Evaluation of the Productivity of Ready Mixed Concrete Batch Plant Using Artificial Intelligence Techniques

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Abstract. An accurate prediction of the productivity of the batch plant is considered an essential element for control and planning the construction project. The actual productivity values of construction equipment in the site not consistent with the nominal ones. Therefore, it is necessary to make a comprehensive evaluation of the nominal productivity of equipment concerning the effected factors and then re-evaluate them according to the actual values. This research involved investigation of the ready mixed concrete batch plant to evaluate the productivity with the actual values. Artificial intelligence techniques that are represented by Artificial Neural Network (ANN) and Support Vector Machine (SVM), in addition to the statistical technique, represented by multi-linear regression (MLR), were used as tools for modeling the actual productivity and produce the predicted model for the productivity. Three of accuracy measurements, correlation coefficient (R), mean absolute error (MAE) and root mean square error (RMSE), were used to develop the model and to make a comparison between the actual and predicted productivity. The researcher developed three mathematical models of MLR, ANN, and SVM used to predict the productivity of ready mixed concrete batch plant and also the results showed that the artificial intelligence techniques were more precise than those calculated by the conventional techniques, and SVM model was the best generalization than ANN model in both the training and the validation data.

Keywords: Construction; batch plant productivity; multilinear regression; artificial intelligence; support vector machine.

1. Introduction
Productivity is considered as an important indicator that effecting the selection of any equipment. Construction equipment is one of the resources needed for the completion and success of construction projects. Recently, Contractors undertaking many kinds of construction activities that need various types and sizes of equipment, and usually, they invest the biggest value for costs of the project, particularly for equipment-heavy projects. The productivity of equipment plays a major role in time and cost estimation of any construction project. The utilization of equipment includes increasing Production rate, low total cost, carry out activities that cannot be carried out manually, maintain the planned production rate when there is a shortage of labor, maintain high-quality standards, and so on. Thus, the correct choice and use of equipment contribute to the economy, safety, quality, speed, and timely completion of the project [1]. Otherwise, delays in project implementation may occur due to incorrect selection of equipment, unavailability of equipment on time, poor technology, and wrong mechanization.

Many researchers have defined the productivity in different ways according to the nature of the work, all agreed that the productivity is the rate of outputs to inputs [1]. Productivity can be defined as a measure of transforming resources of an individual, firm, industry, or overall economy into goods,
services, and generates income. The success of construction projects is closely related to the production of machinery [3,4]. Machine manufacturers generally provide optimal hourly production from their machines to users. This ideal hourly production is called nominal hourly production, which is distinctly different from actual hourly production in construction projects. Actual production depends mainly on the conditions of the sites of the project. Estimation of actual production and hence the discrepancies between the nominal and actual production rate is an essential element in assessing the time and cost required to finish construction. To estimate production, it is very important to know how different the project site conditions affect the machinery production [2].

2. Methodology
One of the most important methodologies used in solving engineering problems is modeling. Many variables can be analyzed and modeled with similar data, and the results can be used in several applications [6]. In this paper, two types of forecasting systems were employed to establish the predicted model of productivity to estimate wet ready mixed concrete (WRMC) plant production, and dry ready mixed concrete (DRMC) plant production. The first one is a statistical method which is represented by multi-linear regression (MLR). The second one is an Artificial Intelligence (AI) which is represented by Artificial Neural Network (ANN) and support vector machines (SVM).

2.1. Model Database
The factors that involved in this context are based on the actual data of batch plant which conducted during observation and documentation processes of the concrete production. Generally, the data are classified into input or independent variables and output or dependent variables. The independent variables of DRMC are: times of cement filling \(N_{\text{cement}}\), times of aggregate filling \(N_{\text{aggregate}}\), the width of the conveyor belt of the aggregate \(W_{\text{belt}}\), power of motor for conveyor belt \(P_{\text{Wbelt}}\), the distance between the truck mixer location and the project site \(D\), speed of the truck mixer \(S_{\text{truck}}\), traffic situation \(T\) and the number of truck mixers \(N_{\text{truck mixers}}\). The independent variables of WRMC are: width of the conveyor belt of the aggregate \(W_{\text{belt}}\), power of the motor for the conveyor belt \(P_{\text{Wbelt}}\), times of the loading of the mixing unit \(N_{\text{mixer}}\), distance between the batch plant location and the project site \(D\), speed of truck mixer \(S_{\text{truck}}\), traffic situation \(T\), number of the truck mixers \(N_{\text{truck mixers}}\). While the output or dependent variables are the actual productivity for both (DRMC) and (WRMC).

