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Hybrid Model for Calculation Transportation Productivity for Ready Mixed Concrete Business

โดย

รศ. ดร.วลัยลักษณ์ อัตธีรวงศ์

สาขาสถิติ คณะวิทยาศาสตร์
สถาบันเทคโนโลยีพระจอมเกล้าเจ้าคุณทหารลาดกระบัง

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Assoc. Prof. Dr. Walailak Atthirawong

School of Statistics

Faculty of Science

King Mongkut's Institute of Technology Ladkrabang

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TABLE OF CONTENTS

TABLE OF CONTENTS (CON'T)

LIST OF TABLES

LIST OF FIGURES

Chapter 1

Introduction

1.1 Statement and significant of the problems

Ready mixed concrete is a common building material used in the construction of commercial and industrial buildings, roadways, infrastructure and other structures. Ready mixed concrete is a perishable product which is a custom specified and availability of ingredients. Ready mixed concrete delivery has limitation due to capacity of plant batching and delivery time. At the same time, customer behavior constraints are variety such as demand fluctuation, placement size, quantity ordered of a specific mix, delivery location and timing, ordering, accuracy of quantity and so on (Tommelein and Li, 1999). Normally, ready mixed concrete industry is produced concrete at several plants, which have to deliver at customers' construction job sites using a mixer truck fleet in a timely with cost-effective management (Schmid et al., 2009). Based on operations of large size ready mixed concrete company located in Bangkok, Thailand, the variation of ready mixed concrete delivery is crucial. The delivery process is complicated, which has many consideration factors involved including amount of concrete volume, concrete batching time, traveling time, delivery distance, waiting time at job site, concrete pouring time and truck return time. So, it is necessary to manage organization's resources in order to minimize the total delivery time and maximize concrete delivery volume. As a result, the rate of delivery of ready mixed concrete is employed to measure transportation productivity (Graham et al., 2006).

In this research, two hybrid models based on artificial neural network and regression models are employed for modeling ready mixed concrete delivery i.e. (1) hybrid artificial neural network-regression model and (2) hybrid multiple regression-artificial neural network model. Then a performance accuracy of both hybrid models will be compared using root mean square error (RMSE) and mean absolute percentage error (MAPE).

This research differs from previous works in several aspects. The related work of ready mixed concrete delivery problem consider mainly on simulation, optimization, and heuristics techniques, while MR and ANN are applied to predict and model in many industries except in ready mixed concrete delivery problem. In the light of these gaps, this research combines multiple regression (MR) and artificial neural network (ANN) for modeling ready mixed concrete delivery. The benefit of the estimate model will be useful for the management to plan an operation and its resources, thus avoiding shelf-life problem.

1.2 Objectives of the research

1.2.1 To propose 2 hybrid models i.e. (1) hybrid multiple regression-artificial neural network model and (2) hybrid artificial neural network-regression model for predicting productivity of transportation.

1.2.2 To compare the performance accuracy of 2 hybrid models using root mean square error (RMSE) and mean absolute percentage error (MAPE).

1.3 Scope of the study

1.3.1 Data is collected from one of the ready mixed concrete businesses in Thailand from October – December 2012.

1.3.2 Seven explanatory variables affecting transportation productivity are selected to validate the model.

1.3.3 Two hybrid models are compared to predict transportation productivity i.e. (1) hybrid multiple regression-artificial neural network model and (2) hybrid artificial neural network- regression model.

1.4 Benefit of the study

1.4.1 Hybrid model can be used to help business to predict productivity accurately.

1.4.2 The proposed hybrid models can be applied to other businesses.

1.5 Definition of the technical term

1.5.1 Ready mixed concrete is an essential material in contemporary construction and engineering projects. Ready mixed concrete is a mixture of four basic ingredients: sand, rock, cement, as well as chemical compounds known as admixtures, which are mixed with water at a plant and transported directly to a construction site.

1.5.2 Hybrid model is a method to merge two methods in order to improve the prediction accuracy, which can be also referred as combined models or ensemble models and often used synonymously. Hybrid model can be implemented in three different ways, i.e. linear models, nonlinear models and both linear and nonlinear models.

Chapter 2
Literature Review

This chapter will summarize literature survey, which are employed in this research including background of ready mixed concrete, multiple regression analysis (MR), artificial neural network (ANN), hybrid model, and related work in this area.

2.1 Ready mixed concrete

Ready mixed concrete is used as a building material because of two main advantages. The first one is cheaper than other materials such as steel, wood and so on. The second is that ready mixed concrete allows great diversity in design and function, which can be poured into molds of any shape. Ready mixed concrete is a perishable product that needs delivery within 1.5 to 2.5 hours before it becomes too stiff to be workable (Dewar and Anderson, 1992).

Ready mixed concrete is consumed by the construction sector to build infrastructure, commercial and residential building, factories, and so on. Demand of ready mixed concrete is inelastic because it is small part of construction cost. Concrete cost is around 10 % of materials cost for any sector of construction. The other substitution products such as precast concrete, prefabrication concrete and asphalt are major threat for ready mixed concrete business. Therefore, the ready mixed concrete market substantially affects the volume of the construction activity.

Ready mixed concrete is produced by blending cement, aggregate, additives and water which is produced in a factory, and then delivered to construction site by truck mounted transit mixers. Ready mixed concrete is also referred as the customized concrete products for commercial purpose and different specific applications. The process of ready mixed concrete production and delivery directly affects to total cost. In high competition market like Thailand, companies in the ready mixed concrete industry are facing the several problem e.g. peak period scheduling, long delivery distance, fluctuated demand, low selling price, high raw material cost and transportation cost, long credit term, high marketing cost, cost-effective manner and so on. The risk of ready mixed concrete goods is that should be laid in the period without any loss of time to avoid the reduction in workability, setting and stiffening of concrete. The time interval in between batching and pouring concrete is very critical. The delay in delivery process reduces the workability of ready mixed concrete, which effect to the difficulty in placement of ready mixed concrete. At the same time, the delay lead to the initial setting and stiffening of concrete, that effect to be unusable goods. So, the transportation of ready mixed concrete must be performed as rapidly as possible.

