.
MALONEY, W. F. 1983. Productivity improvement: The influence of labor. *Journal of construction engineering and management,* 109, 321-334.
MALONEY, W. F. & MCFILLEN, J. M. 1985. Valence of and satisfaction with job outcomes. *Journal of Construction Engineering and Management,* 111, 53-73.
MAO, H. 1999. *Estimating Labour Productivity Using F uvy Set Theory.* University of Alberta.
MARTELLA, R. C., NELSON, J. R. & MARCHAND-MARTELLA, N. E. 1999. *Research methods: Learning to become a critical research consumer*, Allyn & Bacon.
MCDONALD, D. F. & ZACK, J. G. 2004. Estimating lost labor productivity in construction claims. *AACE International Recommended Practice No. 25R,* 3.
MIN, D. & YIH, Y. 2010. Scheduling elective surgery under uncertainty and downstream capacity constraints. *European Journal of Operational Research,* 206, 642-652.
MOHAMMED, K. A. & ISAH, A. D. 2012. Causes of delay in Nigeria construction industry. *Interdisciplinary journal of contemporary research in business,* 4, 785-794.
MOMADE, M. H. & HAININ, M. R. 2018. Review of sustainable construction practices in Malaysian construction industry. *International Journal of Engineering & Technology,* 7, 5018-5021.
MOMADE, M. H. & HAININ, M. R. 2019. Identifying Motivational and Demotivational Productivity Factors in Qatar Construction Projects. *Engineering, Technology & Applied Science Research,* 9, 3945-3948.
MOORE, N. 2000. How To Do Research: The complete guide to designing and managing research project. *Library Association Publication, London*.
MOSELHI, O., ASSEM, I. & EL-RAYES, K. 2005. Change orders impact on labor productivity. *Journal of Construction Engineering and Management,* 131, 354-359.
MOSELHI, O. & EL-RAYES, K. 2002. Analyzing weather-related construction claims. *Cost Engineering,* 44, 12.
MOSELHI, O., LEONARD, C. & FAZIO, P. 1991. Impact of change orders on construction productivity. *Canadian Journal of Civil Engineering,* 18, 484-492.
MUHAMMAD, N. Z., SANI, A., MUHAMMAD, A., BALUBAID, S., ITUMA, E. E. & SULEIMAN, J. H. 2015. Evaluation of factors affecting labour productivity in construction industry: A case study. *JURNAL TEKNOLOGI,* 77, 87-91.

MUQEEM, S., IDRUS, A., KHAMIDI, M. F., AHMAD, J. B. & ZAKARIA, S. B. 2012. Construction labor production rates modeling using artificial neural network. *Journal of Information Technology in Construction (ITcon),* 16**,** 713-726.

NAGHIBI, S., POURGHASEMI, H. & DIXON, B. 2015. GIS-based groundwater potential mapping using boosted regression tree, classification and regression tree, and random forest machine learning models in Iran. *Environmental Monitoring and Assessment,* 188**,** 1-27.

NAOUM, S. G. 2016. Factors influencing labor productivity on construction sites: A state-of-the-art literature review and a survey. *International Journal of Productivity and Performance Management,* 65**,** 401-421.

NASIRZADEH, F. & NOJEDEHI, P. 2013. Dynamic modeling of labor productivity in construction projects. *International journal of project management,* 31**,** 903-911.

NELDER, J. & BAKER, R. 1972. Generalized linear models. Encyclopedia of statistical sciences. Wiley, New York.

NEPAL, M. P., PARK, M. & SON, B. 2006. Effects of schedule pressure on construction performance. *Journal of Construction Engineering and Management,* 132**,** 182-188.

NOOR, S. M. & ABDULLAH, M. A. 2012. Quality work life among factory workers in Malaysia. *Procedia-Social and Behavioral Sciences,* 35**,** 739-745.

ODESOLA, I. A. & IDORO, G. I. 2014. Influence of labour-related factors on construction labour productivity in the south-south geo-political zone of Nigeria. *Journal of construction in Developing Countries,* 19**,** 93.

ODUBA, A. O. 2004. *Predicting industrial construction productivity using fuzzy expert systems.*

OHUERI, C. C., ENEGBUMA, W. I., WONG, N. H., KUOK, K. K. & KENLEY, R. 2018. Labour productivity motivation framework for Iskandar Malaysia. *Built Environment Project and Asset Management,* 8**,** 293-304.

