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PRODUCTIVITY ANALYSIS OF PRECAST CONCRETE OPERATIONS BY ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Productivity estimation is a crucial task for construction managers and general estimators to efficiently allocate the required resources in order to minimize the construction costs. There is a lack of research in terms of productivity modeling for precast erection process. Therefore, this study was designed to develop a model based on Artificial Neural Networks (ANN) to predict the installation times of the most commonly used precast elements namely: walls, columns, beams, and slabs. Installations of 220 precast elements were observed and significant factors influencing productivity were identified through stepwise Multiple Regression Analysis (MRA) to form the inputs of ANN model. Performance of the developed model on the test data showed its accuracy in predicting installation times of different precast components which confirmed the appropriateness of the model to be used by practitioners or construction management research scholars.

Keywords: productivity modeling, artificial neural networks, multiple regression analysis, precast concrete, site management.

1. INTRODUCTION

Precast Concrete (PC) components are manufactured in a controlled environment in the manufacturing yards or in the temporary precast plants which are set up near the construction sites. Generally, use of PC elements results in higher quality products, faster installation of building structure, enhanced safety, reduction of wastage in materials, and more sustainability [1-4].

There are several studies available in the current literature that have focused on planning aspects of precast production as well as IT utilization for efficient tracking and precast yard management such as:

- The use of Genetic Algorithms to develop a model to meet the site demands, optimize production costs of resources, and satisfy resource constraints for the precast manufacturing companies [5].
- Presenting a framework by utilizing Artificial Intelligence to reduce the level of finished goods in precast fabricators' yard [6].
- Developing of flowshop sequencing models for specialized method of PC production as well as bespoke PC production to deal with challenges such as reliability of the product delivery methods and efficient usage of molds [7, 8].
- Utilization of Radio Frequency Identification (RFID) with Global Positioning System (GPS) to design and develop a system for better supply chain management [9].

The main theme of the abovementioned papers is the "off-site" production planning of PC components. There is a need to study "on-site" erection activities to better understand the factors affecting productivity of PC projects in order to develop more accurate estimation tools to be used by construction managers and general estimators for their scheduling purposes. Therefore, this research was designed to collect the factors influencing productivity and utilize Artificial Neural Networks (ANN) to estimate the total installation (erection) times of the most commonly used PC elements namely: walls, columns, beams, and slabs. A brief introduction to ANN and their applications in productivity estimation are provided in the next section followed by research methodology, discussions, and conclusions.

1.2 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) can be defined as a massive parallel distributed processor composed of simple processing units (neurons) which are capable of storing experiential knowledge and retrieving it for future use. Therefore, an ANN resembles human brain system in two respects [10]:

- Knowledge acquisition from its environment through a learning process.
- Storing the acquired knowledge is performed by interneuron connection strengths known as synaptic weights.

A schematic diagram of a neuron (basic processing unit) is shown in Figure-1. Each neuron has two distinct segments: a summing junction and an activation function and its performance can be mathematically represented by:

$$Y_j = F\left(\sum_{i=1}^{m} w_{ji}x_i\right) \tag{1}$$

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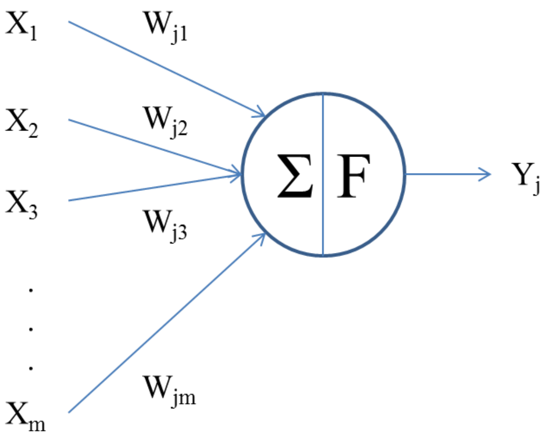

Figure-1. Schematic diagram of a neuron.