2.2 Research methodologies

2.2.1 Multiple regression analysis

Multiple regression (MR) approach is a statistical method to investigate the relationship between one dependent variable and two or more independent variables (Pindyk and Rubinfeld, 1991). The independent variables are also called the predictors. Relationships may be nonlinear, independent variables can be continuous, categorical or both and one can examine the effects of a single variable or multiple variables with or without the effects of other variables taken into account (Cohen et al., 2003).

$$y_i = \beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \ldots + \beta_k x_{i,k} + \varepsilon_i \qquad (2.1)$$

Where β_0 = regression constant

β_k = coefficient on the k^{th} predictor

k = total number of predictors

$x_{i,k}$ = value of the k^{th} predictor

ε_i = random error in Y for observation i

The model of equation *(2.1)* is estimated by least squares method, which yields parameter estimates such that the sum of squares of errors is minimized. The prediction equation is

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{i,1} + \hat{\beta}_2 x_{i,2} + \ldots + \hat{\beta}_k x_{i,k} + \varepsilon_i \qquad (2.2)$$

Where "^" = estimated values

The error term in equation *(2.1)* is unknown because the true model is unknown. Once the model has been estimated, the regression residuals are defined as follows:

$$\varepsilon_i = y_i - \hat{y}_i \tag{2.3}$$

Where y_i = the observed value of the dependent variable for observation i

$\hat{y}_i$ = the predicted value of the dependent variable for observation i

The residual or estimated error measures the closeness of fit of the predicted values and actual predictor in the calibration period. The algorithm for estimating the regression equation (solution of the normal equations) guarantees that the residuals have a mean of zero for the calibration period. The variance of the residuals measures the "size" of the error and is small if the model fits the data well.

2.2.1.1 R, R Square, Adjusted R Square

R is a measure of the correlation between the observed value and the predicted value of the criterion variable. A partial coefficient of determination (R^2) is a measure of the strength of the relationship between the dependent variable and independent variable, when the linear effect of the rest of the variables is being eliminated. R^2 indicates the variation in Y that is explained by the independent variable X in the simple regression model (Berenson et al., 2006). However, R^2 tends to rather over estimate the success of the model when applied to the real applications, so an Adjusted R Square value is calculated which takes into account the number of independent variables in the model and sample size. This Adjusted R Square value gives the most useful measure of the success of the model. For example, if Adjusted R Square value is equal to 0.85, it implies that the model has accounted for 85% of the variance in the criterion variables (Osborne, 2000).

2.2.1.2 Multicollinearity

The term multicollinearity (or collinearity) is used to describe the situation when a high correlation is occurred between two or more predictor variables. Such high correlations cause problems when trying to draw inferences about the relative contribution of each predictor variable to the success of the model (Osborne, 2000).

2.2.2 Artificial neural network

Artificial neural network (ANN) is a mathematical structure designed to mimic the information processing functions of a network of neurons in the brain (see Figure 2.1). ANN that respond to inputs through modifiable weights, thresholds, and mathematical transfer functions that process information through many interconnected units are highly parallel systems. Each unit processes the pattern of activity it receives from other units, and then broadcasts its response to still other units. ANN is particularly well suited for problems in which large datasets contain complicated nonlinear relations among many different inputs (Minsky and Papert, 1988).

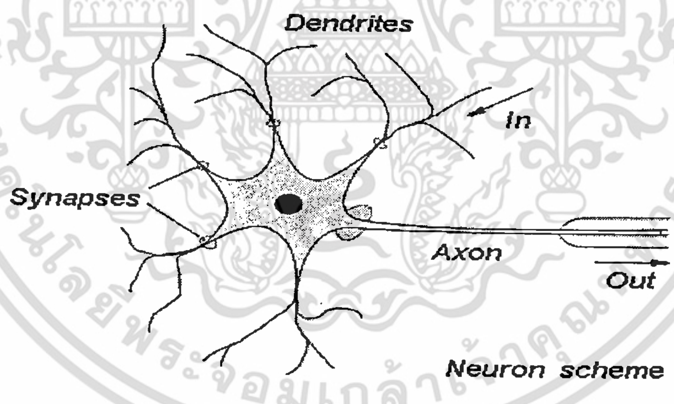

Figure 2.1: Schematic of biological neuron

Source: http://home.agh.edu.pl/~vlsi/AI/intro/

ANN is flexible nonlinear model capability that can approximate a large class of functions with a high degree of accuracy. The prediction of this experiment is used multi-layer perceptron (MLP). MLP consists of a large class of feed forward neural network with hidden nodes between the input and output nodes. All nodes in a layer are connected to all nodes in the adjacent layers through unidirectional links and all links are represented by connection weights. ANN architecture encompasses three nodes, input, hidden, and output node, which shown in Figure 2.2.