OLOMOLAIYE, P. O. 1988. *An evaluation of bricklayers' motivation and productivity.* © Paul Olaniyi Olomolaiye.

PAGE, I. C. 2010. *Construction industry productivity*, BRANZ.

PALIKHE, S., KIM, S. & KIM, J. J. 2019. Critical success factors and dynamic modeling of construction labour productivity. *International Journal of Civil Engineering,* 17**,** 427-442.

PAN, N.-F. 2005. Assessment of productivity and duration of highway construction activities subject to impact of rain. *Expert systems with Applications,* 28**,** 313-326.

PARK, H.-S., THOMAS, S. R. & TUCKER, R. L. 2005. Benchmarking of construction productivity. *Journal of Construction Engineering and Management,* 131**,** 772-778.

PARTHASARATHY, M., MURUGASAN, R. & VASAN, R. 2018. Modelling manpower and equipment productivity in tall residential building projects in developing countries. *Journal of the South African Institution of Civil Engineering,* 60**,** 23-33.

POLICIES, S. I. I. 2018. Available: http://www.sabah.com.my/borneotrade/g5.htm [Accessed 18/11/2018 2018].

POPLAWSKA, J. 2014. *Decision support framework for resources allocation to corporate social responsibility (CSR) programmes.* University of Portsmouth.

POPOVICI, N., MORARU, C. & MUNTEANU, I. 2019. The relationship between earnings and labour productivity in textile industry. *DE REDACTIE*, 9.

PORTAS, J. & ABOURIZK, S. 1997. Neural network model for estimating construction productivity. *Journal of construction engineering and management,* 123, 399-410.

PRATIBHA, M. & GAIKWAD, P. 2015. Analysis of labor productivity in residential construction projects. *Int J Mod Trends Eng Res,* 2, 937-941.

PUBLISHING, O. 2001. *Measuring productivity-OECD Manual: Measurement of Aggregate and Industry-Level Productivity Growth*, Organisation for Economic Co-operation and Development.

PUNCH, K. F. 2013. *Introduction to social research: Quantitative and qualitative approaches*, sage.

PÜSS, T., VIIES, M. & MALDRE, R. 2010. EU-12 countries in the context of European social model types. *International Business & Economics Research Journal,* 9, 37-48.

RAMI HUGES, D. 2014. A review of enabling factors in construction industry productivity in an australian environment. Emerald Insight.

RAZZAK, W. & TIMMINS, J. 2010. Education and labour productivity in New Zealand. *Applied Economics Letters,* 17, 169-173.

REPINA, E., SIMONOVA, M. & SUKHANOVA, E. The development of a forecast model of labour productivity management at industrial enterprises. 2nd International Scientific conference on New Industrialization: Global, national, regional dimension (SICNI 2018), 2019. Atlantis Press.

REZAEI-MOGHADDAM, K. & KARAMI, E. 2008. A multiple criteria evaluation of sustainable agricultural development models using AHP. *Environment, Development and Sustainability,* 10, 407-426.

RIVAS, R. A., BORCHERDING, J. D., GONZÁLEZ, V. & ALARCÓN, L. F. 2010. Analysis of factors influencing productivity using craftsmen questionnaires: case study in a Chilean construction company. *Journal of Construction Engineering and Management,* 137, 312-320.

ROBLES, G., STIFI, A., PONZ-TIENDA, J. L. & GENTES, S. 2014. Labor productivity in the construction industry-factors influencing the Spanish construction labor productivity. *International Journal of Civil, Structural, Construction and Architectural Engineering,* 8, 1009-1018.

ROJAS, E. M. & ARAMVAREEKUL, P. 2003. Labor productivity drivers and opportunities in the construction industry. *Journal of management in engineering,* 19, 78-82.

ROZANTE, J., VILA, D., BARBOZA CHIQUETTO, J., FERNANDES, A. & SOUZA ALVIM, D. 2018. Evaluation of TRMM/GPM Blended Daily Products over Brazil. *Remote Sensing,* 10, 882.

SAATY, T. L. 2008. Decision making with the analytic hierarchy process. *International journal of services sciences,* 1, 83-98.

SAMBASIVAN, M. & SOON, Y. W. 2007. Causes and effects of delays in Malaysian construction industry. *International Journal of project management,* 25, 517-526.

SARRAF, M., RISMANCHI, B., SAIDUR, R., PING, H. & RAHIM, N. 2013. Renewable energy policies for sustainable development in Cambodia. *Renewable and Sustainable Energy Reviews,* 22, 223-229.