The activation function (F) can be in any mathematical form such as threshold function, piecewise linear function, tan hyperbolic function, and sigmoid function which has been considered as the most commonly used activation function because of presenting a graceful balance between linear and non-linear behavior which is shown in Figure-2 [10].

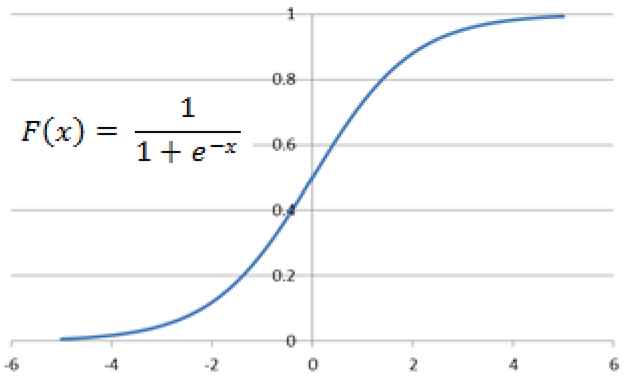

Figure-2. Sigmoid activation function.

To develop any type of ANN, these neurons are grouped together to form several layers namely input, hidden, and output layers. A typical feed forward ANN that is generally referred to as multilayer perceptron is shown in Figure-3. The main objective of such a model is usually to produce the desired set of outputs through training the network by using a set of examples (training data) and applying some types of learning rules to change the connection weights accordingly [11].

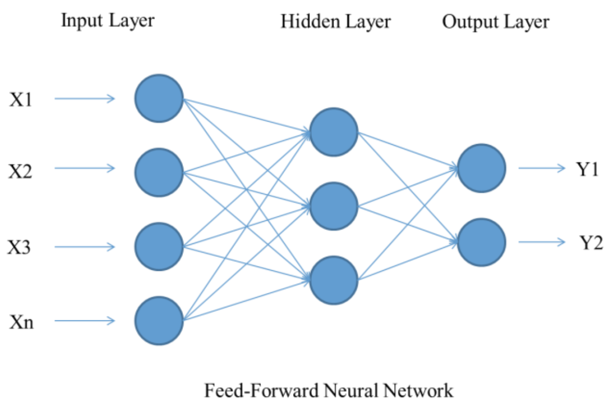

Figure-3. A typical fully connected feed forward ANN (multilayer perceptron).

One of the most commonly used learning algorithms is Back-Propagation algorithm [12] which has two steps: feed forward data generation and backward error propagation. In this algorithm, a set of data is presented to the network (training set) and outputs are calculated based on the activation functions of the hidden and output layers. These "network outputs" (predicted outputs) are compared with the actual (desired) outputs and the difference (error) is propagated back to the network. The connection weights are updated accordingly and the outputs are calculated again. This procedure is repeated for several times (several epochs) until the network reaches its stop criteria.

Conventional back propagation algorithm is based on the gradient descent method which directly minimizes in the direction of the steepest descent. Another alternative that is used in this paper is to apply conjugate gradient approach that is to construct a set of "n" directions that are all conjugate to each other and therefore, the minimization along one of these directions does not spoil minimization along other directions. As a result, faster convergence is achievable [13].

1.3 ANN for productivity estimation

Construction engineering and management has been considered as a fertile area for many expert systems applications including ANN due to the complexities involved in construction projects [14]. There is a substantial amount of research on the usage of ANN in construction management [14-16]. Productivity estimation is one of the vital tasks in areas such as resource allocation and management, scheduling, estimating, accounting, cost control, and payroll [17]. Earlier studies that have utilized ANN for productivity modeling in different construction processes and operations are as follows:

- Effects of change orders, rework, and daily workload on labor productivity [18-21].
- Labor productivity rates for industrial construction activities [22].
- Concrete pouring, formwork, and finishing tasks [15,23-27].
- Hoisting times (hook times) of tower cranes [28-30].

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- Pile construction [31,32].
- Pipe installation [33].
- Plastering activities [34].
- Productivity estimation of construction earthmoving equipment such as excavators, push dozers, scrapers, loaders, and haul trucks [35-39].
- Concrete batch-plant-truck mixer operations and delivery systems [40,41].