The input-output elements are trained by using a back propagation learning algorithm. The data feed forward is the relationship between input and output presented as following;

$$y_i = f(\sum_{j=1}^{N_h}(\mu_{ij} f(\sum_{k=1}^{N_i} w_{jk} x_k + \theta_j) + \lambda_i)). \qquad (2.4)$$

Where y_i = the output of *i-th* node

x_k = the input of *k-th* node

μ_{ij} = the connective weight between hidden node and output node

w_{ij} = the connective weight between input node and hidden node

θ_j or λ_i = bias term, which is the threshold of the transfer function

N_i = the number of nodes in input

N_h = the number of nodes in hidden node

N_o = the number of nodes in output node

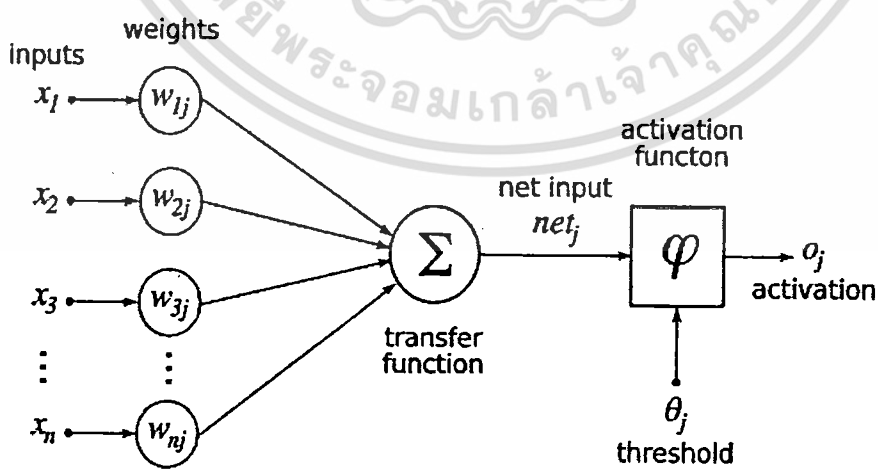

Figure 2.2: Structure of artificial neural network model

Source: http://en.wikibooks.org/wiki/Artificial_Neural_Networks/Activation_Functions

The hidden node transfer function *f* is selected as sigmoid function. Figure 2.3 shows graph of a sigmoid function The sigmoid function has the property of being similar to the step function, but with the addition of a region of uncertainty. It is given by the relationship as follows:

$$f(x) = 1/[1+\exp(-x)] \tag{2.5}$$

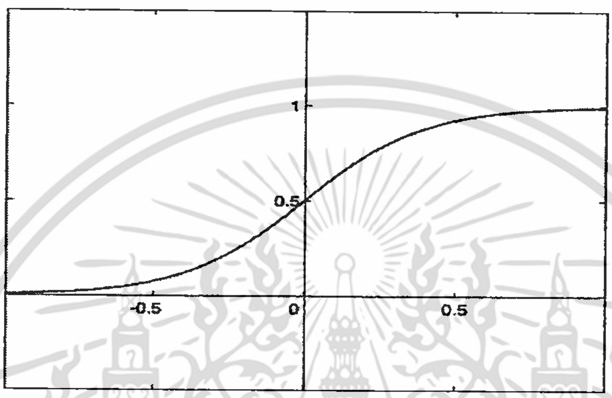

Figure 2.3: Graph of a sigmoid function

Source: http://en.wikibooks.org/wiki/Artificial_Neural_Networks/Activation_Functions

The system has error back-propagation during trained network. To monitor the performance of the network, the system is used error function as following;

$$E(w) = \sum_{p=1}^{P} (\sum_{i=1}^{N_o} (y_i^p - o_i^p)^2 \tag{2.6}$$

Where *E (w)* = the system error function

y_i^p = the actual value of output node *i* for training pattern *p*

o_i^p = the predicted value of output node *i* for training pattern *p*

P = the number of sample

The ANN model procedure starts from collecting the related data. The architecture and parameter are architecture, learning rate, momentum, and epoch. All weights are selected randomly to train. The minimum error is employed to predict the future outcome (Witten and Frank, 2005).

2.3 Literature review

Graham et al. (2006) presented a neural network methodology in ready mixed concrete delivery by comparing two main architectures i.e. a feed-forward network and an Elman network.Many combinations of layers, training algorithms, number of neurons, activation functions and format of data were considered in the study. The results were validated using an independent validation data set with five goodness-of-fit tests. The results indicate that two- and three-layer feedforward networks provide the best estimates of concrete placing productivity and that the Elman network

Fernandes and Teixeira (2008) presented the artificial neural network methodology for forecasting the tourism time series. This study developed models and apply them to sensitivity studies in order to predict the demand. It provided a deeper understanding of the tourism sector in Northern Portugal and contributes to already existing econometric studies by using the artificial neural networks methodology. This work focused on the treatment, analysis, and modeling of time series representing "Monthly Guest Nights in Hotels" in Northern Portugal recorded between January 1987 and December 2005. The model used 4 neurons in the hidden layer with the logistic activation function and was trained using the resilient back propagation algorithm. Each time series forecast for 12 preceding values. The analysis of the output forecast data of the selected ANN model showed a reasonably close result compared to the target data.

Pao (2008) proposed a comparison of neural network and multiple regression analysis in modeling capital structure of the high-tech and traditional industries in Taiwan, respectively. Results of this study showed that the determinants of capital structure are different in both industries. The major different determinants are business-risk and growth opportunities. Based on the values of RMSE, ANN models achieved a better fit and forecast than regression models for debt ratio, and ANN models are able of catching sophisticated non-linear integrating effects in both industries.

Lu and Lam (2009) presented simulation and optimization of computer system, which provided decision support making the best operation strategy for plant managers in order to deliver concrete to multiple site customers. The computer system can be used in practical to serve as a useful parallel to the actual system for enhancing performance, optimizing the best concrete production scheduling, planning truck fleet resources and arranging the pouring time.

Schmid et al. (2009) presented hybrid solution approach for ready mixed concrete delivery which integrated optimization and heuristic techniques. The information of multi-commodity flow component and variable neighborhood search component are considered to find the reasonable time. The high quality solutions of both components are acceptable of producing feasible solution. On the other hand, the integrated approach is more effective which outperformed 6% more than an average.

Areekul et al. (2010) presented an approach for short-term price forecast based on combination of ARIMA and ANN. The linear ARIMA model and the nonlinear ANN model were used to analyze different forms of relationship in the time-series data. They verified the predictive ability of the proposed method by simulations three different cases price forecasting of ARIMA, ANN, and hybrid model approach. The results showed that hybrid model method could provide overall forecasting capability improvement of the price forecasting accuracy and gives better predictions than either ARIMA or ANN.

