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EBITDA based on commercial margin prediction by hybrid model for ready mixed concrete business

Pratchaya Chanprasopchai and Walailak Atthirawong

King Mongkut's Institute of Technology Ladkrabang (KMITL), Bangkok, Thailand

Abstract. This paper proposes 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. The CM from both models was conducted to calculate EBITDA and compared for business proposed. The EBITDA results reveal that mean absolute deviation (MAD), and tracking signal of hybrid MR - ANNs model is the lowest. As such, it can be claimed that the hybrid MR - ANNs model is more suitable approach to evaluate EBITDA based on commercial margin prediction in RMC business between two techniques.

Keywords: EBITDA; ready mixed concrete; commercial margin; hybrid artificial neural networks - regression; hybrid multiple regression - artificial neural networks; tracking signal

Introduction

EBITDA is defined as Earnings Before Interest, Tax, Depreciation, and Amortization that is a key measure operating performance of a company without having factors in capital structure, depreciation policies, financing and accounting decisions, and tax rate environment. EBITDA can be used as a shortcut to estimate the cash flow available to pay debt on long term asset, used to compare profitability between companies against each other and against industry averaged, and used to approximate the fundamental earning power expenditures needed to maintain those operations. EBITDA is very useful tool because it is universal measurement of ongoing profitability that is now commonly quoted by many companies, especially in technology sector [1] as well as ready mixed concrete business.

Related work

Based on a literature survey, Regression, and Artificial Neural Networks (hereafter ANNs) have been conducted in predicting areas for a number of decades. In recently years, hybrid approaches have been combined in order to reduce the forecasting error and to make predictions more accuracy. For instance, Arjan J. Brouwer and Benton E. Gup [1] examined the use of EBITDA by companies from Europe's largest capital markets, and discussed the benefits and shortcomings of this measure. Malcolm Baker and Richard S. Ruback [2] analyzed industry multiple for the S&P 500 for 22 industries and considered the performance of four common multiples: the simple mean, the harmonic mean, the value weighted mean, and the median. They showed that EBITDA is a better single basis of substitutability than EBIT or revenue in the industries. Juan J. Flores et al. [3] presented a hybrid approach by using evolutionary computation to produce a complete design of a neural network for modeling and forecasting time series. The hybrid models had proven to be better than the ARIMA models produced by a statistical analysis procedure and hand-made ANNs. Fengxia Zheng and Shouming 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 the data of Canadian Lynx data. Empirical results indicated that the over-fitting problem can be eased to improve forecasting accuracy by using hybrid methodology. To sum up, this study differs from previous works in several aspects such as relationship between quantitative variables, considering business proposed, and so on. In the light of these gaps, this paper conducts two proposed approaches i.e. (1) hybrid ANNs - regression and (2) hybrid MR – ANNs in order to calculate EBITDA based on commercial margin prediction in ready mixed concrete business and compare their accuracy. The empirical study aims to specify hypotheses concerning the nature of effects, as well as explanatory factors and produce a quantitative estimate of net effects. In addition, the proposed hybrid approaches will combine the strength of MR and ANNs techniques.

Background and data selection

Regarding ready mixed concrete (RMC) business, the concrete product use cement, aggregate, additives and water which is produced in a factory, and then deliver to construction site by truck mounted transit mixers. Generally, EBITDA is an indicator of a company's financial performance that measures by computing earnings from core business operation as following [5]:

EBITDA = Revenue - Expenses (excluding tax, interest, depreciation and amortization) (1)

We propose the method to calculate EBITDA based on CM as following;

EBITDA = Commercial margin - Fixed cost (2)

The main 12 factors affecting CM consist of credit term condition (day, X1), volume demand (cubic meter, X2), delivery distance (kilometer, X3), product price list (THB, X4), extra charge (THB, X5), promotion discount (THB, X6), promotion rebate (THB, X7), freight cost (THB, X8), carrying receivable (THB, X9), marketing cost (THB, X10), raw material cost (THB, X11) and other variable production costs (THB, X12) have also been gathered as explanatory variables for predicting CM in RMC business [6].

Methodology and model development approach

The experiment procedure can be divided into 2 models i.e. (1) Hybrid ANNs - Regression (2) Hybrid Multiple Regression - ANNs. The experimental framework is illustrated in Fig. 1.