2.2. Multiple linear regression model (MLR)
Multiple linear regression model (MLR), can be defined as a statistical process to estimate relationships between the variables and it has been employed to develop a statistical model that used for production the forecasting model of the productivity. Eq. 1 represents the general form of Multiple Linear Regression equations and the figure (1) explains the linear regression modeling:

\[ y = w_0 + w_1 x_1 + w_2 x_2 + ... + w_p x_p + e_i \] (1)

Where: \(x_1, x_2, ..., x_p\) are independent variables (input factors), \(w_0, w_1, ..., w_p\) are the coefficients in the linear relationship, and \(e_1, e_2, ..., e_i\) are the errors that create scattering around the linear relationship at each of the \(i = 1\) to \(n\) observations.
2.3. Artificial neural network (ANN)

Artificial neural networks (ANNs) or conduction systems are computational systems that inspired by the biological neural networks that form human brains. It is a form of artificial intelligence that tries to mimic the function of the nervous system and the human brain [7], the concept of ANNs was introduced in 1943 by the neurophysiologist Warren McCulloch and the mathematician Walter Pitts, researches into applications of ANNs have. However, a neural network is an algorithm used in cognitive tasks, such as improvement and learning, which are based on concepts derived from research into brain nature. The artificial neural network has been evolved and employed as an alternative to regression analysis since the propagation algorithm proposal [8].

It can be learned from several input patterns and associated output patterns, through the process named training, the network becomes able to provide solutions to new problems even if incomplete. Generally, two kinds of ANNs tutorials, feed-forward and feedback of ANN. The feedback network itself feeds and is well appropriate for solving problems optimization, while the feed-forward network transmits the information in a forward direction only. Fig. 2 shows an example of the neural network, consisting of an input layer, a hidden layer, and an output layer, all linked with each other.

\[
Y_t = f_0 \left[ \sum_{j=1}^{HN} W_{Oj} \ast f_h \left( \sum_{i=1}^{m} W_{Hij} \cdot X_{it} + b_j \right) + b_o \right]
\]

Where \( Y_t \) is the output, \( f_h \) and \( f_o \) are the hidden and the output neuron activation functions, \( HN \) is number of hidden neurons, \( W_{Oj} \) is the weight of the correlation between jth neurons hidden and outputs neuron, \( m \) is the number of input neurons, \( W_{Hij} \) is the weight of the relationship between ith inputs and jth hidden neurons, \( X_{it} \) is the input, \( b_j \) is the bias of the hidden jth neurons, and \( b_o \) is The resulting neuron bias. Support vector machine (SVM). SVM employs alternative \( \epsilon \) insensitive loss of function which adjusted to involve a measure of distance [9]. However, present the SVM, a brief overview would be introduced on how to create SVM for the problem of regression [10]. Assume \( y \) an observer variable with a real value, \( f(x, \alpha) \) so \( \alpha \in \mathbb{A} \) is a set of real functions including the regression function \( f(x, \alpha_0) \). Now, if set data of training \( \{(x_{11}, y_1), \ldots, (x_{ip}, y_i) \} \times \in \mathbb{R}^N, y \in \mathbb{R} \) is prepared, which x independent
variable (inputs), y dependent variable (outputs), Rn space of N-dimensional vector and r is the space of one-dimensional vector and has a linear function (3):

\[ f(x, \alpha) = (w, x) + b \]  

(3)

where w is the modifiable vector of weight and b is the numerical threshold. An optimal regression function is gained by reducing experimental risk as in Eq. 4;

\[ R_{emp} = \frac{1}{l} \sum_{i=1}^{l} |y_i - f(x_i, \alpha)|_\varepsilon \]  

(4)

The loss, error, function \( L_\varepsilon \) with an \( \varepsilon \) insensitive zone defined as in Eq. 5

\[ L_\varepsilon = \begin{cases} 0, & \text{if } |y_i - f(x_i, \alpha)| \leq \varepsilon \\ |y_i - f(x_i, \alpha)| - \varepsilon, & \text{otherwise} \end{cases} \]  

(5)