Delijaicov et al. (2010) synthesized a model for peen forming process planning. Statistical methods based on MR and ANN were applied to a data set generated by peen forming designed experiments with aluminum alloy plates, aiming to synthesize quantitative models relating the highest displacement of the plate with the respective variables of the process. The results showed that the estimated displacements from both models comply reasonably well with the experimental data, the obtained results exposed the superiority of the regressive model concerning accuracy.

Ján and Katarína (2010) conducted hybrid ARIMA-neural network model to predict aggregate water consumption. The hybrid model can complement each other in capturing patterns and internal dependencies of time series. The hybrid prediction method was used for prediction of water consumption based on time series collected and the hybrid ANN outperforms the individual forecasting model.

Liu et al. (2010) proposed combinatorial predict model of enterprise profit based on stochastic partial elasticity theory and ANN. Nonlinear model was established to solve the combinatorial weighted coefficients by advance the predict accuracy to get a new predict value. Numerical simulation results showed that the new predict model of enterprise profit has strong generalization ability and could improve the predict accuracy effectively.

Merh et al. (2010) developed hybrid models ANN and ARIMA for forecasting the future index value and trend of Indian stock market. Simulation have been done using prices of daily open, high, low and close of SENSEX, BSE IT, BSE Oil & Gas, BSE 100 and S& P CNX Nifty. Simulation results of hybrid models were compared with results of ANN based models and ARIMA based models.

Zheng and Zhong (2010) proposed a hybrid methodology that combines both radial basis function (RBF) neural network and auto regression (AR) model based on binomial smoothing (BS) technique which is efficient in data processing. This method was examined by using data of Canadian Lynx. Empirical results indicated that the over-fitting problem can be eased to improve forecasting accuracy by using hybrid methodology.

Zhang et al. (2011) presented mathematical model in order to improve the operation of ready mixed concrete production as well as to decrease the dispatching cost of the whole delivery process. They considered both trucks and pump dispatching. Genetic algorithm was proposed to solve the large size of solution space.

Aladag et al. (2012) presented a new hybrid model approach combining ARFIMA and feedforward neural network (FNN) to analyze long memory time series by applying in tourism data in Turkey. Data were collected fro the number of tourists coming to Turkey during 1995-2005. Mean absolute percentage error (MAPE), and root mean square error (RMSE) were employed to compare the performance accuracy. The best forecast models were obtained by using ARFIMA and FNN2 (1-1-1). The results showed that via using only FNN model are ineffective for long time series data.

Chanprasopchai and Atthirawong (2012) proposed EBITDA calculation methodology based on commercial margin (CM) prediction by hybrid ANNs - regression and hybrid multiple regression (MR) - ANNs models for ready mixed concrete (RMC) business, which both hybrid models are suited to evaluate EBITDA. The CM accuracy performance was measured by mean absolute percentage error (MAPE), and root mean square error (RMSE), that can imply to calculate EBITDA. Commercial margin from both models was conducted to calculate EBITDA and compared for business proposed. The EBITDA results revealed that mean absolute deviation (MAD), and tracking signal of hybrid MR-ANNs model is lower than another model. Therefore, it can be claimed that hybrid MR-ANNs model is more suitable approach to evaluate EBITDA based on commercial margin prediction in RMC business between two techniques.

Anyaeche and Ighravwe (2013) conducted artificial neural network, Back Propagation Artificial Neural Network (BP-ANN), as an alternative predictive tool to multi-linear regression, for establishing the interrelationships among productivity, price recovery and profitability as performance measures. A 2-20-20-1 back propagation artificial neural network was proposed to predicting performance measures. Productivity and price recovery were used as independent variables while profitability was used as dependent variable in the BP-ANN architecture. It was indicated that BA-ANN model has mean square error (MSE) lower than multiple linear regression. The study concluded that artificial neural network is more efficient tool for modeling interrelationships among productivity, price recovery and profitability. This approach can be help to predict performance measures of firms.

To sum up, simulation, optimization, and heuristics techniques have been widely considered in a number of studies on ready mixed concrete delivery problem, for instance: Lu and Lam (2009); Schmid et al.(2009) and Zhang et al. (2011) and so on. At the same time, multiple regression (MR) and artificial neural network (ANN) are widely applied in many applications but it is still rare in ready mixed concrete business. According to the former studies, it has been claimed that over-fitting problem can be eased to improve forecasting accuracy by using hybrid methodology. In the light of these gaps, this research will employ hybrid models based on MR and ANN for modeling ready mixed concrete transportation productivity. Two hybrid models will be compared their accuracy for the target data in RMC. The benefit of the estimate model will be useful for the management in this business to plan an operation and its resources, thus avoiding shelf-life problem.

Chapter 3

Research Methodology

3.1 Ready mixed concrete transportation

Ready mixed concrete has a shelf life roughly around one and a half hour (ASTM International, 2004). As a result, both a batching plant and customers need to rely on time restriction constraint. Ready mixed concrete batching is operated at plants that mixing ingredients to be concrete and then load concrete into the mixer truck. The quality and quantities are fully control by computer system, which can be automated or semi-automated procedure. The concrete batching time is measured in order to optimize operation plan. Concrete is transited to construction site by using mixer truck that is considered by their volume, delivery distance and traveling time. In many cases, the construction site is not ready to pour concrete into customer's construction structure. Therefore, it is necessary to wait at job site until pouring process can be fixed. The main effects of pouring time are the difference of experience, equipment and behavior of customers. The last step is return mixer truck to the batching plant. Figure 3.1 shows a whole concrete delivery process starting from batching plant transformed raw material into concrete, truck mixer traveling to construction site, waiting time in order to pour concrete at job site, pouring concrete, until returning truck to batching plant respectively. According to the whole process of concrete delivery, Table 3.1 demonstrates the specific variables employed in this research in order to measure transportation performance of ready mixed concrete business.