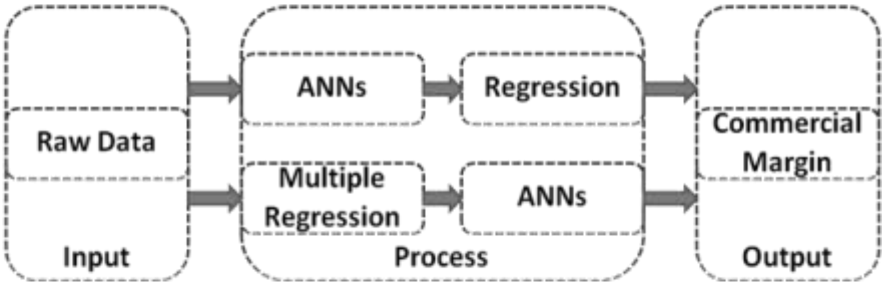

Fig. 1. Experimental framework

ANNs approach

The prediction of this experiment is used multi - layer perceptron (MLP). MLP consists of a large class of feed forward neural networks 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. The input - output elements are trained by using a back propagation learning algorithm. The data feed forward, the relationship between input and output, is presented as following [7]:

$$y_i = f(\sum_{j=1}^{N_h}(\mu_{ij} f(\sum_{k=1}^{N_i} v_{jk} x_k + \theta_j) + \lambda_i)). \tag{3}$$

The hidden node transfer function f is selected as Sigmoid function as following:

$$f(x) = 1/[1+\exp(-x)] \tag{4}$$

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

$$E(w) = \sum_{p=1}^{P}(\sum_{i=1}^{N_o}(y_i^p - o_i^p)^2 \tag{5}$$

The ANNs model consist of architecture, learning rate, momentum, and epoch. All weights are selected randomly to train. The minimum error is employed to predict the future outcome. Multilayer perceptron (MLP) is a function that learns through back propagation algorithm, which multilayer perceptron pseudo-code is explained as following:

Step 0. Initialize weights and biases.
Step 1. While stopping condition is false, do steps 2-9.
Step 2. For each training pair, do steps 3-8.
Step 3. Feed forward: Each input unit (x_k , *k = 1, . . ., N*$_i$) receives input signal x_k and broadcasts this signal to all units in hidden layer.
Step 4. Each hidden unit (μ_{ij} *; j = 1, . . . , N*$_h$ *; k = 1, . . . , N*$_i$) sums its weighted input signals, and applies its transfer function f to compute its output signal, $f(\sum_{k=1} v_{jk} x_k + \theta_j)$, and sends this signal to all units in the output layer.
Step 5. Each output unit (μ_{ij} *; i = 1, . . . , N*$_o$ *; k = 1, . . . , N*$_i$) sums its weighted output signals, and applies its transfer function f to compute its output signal, eq. (3).
Step 6. Back propagation of error: Each output unit (y_i *; i = 1, . . . , N*$_o$) receives a target pattern corresponding to input training pattern, system error function term, eq. (5).
Step 7. Each hidden unit (μ_{ij} *; j = 1, . . . , N*$_h$ *; k = 1, . . . , N*$_i$) sums its data inputs from units in the output layer, and multiplies by its transfer function f to calculate its system error function term, eq. (4).
Step 8. Each output unit (y_i *; i = 1, . . . , N*$_o$) updates its weights and bias, and each hidden unit (μ_{ij} *; j = 1, . . . , N*$_h$ *; k = 1, . . . , N*$_i$) updates its weights and bias.
Step 9. Test stopping condition.

Multiple regression approach

Multiple regression, MR, is a flexible method of data analysis that can appropriate whenever a quantitative variable is to be examined in relationship to any other factors [8]. A multiple regression equation for predicting Y can be expressed as following:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn \tag{6}$$

Hybrid model approach

Regression model has achieved successes based on linear relationship. On the other hand, ANNs model is more suitable for non-linear relationship. However, neither regression nor ANNs is suitable for all circumstances. Hybrid model approach can, therefore, combine the strength of regression and ANNs models to capture both linear and non-linear relationship [9]. Both Hybrid ANNs - regression and MR - ANNs are combined two method together, which is shown in Fig. 2.