SCHEUREN, F. What is a Survey? , 2004. American Statistical Association Alexandria.

SCHWEBER, L. & LEIRINGER, R. 2012. Beyond the technical: a snapshot of energy and buildings research. *Building Research & Information,* 40, 481-492.
SEDDEEQ, A. B., ASSAF, S., ABDALLAH, A. & HASSANAIN, M. A. 2019. Time and Cost Overrun in the Saudi Arabian Oil and Gas Construction Industry. *Buildings,* 9, 41.
SHAN, Y., ZHAI, D., GOODRUM, P. M., HAAS, C. T. & CALDAS, C. H. 2015. Statistical analysis of the effectiveness of management programs in improving construction labor productivity on large industrial projects. *Journal of Management in Engineering,* 32, 04015018.
SHASHANK, K., HAZRA, S. & PAL, K. N. 2014. Analysis of key factors affecting the variation of labour productivity in construction projects.
SHEREKAR, V., TATIKONDA, M. & STUDENT, M. 2016. Impact of factor affecting on labour productivity in construction projects by AHP method. *Int. J. Eng. Sci. Comput,* 6.
SHI, Y. & SONG, L. 2015. Spatial Downscaling of Monthly TRMM Precipitation Based on EVI and Other Geospatial Variables Over the Tibetan Plateau From 2001 to 2012. *Mountain Research and Development,* 35, 180-194.
SHI, Y., SONG, L., XIA, Z., LIN, Y., MYNENI, R. B., CHOI, S., WANG, L., NI, X., LAO, C. & YANG, F. 2015. Mapping Annual Precipitation across Mainland China in the Period 2001–2010 from TRMM3B43 Product Using Spatial Downscaling Approach. *Remote Sensing,* 7, 5849-5878.
SHOAR, S. & BANAITIS, A. 2019. Application of fuzzy fault tree analysis to identify factors influencing construction labor productivity: a high-rise building case study. *Journal of Civil Engineering and Management,* 25, 41-52.
SOEKIMAN, A., PRIBADI, K., SOEMARDI, B. & WIRAHADIKUSUMAH, R. 2011. Factors relating to labor productivity affecting the project schedule performance in Indonesia. *Procedia engineering,* 14, 865-873.
SOFIA LOPES, A. & TEIXEIRA, P. 2013. Productivity, wages, and the returns to firm-provided training: fair shared capitalism? *International Journal of Manpower,* 34, 776-793.
SONG, L. & ABOURIZK, S. 2008. *Measuring and Modeling Labor Productivity Using Historical Data.*
SONGER, A. D., IBBS, C. W. & NAPIER, T. R. 1994. Process model for public sector design-build planning. *Journal of construction engineering and management,* 120, 857-874.
STUMPF, A. & KERLE, N. 2011. Combining Random Forests and object-oriented analysis for landslide mapping from very high resolution imagery. *Procedia Environmental Sciences,* 3, 123-129.
SVEIKAUSKAS, L., ROWE, S., MILDENBERGER, J., PRICE, J. & YOUNG, A. 2016. Productivity growth in construction. *Journal of Construction Engineering and Management,* 142, 04016045.
SWEIS, R. J., SWEIS, G. J., HAMMAD, A. A. A. & RUMMAN, M. A. 2009. Modeling the variability of labor productivity in masonry construction. *Jordan Journal of Civil Engineering,* 3, 197-212.
TAN, K. G. & TAN, Y. Y. 2014. Promoting SMEs and enhancing labor productivity in Singapore: A policy analysis. *Journal of International Commerce, Economics and Policy,* 5, 1440012.
TANYILDIZI, H. 2018. Prediction of the strength properties of carbon fiber-reinforced lightweight concrete exposed to the high temperature using artificial