Figure 3.1: Ready mixed concrete delivery process

Table 3.1: Dependence variables employed in this research

Variables	Descriptions	Unit
Concrete volume	The amount of ready mixed concrete is placed at the construction job site.	Cubic mater
Delivery distance	The length of transportation route is measured between batching plant and construction job site.	Kilometer
Batching time	The time is needed to blend raw material to be concrete including unload into mixer truck.	Minute
Travelling time	The duration is used during transit concrete from batching plant and construction job sit.	Minute
Waiting time	The period is measured from mixer truck arrived at construction site until unload concrete.	Minute
Pouring time	The period is determined unloading concrete from mixer truck to the construction site.	Minute
Returning time	The duration is used during return truck from construction site and batching plant.	Minute
Productivity	The transportation productivity is calculated to measure the performance.	Cubic meter per minute

The risk of ready mixed concrete goods is that should be laid in the period without any loss of time to avoid the reduction in workability, setting and stiffening of concrete. The time interval in between batching and pouring concrete is very critical. The delay in delivery process reduces the workability of ready mixed concrete, which effect to the difficulty in placement of ready mixed concrete. At the same time, the delay lead to the initial setting and stiffening of concrete, that effect to be unusable goods. So, the transportation of ready mixed concrete must be performed as rapidly as possible.

3.2 Proposed model

This research presents two approach hybrid models in order to optimize ready mixed concrete transportation modeling, which are (1) hybrid artificial neural network-regression (ANN-regression) model and (2) hybrid multiple regression-artificial neural network (Multiple

Regression-ANN) model. The experimental procedure of two hybrid models is demonstrated in Figure 3.2.

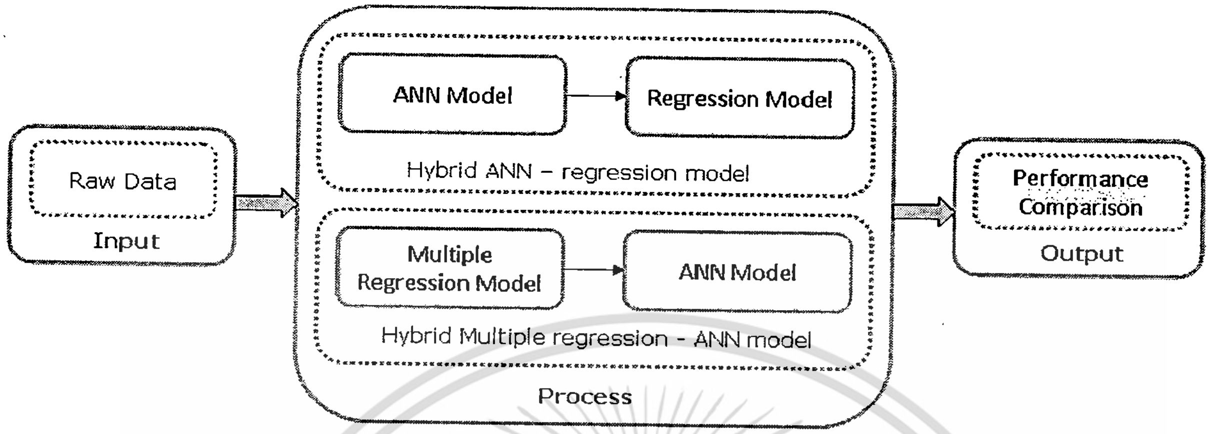

Figure 3.2: Experimental framework of two hybrid models

Hybrid models have been proposed to predict transportation productivity. Regression /multiple regression models have achieved successes based on linear relationship. On the other hand, ANN model is more suitable for non-linear relationship. However, neither regression/multiple regression nor ANN is suitable for all aspects. Hybrid model can combine the strength of regression/multiple regression and ANN models to capture both linear and non-linear relationship. The hybrid model can be written as following:

$$Y_t = N_t + L_t \tag{3.1}$$

Y_t is the hybrid model at time t,

N_t is the non-linear component at time t, and

L_t is the linear component at time t.

Hybrid ANN-regression model is the combination of ANN with regression model. The non-linear and linear component can solve and analyze the data in order to evaluate transportation productivity. The proposed hybrid ANN-regression scheme is displayed in Figure 3.3.

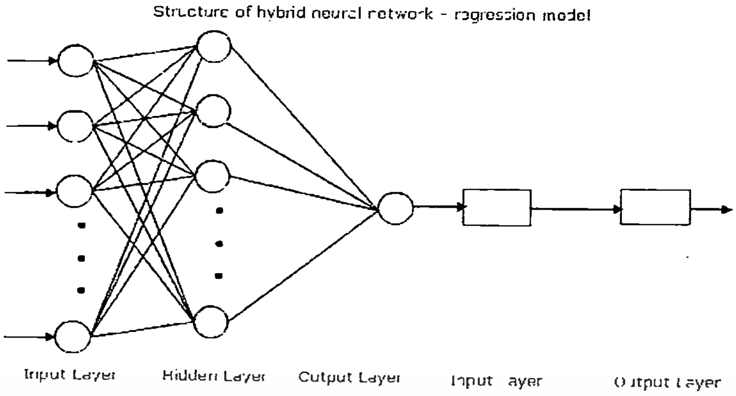

Figure 3.3: Structure of hybrid ANN-regression model

The hybrid multiple regression with ANN model is combined multiple regression with ANN model, which has the same component as hybrid ANN-regression model. The proposed hybrid multiple regression-ANN model is demonstrated in Figure 3.4.