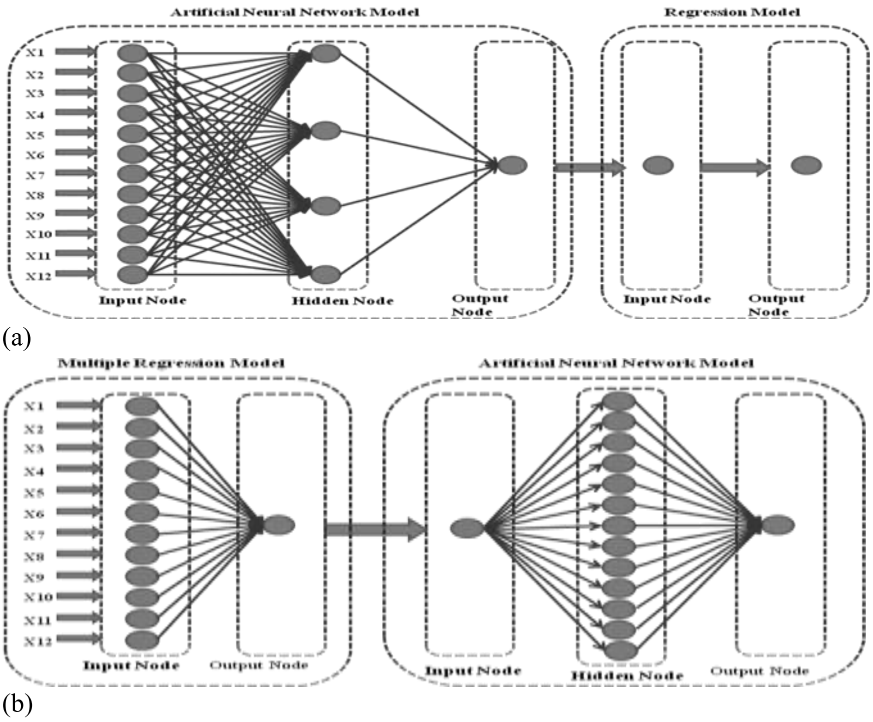

Fig. 2. Structure of Hybrid ANNs - Regression (a) and MR - ANNs (b) models

Evaluation

The actual CM and predicted CM from both models are compared and the forecast accuracy is computed by calculating two different evaluation statistics. Mean absolute percentage error (MAPE), and root mean squared error (RSME) are applied to measure the error between actual and prediction values in this experiment [10, 11]. The formulas are shown as following:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2} \tag{8}$$

EBITDA is calculated by equation (2). The actual EBITDA and EBITDA based on commercial margin prediction are evaluated and compared each predicted models and find the way to minimize the error. The other forecast accuracy measurement for business proposed is conducted by mean absolute deviation (MAD) and tracking signal which are widely used to measure predicting accuracy. Mean absolute deviation (MAD) can be calculated as following [10, 11]**:**

$$MAD = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right| \tag{9}$$

Generally, tracking signal is a method that can be used to control predicting value and to monitor the quality of predicting which can be written as following [10, 11]:

$$TrackingSignal = \frac{1}{MAD}\sum_{t=1}^{n}(Y_t - \hat{Y}_t) \tag{10}$$

The tracking signal can be ranged within ±8 while the accepted values are generally within ±4, which depend on each industries and environments [11].

Experimental results

The results of predicted CM compared with the actual CM from both models are shown in Fig. 3. The results show that the relationship between dependent variable and independent variable is closely to linear. The performance measurement of predicting CM from both methods are analyzed by MAPE and RSME which shown in Table 1. Regarding the experimental results, it can be indicated that the predicted CM from both methods are closely the actual CM. It can confirm by experimental results that the accuracy of predicting CM can lead to estimate EBITDA. So, predicting CM by both methods can be used to evaluate EBITDA. EBITDA value from two models is derived and evaluated by equation (2). The EBITDA results from both models are employed to evaluated accuracy with MAD and tracking signal. The predicting performance and comparison are shown in Table 2.