According to the current literature, there is no study on precast installation productivity modeling and therefore, this study was designed to address this research gap.

1.4. Factors affecting productivity of precast installation

Figure-4 shows that a typical erection cycle consists of several activities with various resources.

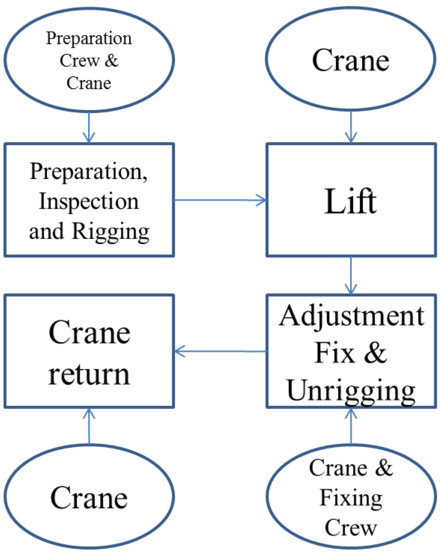

Figure-4. A typical PC erection process.

Based on Figure-4, total of 18 variables were chosen to be relevant to productivity estimation of PC installation process. Crane productivity factors were extracted from literature [29,30] and other variables were selected based on several preliminary site visits and expert discussions. Because of the tropical weather of Singapore and Malaysia, factors relevant to weather conditions such as humidity, temperature, and wind speed were not included in the analysis. It is confirmed by crane operators that hoisting speed is affected by adverse weather conditions and hoisting will be stopped during strong wind or raining [42]. Some other qualitative factors such as crew skills and crane operator efficiency were not included as well due to the complexity of the measurement of these variables. However, expert interviews confirmed that after 1 or 2 years of relevant work in the PC erection, crew can be considered as being trained and data for this study were collected from contractors with more than 2 years of experience in PC activities. Variables that were considered for PC erection productivity are as follows:

- X_1: Component weight (ton)
- X_2: Area of the load: biggest surface area of the component (m^2)
- X_3: Component length: longest length of the element (m)
- X_4: Component height (m)
- X_5: Component orientation: (X_{5a}: vertical; X_{5b}: horizontal)
- X_6: Storage type: the element is stored among others (X_{6a}) or being isolated (X_{6b})
- X_7: Storage to crane: distance form component to crane center at the storage area (m)
- X_8: Installation to crane: distance from installation point to the center of the crane (m)
- X_9: Crane angle: angular movement of the crane (angle between storage and installation in degree)
- X_{10}: Crane type: tower crane (X_{10a}) or mobile crane (X_{10b})
- X_{11}: Installation type: the component is installed among others (X_{11a}) or isolated (X_{11b})
- X_{12}: Location type: exterior (X_{12a}) or interior (X_{12b})
- X_{13}: Reinforcement bars: number of reinforcement bars (rebars) to fix the component (for vertical elements)
- X_{14}: Props: number of diagonal props for temporary support of vertical elements
- X_{15}: Lifting inserts: number of lifting inserts to be attached to the crane hook
- X_{16}: Props inserts (holes): number of drills required for props installation
- X_{17}: Fixing crew size: crew size in charge of PC fixing activities
- X_{18}: Elevation: elevation of the installation point (m)

Note that in most of the cases, only one signal man was in charge of preparation, inspection and pick up activities, therefore, the number of preparation crew was not considered as a separate factor.

2. RESEARCH METHODOLOGY

The main objective of this study is to estimate the total installation times for different PC elements by using ANN. Therefore, installation time will be served as the final output of the network. There are two options available for considering the network inputs:

a) Consider all of the 18 variables as the inputs and develop an ANN to predict the total installation time.
b) Categorize the variables into 3 groups for each of the main activities shown in Figure-4 (these activities are: 1- Preparation, inspection, and rigging; 2- Lifting; 3- Adjustment, fix, and unrigging). As a result 3 smaller networks will be developed with grouped variables as the inputs and preparation, lifting, and fixing times as the network outputs, respectively. In this case, the total installation time is the sum of smaller network outputs (installation time = preparation time + lifting time + fixing time).