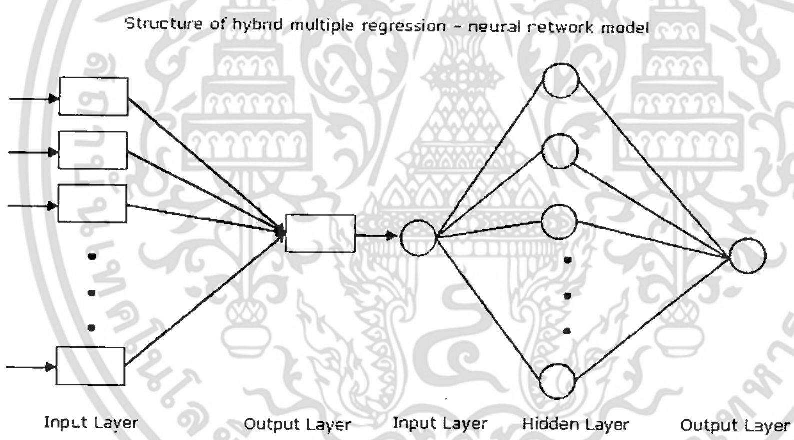

Figure 3.4: Structure of hybrid multiple regression-ANN model

In this research, the back propagation neural network learning algorithm is utilized to train the networks using WEKA software. The related parameters including learning rate, learning momentum, training epochs and hidden node are determined to obtain the optimum solution (Atthirawong and Chatchaipun, 2005). The experimental design presented in Table 3.2 was developed to generate ANN model. The parameters have been determined by trial and error in order to evaluate the optimal solution.

Table 3.2: The experimental design for ANN model

Parameters	Experimental design
Number of layers	3 layers (Input: 1, Hidden: 1, Output 1)
Activation function	Sigmoid
Learning rate	0.1 - 0.9
Momentum	0.1 - 0.9
Number of iteration	500, 1000, 5,000, 10,000 and 50,000
Number of instance	843

3.3 Data collection

The study area is located in greater Bangkok, which has traffic congestion. The mixer truck has capacity only 6 cubic meters because of law and regulation. The total 843 trips of ready mixed concrete delivery with all relevant variables were recorded during October to December 2012 in order to develop both hybrid models. Table 3.3 shows statistical information values, which were collected from the field.

Table 3.3: The statistical values of ready mixed concrete delivery

Variables	Unit	Min	Max	Mean	Median	SD
Concrete volume	m^3	0.25	6.00	4.66	5.00	1.30
Distance	Kilometer	0.10	23.15	7.49	6.50	6.27
Batching time	Minute	2.22	46.22	14.85	14.17	6.32
Travelling time	Minute	1.00	95.00	17.80	16.02	10.94
Waiting time	Minute	0.02	97.12	12.52	7.05	14.47
Pouring time	Minute	0.47	155.78	27.45	28.43	25.53
Returning time	Minute	1.00	92.02	15.26	13.00	12.14
Productivity	m^3/min	0.28	12.24	3.75	3.28	1.98

3.4 Performance comparison of two hybrid models

The actual and predicted data are then compared performance accuracy. In this research, the performance accuracy of both models are evaluated using mean absolute percentage error (MAPE) and root mean square error (RMSE), which are calculated by equations (3.2) and (3.3) respectively.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100 \qquad (3.2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2} \qquad (3.3)$$

The value of MAPE and RMSE will be compared in order to evaluate the performance. The model, which has the lower MAPE and RMSE, will be superior and then used in prediction transportation productivity.

Chapter 4

Empirical Results

This chapter presents the analysis of 2 proposed hybrid models. The results of hybrid multiple regression-artificial neural network model will be presented in Section 4.1, and the results of hybrid artificial neural network-regression model will be presented in Section 4.2. Then, the comparison results will be demonstrated in Section 4.3.

4.1 Results of hybrid multiple regression - artificial neural network model

4.1.1 Statistical analysis of the correlated inspection results

As mentioned earlier in Chapter 3, in this research, transportation productivity is considered as a dependent variable. Whereas, seven independent variables are employed to predict transportation productivity, which are concrete volume per trip (Cubic meter: X_1), delivery distance (Kilometer: X_2), batching time (Minute: X_3), travelling time (Minute: X_4), waiting time (Minute: X_5), pouring time (Minute: X_6) and returning time (Minute: X_7).

At the beginning step of the research, it is necessary to test whether the model is unaffected multicollinearity issue. As such, correlation values between independent variables were conducted (Table 4.1). In order to reconfirm whether there is no problem with multicollinearity, the Durbin – Watson and VIF test were further investigated. The ranging value of Durbin – Watson should be in between 1.5 and 2.5 (Atici, 2011) and VIF value should lower than 20 (Pao, 2008). Table 4.2 shows the results of VIF test. It is indicated that both Durbin – Watson (1.83) and VIF tests are complied well.

Table 4.1: Correlation values between independent variables

X_i^a	X_1	X_2	X_3	X_4	X_5	X_6	X_7
X_1	1						
X_2	0.03	1					
X_3	0.27	0.03	1				
X_4	0.02	0.06	0.04	1			
X_5	0.17	-0.03	0.07	-0.09	1		
X_6	-0.13	-0.01	-0.01	0.02	-0.02	1	
X_7	-0.06	0.04	0.02	0.05	-0.09	0.09	1

Table 4.2: Results of VIF test

Variables	VIF value
X_1: Concrete volume	1.128
X_2: Deliver distance	1.544
X_3: Batching time	1.080
X_4: Travelling time	1.650
X_5: Waiting time	1.042
X_6: Pouring time	1.028
X_7: Returning time	1.402

4.1.2 Multiple regression analysis

Multiple regression analysis was then developed in order to be an input in a hybrid model. Table 4.3 shows regression statistic results. R^2 value is closely to 1, which can be claimed that the model is acceptable.