Where \( \varepsilon \) represents the zone that the regression function lies within. When the expected value is within the region, the loss becomes zero and if the expected value is outside the area, the loss will be equal to the absolute value of the deviation \( \varepsilon \) [11]. Equivalence to minimize the performance which reflects the objective of SVM to discover the function of \( f(x, \alpha) \) which has the greatest deviation of \( \varepsilon \) from the actual output, for all data of training, [12]. Figure 3 explains \( \xi^* \) and \( \xi \) which can be defined as the parameters represent the slack variables that determine the amount the errors on the samples or They are minimal and upper limits on system output [13]. The constant \( c \) is a predefined value, \( C \) is greater than 0, that determines trade-off among the flatness \( f \) and amount which the deviations more than \( \varepsilon \) are allowable [14].

![Figure 3. The accuracy \( \varepsilon \) and Slack Variable \( \xi \) in SVM.](image)

In respect to the proposed predictive model of the delay in this study, the linear regression doesn’t appropriate. And therefore, kernel (K) for nonlinear mapping is employed to remap the data in the space with a higher-dimensional feature to perform a linear regression [15] as in Fig. 4. [16] and formula (6).

\[ f(x) = (w_0, x) + b_0 \]  

(6)
Figure 4. Non-linear SVM conception.

Many kernels utilized for non-linear regression such as Gaussian function and multilayer perceptron, as shown in Table 1.

Table 1. Popular kernel function

| Type of Classifier                      | Kernel Functions                                      |
|-----------------------------------------|-------------------------------------------------------|
| Linear, dot product, kernel             | $K(x, x_i) = (x^T x_i)$                               |
| Complete polynomial of degree $d$       | $K(x, x_i) = [(x^T x_i)]^d$                           |
| Gaussian RBF                            | $K(x, x_i) = e^{\frac{1}{2}[(x−x_i)^T \Sigma^{-1}(x−x_i)]}$ |
| Multilayer perceptron                   | $K(x, x_i) = \tanh [(x^T x_i) + b]$                   |
| Inverse multi quadric function          | $K(x, x_i) = \frac{1}{\sqrt{||x − x_i||^2 + B}}$     |

3. Results and Discussion

As mentioned previously, the gathering data of dry and wet ready mixed concrete (RMC) were employed to establish the three mathematical models. The first model was depended on the statistical technique which represented by the regression using the statistical product and solutions services (SPSS V. 25) software. The second model was based on (ANN) using Neuframe 4 software. While the third one was depended on support vector machine (SVM) using (WEKA 3.9.1©2016) software.

3.1. MLR Model

A multiple linear regression (MLR) can be used to establish the statistical model and produce the predicted equation for both dry ready mixed concrete (DRMC) and wet ready mixed concrete (WRMC). The final MLR model was established using statistical product and solutions services (SPSS). Table 2. summarizes the factors that were used in developing the MLR equation, the weights and the standard error

Table 2. The summary of DRMC model using MLR

| Factor          | Unstandardized Coefficients | Std. Error |
|-----------------|-----------------------------|------------|
| Constant        | -3.667                      | 6.388      |
| $W_{belt}$      | 82.695                      | 18.703     |
| $P_{belt}$      | 0.084                       | 0.689      |
| $N_{cement}$    | -0.231                      | 0.415      |
| $N_{aggregate}$ | -0.891                      | 1.657      |
| D               | -0.457                      | 0.311      |
| $S_{truck}$     | 0.147                       | 0.064      |
| T               | -1.475                      | 1.815      |
| No. truck mixers| 0.447                       | 0.621      |
Eq. 7 represents the final model used to estimate DRMC productivity.

\[
\text{DRMC Productivity} = 82.69W_{\text{belt}} + 0.084PW_{\text{belt}} - 0.231N_{\text{cement}} - 0.891N_{\text{aggregate}} - 0.457D + 0.147S_{\text{truck}} - 1.475 + 0.447N_{\text{truck mixers}} - 3.667
\]  

(7)

Where:

- DRMC Productivity is the dry ready mixed concrete productivity (m³/h unit)
- \(W_{\text{belt}}\) is the width of the conveyor belt of the aggregate (m)
- \(PW_{\text{belt}}\) is the power of motor for the conveyor belt (kW)
- \(N_{\text{cement}}\) is the number times of the cement filling that calculated by \(\frac{V_{\text{truck}} \times Cc}{M_{\text{cement}}}\) where \(N_{\text{cement}}\) is round up
- \(V_{\text{truck}}\) is a truck volume (m³)
- \(Cc\) is a cement content in (1 m³) of concrete
- \(M_{\text{cement}}\) is a capacity of the cement weight scale of batch plant (kg)
- \(N_{\text{aggregate}}\) is the number times of the aggregate filling that calculated by \(\frac{V_{\text{truck}} \times A_w}{M_{\text{aggregate}}}\) where \(N_{\text{aggregate}}\) is round up.
- \(A_w\) is an aggregate content (kg) in 1 m³ of concrete
- \(M_{\text{aggregate}}\) is the capacity of the aggregate weight scale of batch plant (kg)
- \(D\) is the distance between the truck mixer location and the project site (km)
- \(S_{\text{truck}}\) is the speed of the truck mixer (km/hr)
- \(T\) is the traffic situation.
- \(N_{\text{truck mixers}}\) is the number of truck mixers that available in one hour.

The final model was created to estimate WRMC productivity by using SPSS. Table 3. summarizes the factors that are employed in developing the MLR equation for WRMC which comprises the weights and the standard error.

| Factor            | Unstandardized Coefficients | Beta (β) | Std. Error |
|-------------------|----------------------------|----------|------------|
| Constant          | 7.408                      | 25.431   |
| \(W_{\text{belt}}\) | -3.292                     | 28.973   |
| \(PW_{\text{belt}}\) | 2.189                      | 0.590    |
| \(N_{\text{mixer}}\) | 0.139                      | 1.257    |
| \(D\)          | -2.167                     | 0.600    |
| \(S_{\text{truck}}\) | 0.043                      | 0.175    |
| \(T\)          | 0.393                      | 4.964    |
| \(N_{\text{truck mixers}}\) | 2.656                 | 0.985    |

Eq. 8 represents the final model used to estimate WRMC productivity by MLR.

\[
\text{WRMC Productivity} = -3.29W_{\text{belt}} + 2.19PW_{\text{belt}} + 0.139N_{\text{mixer}} - 2.167D + 0.043S_{\text{truck}} - 0.393T + 2.656N_{\text{truck mixers}} - 7.408
\]  

(8)

Where

- \(N_{\text{mixer}}\) is the number times of the loading the mixing unit for one truck mixer that calculated by:
  \[
  N_{\text{mixer}} = \frac{V_{\text{truck}}}{V_{\text{mixer}}}
  \]
  where \(N_{\text{mixer}}\) is round up.
- \(V_{\text{mixer}}\) is a mixer capacity (m³).
- \(D\) is the distance between the truck mixer location and the project site (km).
3.2. ANN Model

The simulation of the artificial neural network using NEUFRA ME V.4 software was employed in this study that works underlying the mathematical formulas and supervised learning. After the training of DRMC algorithm using ANN successfully, the optimal model of estimating the value of the productivity was determined from the sigmoid transfer function as shown in Eq. 9.

\[
\text{DRMC Productivity} = \frac{P_{\text{Range}}}{1 + e^{(-5.88 \times \text{tanh}(k) + 2.98)}} + P_{\text{min}}
\]  

(9)

Where

- \( P_{\text{Range}} \) is the difference between maximum and minimum values of actual productivity which used in training the network which equal to 85.
- \( P_{\text{min}} \) is the minimum value of actual productivity which used in training the network which equals to 20.

Note before using the equation (k), all the input of variables should be changed between 0 to 1 utilizing the data ranges in the training of ANN model with Eq. 10 applied.

\[
x_n = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}
\]

(10)

\[
k = [-1.2 + 1.78 \times W_{\text{belt}} + 0.042 \times P_{\text{belt}} - 0.024 \times N_{\text{cement}} - 0.058 \times N_{\text{aggregate}} - 0.024 \times D + 0.0068 \times S_{\text{truck}} + 0.007 \times T + 0.0366 \times \text{No. of truck mixers}]
\]

(11)

\[
\cdot N_{\text{cement}}, N_{\text{aggregate}}, W_{\text{belt}}, P_{\text{belt}}, D, S_{\text{truck}}, T, \text{No. of truck mixers}.
\]

The optimum Eq. 12 of the wet ready mixed concrete (WRMC) productivity was a sigmoid transfer function type that was established during the training process of the artificial neural network (ANN).

\[
\text{WRMC Productivity} = \frac{P_{\text{Range}}}{1 + e^{(-8.11 \times \text{tanh}(k) + 4.14)}} + P_{\text{min}}
\]

(12)

Where

- \( P_{\text{Range}} \) is the difference between the maximum and the minimum values of the actual productivity which is used in training the network which equal to 70.
- \( P_{\text{min}} \) is the minimum value of the actual productivity which is used in training the network which equals to 20.