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Our draft analysis showed that option 2 is more appropriate for this study. One reason is that the training of the smaller networks will be more efficient when compared to a bigger network including all of the input variables (especially, considering an average sample size of this study). Another reason is related to the distribution of the collected data from different projects. As an example, 65% of the horizontal elements were collected from a project that used a crawler crane instead of tower crane for lifting purposes. Generally, installations of horizontal elements take less time than vertical elements. Therefore, if only one network is developed considering all of the input factors, the network will be trained in such a way that using crawler crane (or mobile crane) results in shorter installation time (all other inputs being on average values) which is not correct in the actual project settings (tower cranes are faster than mobile cranes for lifting purposes). In other words, developing smaller networks eliminates the bias included in the data collection and therefore provides more accurate and valid results.

Furthermore, based on the observations, the crane may not directly return to the storage area right after the installation of the previous element due to other lifting purposes. As a result, the crane return times were not included in the analysis for this research. However, an average of 2 minutes can be considered for the crane return time (this is based on the collected data). If a more accurate estimate is needed, researchers should refer to the available literature on crane productivity studies [28,29].

3.2 Data collection

The primary data for this study were collected from 4 residential and school projects each including several blocks of multi-storey buildings using precast system in Singapore and Malaysia. To ensure the quality and validity of the data, the research team collected the primary data through direct observations of 220 PC panels and no questionnaires were used for data collection purposes. Characteristics of the collected data are shown in Table-1.

Table-1. General characteristics of the PC components.

	Wall	**Column**	**Beam**	**Slab**
No. of cases	76	61	20	63
Length (m)	1.40 – 5.75	0.40 – 2.00	5.57 – 9.22	2.40 – 8.73
Width (m)	0.10 – 0.25	0.20 – 0.75	0.30 – 0.80	0.37 – 2.40
Height (m)	2.80 – 3.58	2.80 – 5.80	0.32 – 0.60	0.07 – 0.27
Weight (t)	0.95 – 7.31	1.00 – 3.50	2.06 – 5.66	0.80 – 3.09

Elements were installed at different elevations between 12.6 m to 68.9 m (level 3 to level 23) which can be considered an acceptable range for most of the typical construction projects in the region.

3. ANALYSIS, RESULTS, AND DISCUSSIONS

3.1 Selection of the significant factors through multiple regression analysis (MRA)

As mentioned in the research methodology, the input factors will be grouped into smaller categories for different activities involved in the erection process. Variables to be considered for each group are:

- *Preparation, inspection, and rigging*: storage type, component weight, length, area, height, and number of lifting inserts.
- *Lifting (hoisting)*: distance from storage to crane, distance from installation to crane, crane angular movement, crane type, component orientation, length, area, weight, and elevation of the installation point.
- *Adjustment, fix, and unrigging*: component weight, length, area, height, location type, installation type, fixing crew size, props, props' inserts (holes required to be drilled), and number of lifting inserts (to be detached from the crane hook after installation).

Stepwise regression analysis was used to determine the most significant factors from the abovementioned list for each group of activities. Table-2 shows summary of the analysis including the selected variables (factors with p-value less than 0.05). Out of 220 elements, 190 of the data points were used for the regression analysis and the remaining 30 data points were kept for testing purposes (selection of the test data is described later).

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Table-2. Results of stepwise regression analysis.