Table 4.3: Regression statistic results

Regression statistics	value
Multiple R^2	0.96356
R^2	0.92845
Adjust R^2	0.92674
Standard error	1.13882

Table 4.4 presents the results of statistics summary form multiple regression model. Concrete volume per trip, deliver distance, batching time, travelling time, waiting time, pouring time, and return time variables were performed significant confidence at 99 % level (p - value < 0.01) while distance variable was performed significant confidence at 95 % level (p – value < 0.05).

Table 4.4: Results of ANOVA for ready mixed concrete delivery

	β	Standard error	t-value	p-value
Concrete volume	1.2935	0.02454	36.0942	0.00**
Deliver distance	- 0.0092	0.00598	-2.1085	0.03*
Batching time	- 0.0165	0.00496	-10.2694	0.00**
Travelling time	- 0.0353	0.00354	-14.4371	0.00**
Waiting time	- 0.0392	0.00213	-20.5561	0.00**
Pouring time	- 0.0243	0.00120	-27.7891	0.00**
Returning time	- 0.0223	0.00294	-10.8420	0.00**

Multiple regression model can be written as the following equation:

$$Y = 1.2935*Volume - 0.0092*Distance\ \text{time} - 0.0165*Batching\ time - 0.0353*Travelling\ time - 0.0392*Waiting\ time - 0.0243*Pouring\ time - 0.0223*Return\ time \quad (4.1)$$

4.1.3 Development of artificial neural network model

The results from Section 4.1.1 are used as an input in artificial neural network model to optimize ready mixed concrete delivery model. Artificial neural network was analyzed by using multilayer perceptron feed forward structure .The experimental design, presented in Table 3.2 in Chapter 3, was develop to generate the ANN model. The collected data were randomly selected 70% to be the training set of ANN, while the rest 30% were prepared for validation (Kumar et al., 2013). The optimal potential structure of ANN model (in terms of MSE) for ready mixed concrete transportation productivity (Y) is shown in Table 4.5.

Table 4.5: Optimal potential structure of ANN model

Parameters	Optimal potential structure
Structure	7:7:1
Learning rate	0.3
Momentum	0.6
Iteration	50,000
Trained : Tested	70:30

The results from Table 4.5 are then used to predict the value of Y. The comparison between actual and predicted values of transportation productivity is exhibited in Figure 4.1. The result indicates that the relationship between actual and predicted data of this model is not fit well.

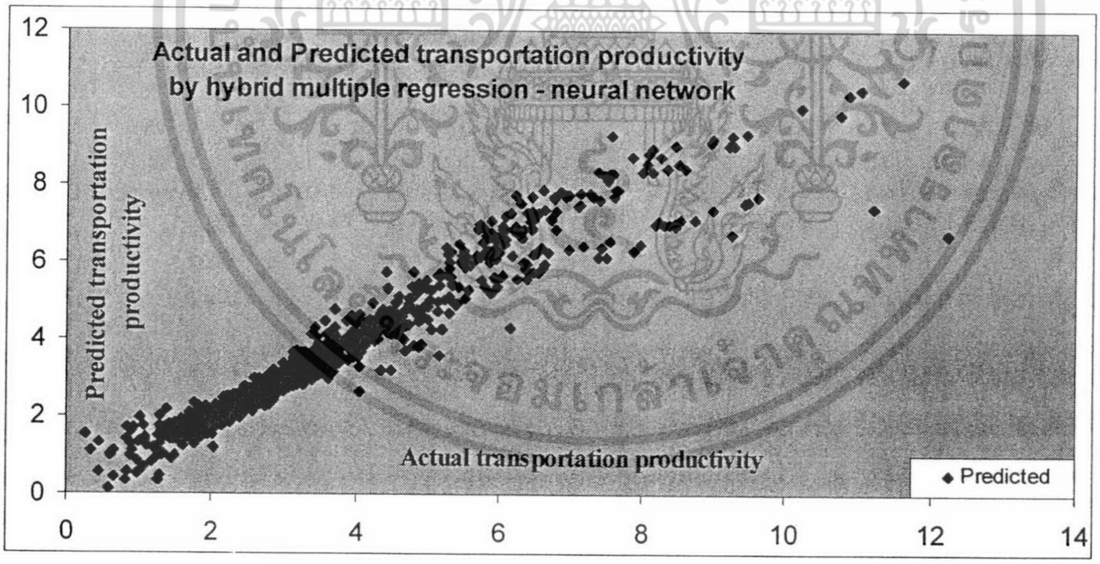

Figure 4.1: Performance of hybrid multiple regression– artificial neural network model

4.2 Results of hybrid artificial neural network - regression model

4.2.1 Development of artificial neural network model

Artificial neural network was analyzed by using multilayer perceptron feed forward structure to optimize ready mixed concrete delivery model. The experimental design presented in Table 3.2 in Chapter 3 was develop to generate the ANN model. The collected data were randomly selected 70% to be trained the proposed ANN, while the rest 30% were prepared for validation (Kumar et al., 2013). The optimal potential structure of ANN model for ready mixed concrete delivery is shown in Table 4.6. The mean square error is used in training the proposed NN architecture, after training the proposed model, the optimal results of ANN model is obtained as shown in Table 4.7.

Table 4.6: Optimal potential structure of ANN model

Parameters	Optimal potential structure
Structure	7:7:1
Learning rate	0.4
Momentum	0.7
Iteration	50,000
Trained : Tested	70:30

Table 4.7: Optimal results of ANN model

Optimal potential structure	
Correlation	0.9995
Mean absolute error	0.0166
Root mean square error	0.03299
Relative absolute error	1.1318%
Root relative square error	1.7718%

4.2.2 Development of Regression Model

For the second proposed hybrid model, the dependent variable is transportation productivity and the independent variable is the output data obtained from ANN model. Tables 4.8 and 4.9 show results from ANOVA and regression statistics, respectively. F ratio was significant indicating the overall explanatory power of this model. The coefficient of determination (R^2) was found to be 0.9997 indicating that 99.97 percent of transportation productivity was explained by independent variable. From the regression analysis, independent variable which obtained from ANN model did have a significant influence on transportation productivity.