neural network and support vector machine. *Advances in Civil Engineering,* 2018.
THOMAS, A. V. & SUDHAKUMAR, J. 2013. Critical analysis of the key factors affecting construction labour productivity–An Indian Perspective. *International Journal of Construction Management,* 13, 103-125.
THOMAS, H. R., MALONEY, W. F., HORNER, R. M. W., SMITH, G. R., HANDA, V. K. & SANDERS, S. R. 1990. Modeling construction labor productivity. *Journal of Construction Engineering and Management,* 116, 705-726.
THOMAS, H. R. & YIAKOUMIS, I. 1987. Factor model of construction productivity. *Journal of construction engineering and management,* 113, 623-639.
TSAI, C. C. & LYDIA WEN, M. 2005. Research and trends in science education from 1998 to 2002: A content analysis of publication in selected journals. *International journal of science education,* 27, 3-14.
TSEHAYAE, A. A. 2015. *Developing and optimizing context-specific and universal construction labour productivity models.* University of Alberta Edmonton, Canada.
TSEHAYAE, A. A. & FAYEK, A. R. 2016. System model for analysing construction labour productivity. *Construction Innovation,* 16, 203-228.
TSEHAYAE, A. A. & FAYEK, A. R. 2018. Context Adaptation of Fuzzy Inference System-Based Construction Labor Productivity Models. *Advances in Fuzzy Systems,* 2018.
USBLS. 2016. Productivity Law and Legal Definition.
VAPNIK, V. N. & VAPNIK, V. 1998. *Statistical learning theory,* Wiley New York.
VEISETH, M., ROSTAD, C. & ANDERSEN, B. Productivity and logistics in the construction industry. Conference Proceeding, Nordnet, 2003.
VENKATESH, M. & PS, S. N. 2019. Improvement of Manpower and Equipment Productivity in Indian Construction Projects. *International Journal of Applied Engineering Research,* 14, 404-409.
WALEWSKI, J. & GIBSON, G. 2003. International project risk assessment: Methods, procedures, and critical factors. *Center for Construction Industry Studies, University of Texas at Austin, Report,* 31.
WANG, F. 2005. *On-Site labor productivity estimation using neural networks.* Concordia University.
WATKINS, M., MUKHERJEE, A., ONDER, N. & MATTILA, K. 2009. Using agent-based modeling to study construction labor productivity as an emergent property of individual and crew interactions. *Journal of construction engineering and management,* 135, 657-667.
WESTOVER, J. H., WESTOVER, A. R. & WESTOVER, L. A. 2010. Enhancing long-term worker productivity and performance: The connection of key work domains to job satisfaction and organizational commitment. *International Journal of Productivity and Performance Management,* 59, 372-387.
WHEELER, D. & MODY, A. 1992. International investment location decisions: The case of US firms. *Journal of international economics,* 33, 57-76.
WILCOX, S., STRINGFELLOW, B., HARRIS, R. & MARTIN, B. 2000. Management and productivity. *Transportation research board, committee on management and productivity. Washington, USA.*
WILFRED, A. & SHARAFUDEEN, M. 2015. A methodology to identify the delays and rank its causative factors in Indian construction industry. *International Research Journal of Engineering and Technology (IRJET),* 2, 2214-2218.

WILK-KOLODZIEJCZYK, D., REGULSKI, K. & GUMIENNY, G. 2016. Comparative analysis of the properties of the nodular cast iron with carbides and the austempered ductile iron with use of the machine learning and the support vector machine. *The International Journal of Advanced Manufacturing Technology,* 87, 1077-1093.
WILMOT, C. G. & MEI, B. 2005. Neural network modeling of highway construction costs. *Journal of construction engineering and management,* 131, 765-771.
WIND, Y. & SAATY, T. L. 1980. Marketing applications of the analytic hierarchy process. *Management science,* 26, 641-658.
WONG, K. W. J. 2007. *Development of selection evaluation and system intelligence analytic models for the intelligent building control systems.* The Hong Kong Polytechnic University.
YI, W. & CHAN, A. P. 2013. Critical review of labor productivity research in construction journals. *Journal of management in engineering,* 30, 214-225.
ZHAI, D., GOODRUM, P. M., HAAS, C. T. & CALDAS, C. H. 2009. Relationship between automation and integration of construction information systems and labor productivity. *Journal of Construction Engineering and Management,* 135, 746-753.
ZHAO, H. & ZHU, G. 2000. Location factors and country-of-origin differences: An empirical analysis of FDI in China. *Multinational Business Review,* 8, 60.
ZHI, M., HUA, G. B., WANG, S. Q. & OFORI, G. 2003. Total factor productivity growth accounting in the construction industry of Singapore. *Construction management and economics,* 21, 707-718.
ZHIQIANG, C., BALASUBRAMANIAM, G. & EDIRISINGHE, R. 2019. Productivity Improvement in the Construction Industry: A Case Study of Mechanization in Singapore. *Advances in Informatics and Computing in Civil and Construction Engineering.* Springer.