Variable (Preparation)	**B**	**Std. Error**	**Beta**	**t**	**Sig.**	**VIF**
(Constant)	-.565	.172		-3.293	.001	
Storage Type	1.062	.100	.662	10.628	.000	1.275
Length	.080	.020	.274	3.982	.000	1.559
Area	.028	.013	.137	2.138	.034	1.351
Variable (Lift)	B	Std. Error	Beta	t	Sig.	VIF
(Constant)	-1.418	.485		-2.924	.004	
Crane Angle	.011	.001	.527	10.647	.000	1.279
Storage to Crane	.024	.008	.246	3.083	.002	3.334
Orientation	-1.155	.128	-.471	-9.034	.000	1.419
Crane Type	1.856	.186	.775	9.992	.000	3.146
Elevation	.037	.005	.513	7.352	.000	2.544
Weight	.144	.043	.172	3.319	.001	1.397
Variable (Fix)	B	Std. Error	Beta	t	Sig.	VIF
(Constant)	3.534	1.033		3.419	.001	
Weight	1.477	.173	.304	8.527	.000	1.187
Location Type	-2.415	.513	-.174	-4.704	.000	1.274
Holes	1.551	.137	.419	11.322	.000	1.282
Props	1.780	.166	.391	10.733	.000	1.242

In this Figure ovals and rectangles represent resources and activities, respectively. Therefore, for a typical erection process, four major activities are as follows:

3.3 ANN for PC erection activities

This section discusses the details about the selection of architecture and training of different neural networks to be developed for preparation, lifting, and fixing activities. In this study, fully connected feed forward networks were developed using back propagation algorithm (with conjugate gradient method) for training purposes.

A set of 160 data points were randomly selected for training, 30 data points for cross validation, and 30 data points (the same set used in MRA) to test the performance of the developed ANN. Use of cross validation technique ensures that the network is not over trained. In this method the stop criteria is chosen in such a way that as soon as the error in the cross validation set starts to increase, the training will be stopped.

Before the training phase, data (inputs and output) were scaled using Eq. 2 which transforms the actual data to be between 0 and 1.

$$Scaled\ Value = \frac{Unscaled\ value - min.value}{max.value - min.value} \quad (2)$$

There is no specific rule regarding the architecture of ANN (number of hidden layers as well as number of neurons in hidden layers) and it is usually determined by trial and error. For each of the preparation, lifting, and fixing activities, several network architectures (containing 1 and 2 hidden layers with sigmoid activation function for all of the hidden and output layers) were developed and trained for 10,000 epochs. To deal with local minima (which is a common problem in back propagation algorithm) each of the developed networks were redesigned for several times by using different initial random weights. Mean Absolute Error (MAE) and Mean Square Error (MSE) were calculated using Eq. 3 and Eq. 4 and the networks with the least MSE were selected as the optimal models.

$$MAE = \frac{\sum_i^n |Y_P - Y_A|}{n} \quad (3)$$

$$MSE = \frac{\sum_i^n (Y_P - Y_A)^2}{n} \quad (4)$$

Table-3 shows network architectures, optimal models (highlighted in the table), and related errors for each of the activities involved in PC erection process. Significant factors obtained from stepwise MRA were used as the network inputs and network outputs are preparation, lifting, and fixing times (in minutes). For nominal variables such as storage type (isolated or among others), crane type (tower crane or mobile crane), orientation (vertical or horizontal), and location type (exterior, interior) two input signals are required to

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represent each of the values respectively. In Table-3, a 4-10-4-1 architecture represents a network with 4 input signals, two hidden layers containing 10 and 4 neurons, and 1 output.

Table-3. Selection of optimal models for preparation, lifting, and fixing activities.

Preparation								
Architecture	4-10-1	4-15-1	4-8-4-1	4-10-4-1	4-6-4-1	4-4-1	4-8-1	4-6-1
MSE	0.549	0.549	0.565	0.568	0.530	0.513	0.520	0.511
MAE	0.562	0.533	0.558	0.559	0.545	0.540	0.512	0.535
Lifting								
Architecture	8-15-1	8-12-1	8-10-1	8-12-6-1	8-14-5-1	8-10-5-1	8-13-1	8-12-4-1
MSE	0.607	0.683	0.556	0.767	0.656	0.668	0.611	0.531
MAE	0.614	0.598	0.567	0.636	0.593	0.627	0.614	0.565
Fixing								
Architecture	5-7-1	5-8-1	5-10-1	5-11-1	5-8-4-1	5-9-4-1	5-8-5-1	5-9-1
MSE	7.086	7.168	8.288	8.745	7.066	7.274	7.231	6.846
MAE	1.672	1.713	1.996	2.000	1.632	1.661	1.661	1.646

Based on Table-3, the final model to be used for total installation times includes architectures of 4-6-1, 8-12-4-1, and 5-9-1 for preparation, lifting, and fixing activities, respectively which are graphically shown in Figure-5.