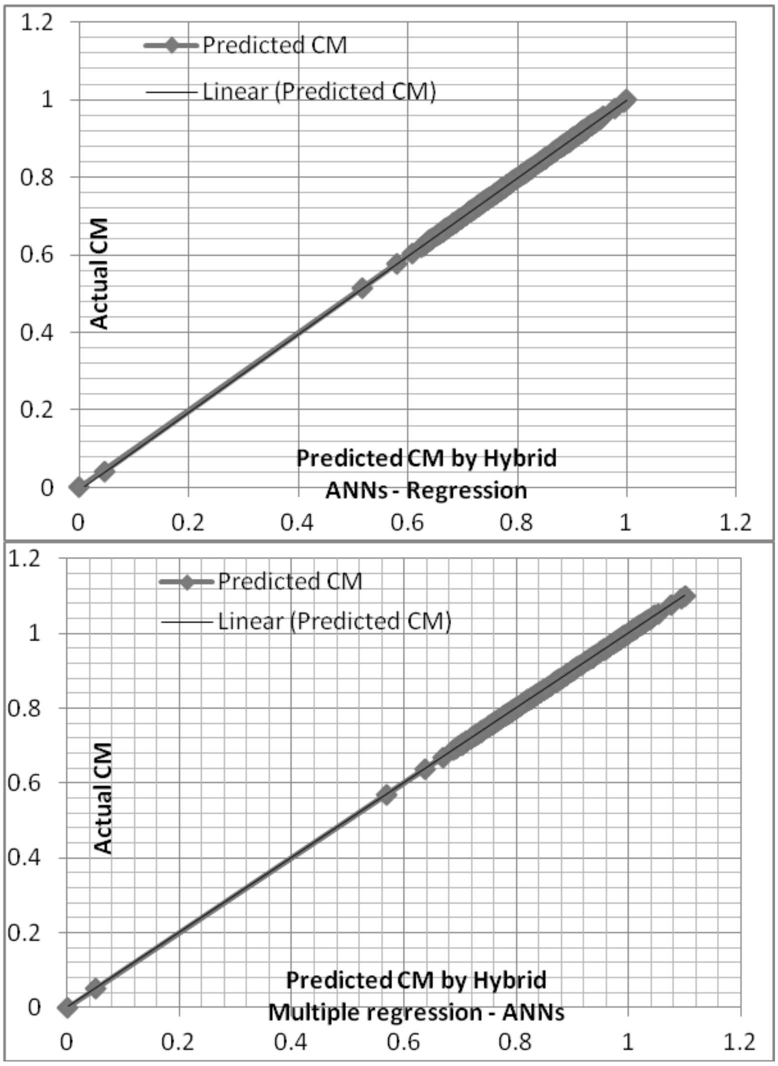

Fig. 3. Actual and Predicted performance for the validation set by both hybrid models

Table 1. CM performance measurement.

Model	*MAPE*	*RMSE*
Hybrid ANNs – Regression	0.8253	0.4047
Hybrid Multiple Regression – ANNs	0.5284	0.1212

Table 2. EBITDA performance comparison.

Model	*MAD*	*Tracking Signal*
Hybrid ANNs – Regression	0.1340	-2.7157
Hybrid Multiple Regression – ANNs	0.0401	0.4711

The value of MAD and tracking signal from both models indicate that they comply well with the experimental data. The comparison of MAD value can imply that EBITDA calculation based on commercial margin prediction from hybrid multiple regression - ANNs model is better than hybrid ANNs - regression model which is confirmed by the value of tracking signal. As the results from the experiment, it can be concluded that hybrid multiple regression - ANNs model is more suitable to evaluate EBIDA based on CM predicting in RMC business.

Conclusion and further work

Theoretical and review literature recommend that the hybrid model will generate lower variance and can decrease model uncertainty. Regarding this study, the experimental results of hybrid multiple regression - ANNs is generally better than hybrid ANNs - regression approach in order to evaluate EBITDA based on CM prediction using MAD and tracking signal performance measurement, which will help business to calculate EBITDA effectively. Future interesting issue is the possibility of developing a model by incorporating other methods including case base reasoning and fuzzy logic. Lastly, the other statistics models may lead to better performance.

References

Arjan J. Brouwer and Benton E. Gup (2008). EBITDA: Down but not out. Department of Economics, Finance and Legal studies working paper series index: 08-08-03. The University of Alabama. www.cbu.ua.edu.

Malcolm Baker and Richard S. Ruback (2000). Estimating industry multiples. Division of research of the Harvard Graduate School of Business Administration.

Juan J. Flores, Roberto Loaeza, Hector Rodriguez, Federico Gonzalez, Beatriz Flores and Antonio Terceno Gomez (2009). Financial time series forecasting using a hybrid neural - evaluative approach. XV SIGEF Congress, Economic and Financial Crisis: New Challenges and Perspectives: 1-9.

Fengxia Zheng and Shouming Zhong (2010). Time series forecasting using a hybrid RBF neural network and AR model based on binomial smoothing. International Journal of Information and Mathematical Sciences, Vol. 6, No. 3: 208 – 212.

Martin Fridson and Fernando Alverez (2011). Financial Statement Analysis: A Practitioner's Guide. 4th ed., John Wiley & Sons, Inc., Hoboken, NJ.

Pratchaya C. and Walailak A. (2011). Commercial margin prediction based on multiple regression and neural network for ready mixed concrete business. 1st International Symposium on Technology for Sustainability (APS002), Bangkok, Thailand, January 25-29, 2012.

S. J. Li and Y. X. Liu (2006). An improved approach to nonlinear dynamical system identification using PID neural networks. International Journal of Nonlinear Sciences and Numerical Simulation, Vol. 7: 177–182.

Cohen, J., Cohen, P., West, S. G., and Aiken, L.S. (2003). Applied Multiple Regression/ Correlation Analysis for the Behavioral Sciences. 3rd ed., Mahwah, NJ: Lawrence Erlbaum Associates.

Phatchakorn Areekul, Tomonobu Senjyu, Hirofumi Toyama and Atsushi Yona (2010). A hybrid ARIMA and neural network model for short-term price forecasting in deregulated market. IEEE Transactions on Power Systems, Vol. 25, No. 1: 524-530.

Naroumon Y. and Siripun S. (2010). Safety stock based on consumption forecast by the artificial neural network. International Conference on Software and Computing Technology (ICSCT 2010), October 18-19, 2010, Vol. 1: 254–258.

R.Dan Reid and Nada R. Sanders (2010). Operations Management and Integrated Approach. John Wiley & Sons, Inc., Hoboken, NJ.