Note before using the equation (k), all the input of variables should be changed between 0 to 1 utilizing the data ranges in the training of ANN model with Eq. 13 and Eq. 14 applied.

\[
x_n = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}
\]

(13)

\[
K = -0.54 - 0.28 \times W_{\text{belt}} + 0.09 \times P_{\text{belt}} + 0.025 \times N_{\text{mixer}} - 0.076 \times D - 0.003 \times S_{\text{truck}} - 0.063 \times T + 0.117 \times \text{No. truck}
\]

(14)

3.3. SVM Model

The training data were used to develop the support vector machine (SVM) model using (WEKA 3.9.1©2016) software. Two models were created; The first model was employed to estimate the dry ready mixed concrete (DRMC) and the second one was used to estimate the wet ready mixed concrete (WRMC). Once the training of the algorithm finished successfully, the optimum equation was found at poly kernel function, whereas C and Epsilon parameters were equal to 0.3 and 0.001 respectively. Eq. 15 represents the best of the DRMC Algorithm using SVM.

\[
\text{DRMC Productivity} = 14.77 \times W_{\text{belt}} + 2.04 \times P_{\text{belt}} - 0.0215 \times N_{\text{cement}} - 0.145 \times N_{\text{aggregate}} - 1.091 \times D + 0.2248 \times S_{\text{truck}} - 2.7768 \times T + 1.1423 \times N_{\text{truck mixers}} + 11.9934
\]

(15)

Eq. 16 represents the optimum model of WRMC productivity after completing the training processes.
WRMC Productivity = 10.0688W_{belt} + 1.447PW_{belt} - 0.904N_{mixer} - 1.9998D + 0.1S_{truck} - 4.7914T + 2.5222N_{truck mixers} + 22.183 \quad (16)

4. Performance and Validation of Model
The validation and performance of the model were satisfied using three common statistical parameters which are used to measure the quantification of the error which are; Mean absolute error (MAE), Root mean squared error (RMSE), and the correlation (r) between the actual and the predicted values of the productivity for validation the data. The validation of the data comprises fifteen batch plant which are not used in the training process. Table 4. presents the performance of DRMC productivity and table 5. shows the performance of WRMC productivity with the different types of modeling techniques.

**Table 4. The performance of DRMC productivity.**

| Performance measure | MLR | ANN | SVM |
|---------------------|-----|-----|-----|
| R                   | 0.91| 0.87| 0.99|
| (MAE)               | 15.46| 12.66| 6.14|
| (RMSE)              | 17.98| 17.82| 6.50|

**Table 5. The performance of WRMC productivity.**

| Performance measure | MLR | ANN | SVM |
|---------------------|-----|-----|-----|
| R                   | 0.52| 0.70| 0.99|
| (MAE)               | 31.84| 25.04| 8.87|
| (RMSE)              | 45.92| 36.23| 12.45|

Figures 5 and 6 present the comparison between the actual productivity and the predicted values calculated using the three modeling techniques. Figures 5 and 6 show that the SVM model is the best followed by the neural network while the regression results are the least because the regression technique is based on the principle of data preservation as for the neural network technique is only acceptable when it is within training limits, as opposed to SVM technique that exceeds the shortage in the two techniques above.

![Figure 5. Predicted and Actual DRMC productivity.](image-url)
5. Conclusion

After obtaining the predicted model of productivity for both the dry ready mixed concrete DRMC and the wet ready mixed concrete WRMC successfully, the conclusion can be summarized as below:

- MLR model presented good results with the validation of training dataset, but poor results with the external dataset. Therefore, the lack of data division into training and testing technique to obtain the minimum risk rate during the process of obtaining the mathematical model.
- ANN model showed satisfying results of the validation dataset with a range of the training dataset and poor results with the data that exceeded the range of the training.
- SVM model produced good results for both the training and the validation dataset, best generalization, where the SVM model was the optimum.
- Generally, the results of the artificial intelligence techniques were more précised than those calculated by the conventional techniques.

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