Table 4.8: Measure of variation in regression

	df	SS	MS	F	p- value
Regression	1	3294.607611	3294.608	3983657	0.0000***
Residual	841	0.695532982	0.000827		
Total	842	3295.303144			

Table 4.9: Regression output

Regression Statistics	
Multiple R	0.999894460
R Square	0.999788932
Adjusted R Square	0.999788681
Standard Error	0.028758145
Observations	843

Table 4.10: The least-square method result

	Coefficients	Standard Error	t Stat	p-value
Intercept	-0.00783551	0.002127647	-3.68271	0.000246***
Predicted	1.00209456	0.000502074	1995.91	0.000000***

Then, the point-to-point comparison between actual and predicted values via using hybrid neural network with regression model is given in Figure 4.2. The results show that the relationship between actual and predicted transportation productivity of hybrid neural network with regression model is closely to linear relationship.

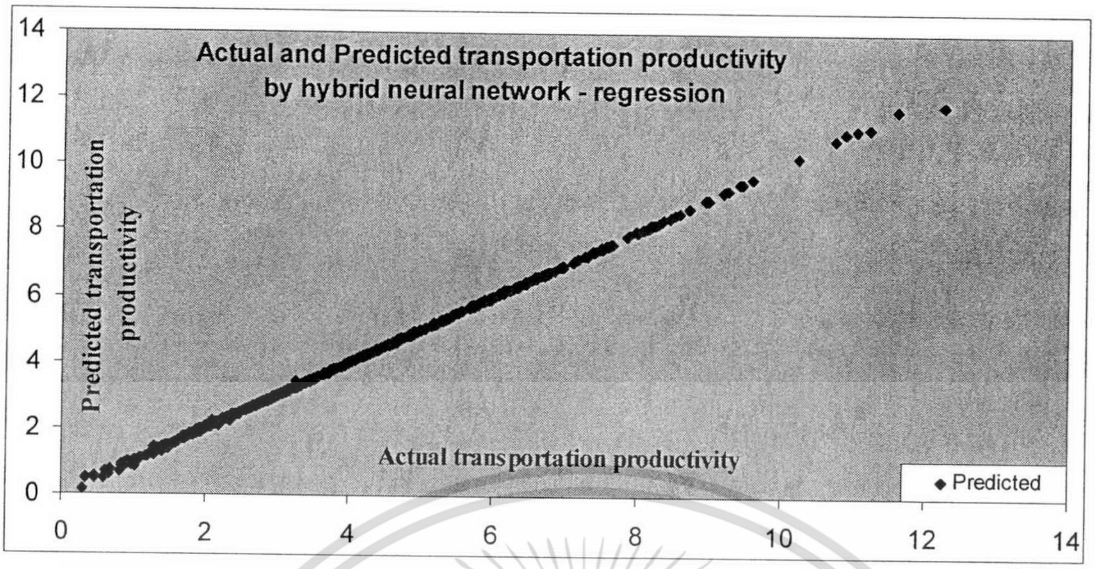

Figure 4.2: Performance of hybrid artificial neural network–regression model

4.3 Performance evaluation

The performance measurements of transportation productivity from both models are compared by using mean absolute percentage error (MAPE) and root mean square error (RMSE). Table 4.11 shows the comparison results of MAPE and RMSE values of both hybrid models. The result indicates generally that the error from hybrid neural network with regression model is lower than hybrid multiple regression with artificial neural network model. Therefore, it can be summarized that combining hybrid artificial neural network with regression model has a better performance than combining multiple regression with artificial neural network.

Table 4.11: Performance comparison

Models	RMSE	MAPE
Hybrid artificial neural network–regression model	0.028724	0.860352
Hybrid multiple regression-artificial neural network model	0.519427	10.830478

Chapter 5

Conclusion and Future Directions

5.1 Conclusion

Ready mixed concrete delivery models are implemented to investigate transportation productivity, which depend on variant variables including concrete volume, delivery distance, batching time, travelling time, waiting time, pouring time and returning time. Hybrid artificial neural network–regression and hybrid multiple regression–artificial neural network models were developed to predict the ready mixed concrete transportation productivity using actual collected data from the case company in greater Bangkok, Thailand. 843 trips of transportation delivery were observed from October to December 2012.The actual values and predicted transportation productivity values were compared in order to measure the performance accuracy of the both models. The predicted values of hybrid artificial neural network - regression model were found closely to the actual values more than another proposed model. Moreover, the values of RMSE and MAPE of hybrid artificial neural network - regression model is lower than hybrid multiple regression-artificial neural network model. The following conclusions are drawn from this study:

Hybrid artificial neural network-regression model is better alternative approach for developing ready mixed concrete transportation productivity model than hybrid multiple regression-artificial neural network model. The findings suggest that due to the unstable or changing patterns in the data, using hybrid model can reduce such uncertainty. However, by fitting multiple regression model first to the data, the over fitting problem is more strongly than fitting with ANN first. The reason for this could be explained that ANN model is more suitable for non-linear relationship than multiple regression model, so it can be capable of accuracy for uncertainty data. Therefore, fitting ANN first to the data could provide accurate estimates of the productivity of transportation delivery process.

5.2 Directions for future research

Continued work could be undertaken to compare other ANN architectures; for instance, Elman recurrent neural network. Additionally, it can be studied the effect of the training set on the model performance (Graham et al., 2006). Furthermore, the ready mixed concrete transportation productivity model can be considered other techniques in order to compare performance; for example, fuzzy logic, genetic algorithm and so on. Future studies may also replicate this study by looking at other independent variables which may affect transportation delivery.

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