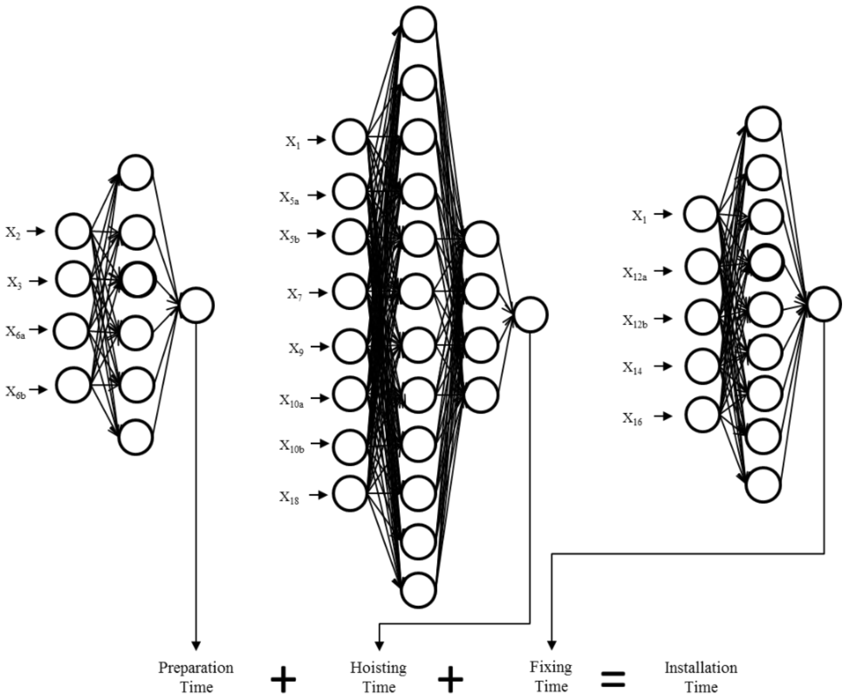

Figure-5. Graphical representation of the final ANN model.

3.4 Performance of the developed ANN model

As mentioned earlier, a set of 30 data points was used to test the predictive ability of the model. It should be noted that during data collection, in each construction project, one block was used to collect the test data and others for model development. This ensures the generalizability of the model and minimizes the need for further case studies. This is because conditions in testing blocks are different from model blocks. In other words, in most of the projects, each block has its own storage area with separate tower crane and with different crew who are in charge of precast installation. As a result, testing blocks

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can be treated as separate case studies. Actual installation times versus predicted installation times using ANN and MRA are shown in Figure-6 and Table-4 shows comparison between developed models using ANN and MRA.

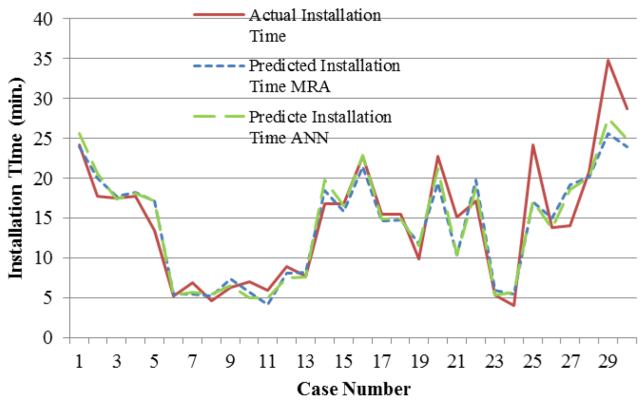

Figure-6. Comparison of the actual and predicted installation times using MRA and ANN.

Figure-7 shows the scatter plot that depicts the regression line and equation between actual and predicted installation times (using ANN).

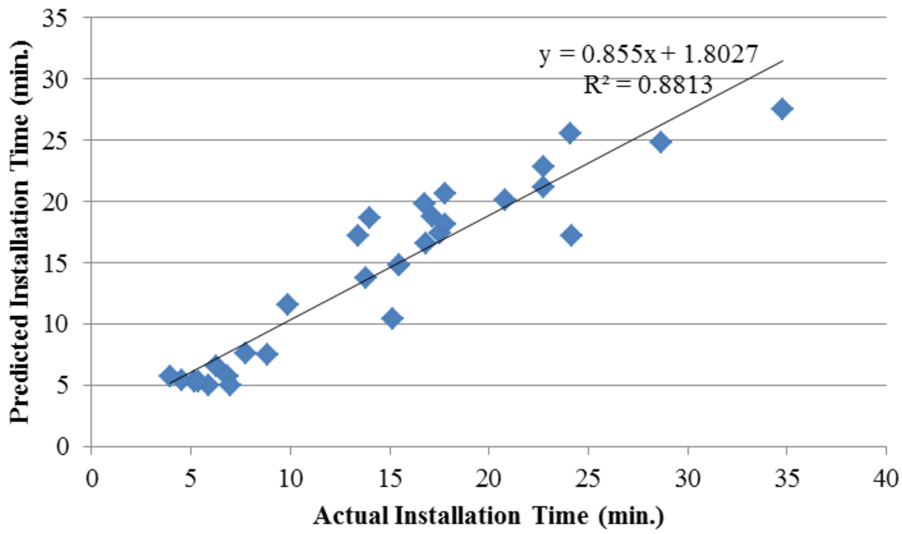

Figure-7. Correlation between actual and predicted installation times using ANN.

Table-4 shows that all of the error estimates as well as the error range are smaller in the developed ANN model when compared to MRA. Mean Absolute Percentage Error (MAPE) was calculated using Eq. 5 which shows that on average, predicted installation times will be only 13.13% higher or lower than the actual installation time. In other words, the prediction accuracy of the developed ANN model is 86.87% with an average of 1.82 minutes error estimate (12.5% reduction in error estimate compared to MRA) between the predicted and actual installation times.

$$MAPE = (\sum_i^n 100 * \frac{|Y_P - Y_A|}{Y_A})/n \quad (5)$$

Table-4. Comparison of MRA and ANN for productivity estimation of PC installation.

Method	MAE	MAPE	MSE	Min. abs. error	Max. abs. error
MRA	2.08	14.74	8.86	0.18	9.18
ANN	1.82	13.13	7.11	0.06	7.22

The results from Figure-7 and Table-4 also shows that both ANN and MRA provide well accepted results considering high uncertainties involved in construction estimations. Therefore, these models can be considered as quick and simple tools to be used by estimators for site management planning in precast projects.

4. CONCLUSIONS

The main contribution of this research was to provide an accurate estimation model to be used by construction managers and general estimators to predict installation times of different precast elements such as walls, columns, beams, and slabs. Therefore, installations of 220 precast concrete panels were observed and an ANN model was developed containing 3 smaller networks for preparation, hoisting, and fixing activities. Basically, 18 variables were selected through literature review and site visits as influencing factors affecting precast erection productivity. Stepwise regression analysis was used to identify the significant factors to form the inputs of ANN while the main output was the installation time (in minutes). Results showed that the prediction ability of the model was 86.87% which confirmed the accuracy of the model to be used for productivity estimation purposes. Although the developed ANN model showed better performance when compared to regression analysis, both models were well within the accepted range for predicting the total installation times of precast components.

This study used an average sample size for the analysis. Therefore, one possible direction for future research is to gather more data especially on other precast components such as staircases, balconies, etc. and conduct case studies to test the model performance. Another direction is to develop a computer program based on the models described in this study. The program will be capable of generating meaningful reports for site managers for their scheduling purposes. One issue to be noted is that, to predict the installation time for each precast element, end users should enter many input data manually. One suggestion is to integrate the developed models with Building Information Modeling (BIM) packages. Since most of the data (including details about precast elements) are already available in the BIM systems, manual data entry will be minimized.

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