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CO_2 Emissions Forecast in Precast Concrete Production

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Abstract: With increasing demands for detailed estimations of environmental impacts of construction materials, this research was intended to produce a CO_2 emissions forecasting model in precast concrete production using Artificial Neural Network (ANN). Due to its ability to correlate non-linear and non-unique problems, ANN has received increasing attention for forecasting applications in recent years. Prior to the model development, questionnaires were distributed to 107 precast concrete plants throughout Japan to obtain actual data related to all indicators contributing the CO_2 emissions in the production. The dimensionality of the indicators was reduced by Principal Component Analysis (PCA), and further used as inputs in developing the CO_2 emissions model. Here after, the significant indicators consisted of ordinary Portland cement, coarse aggregates, fine aggregates, heavy oil, kerosene and electricity. A three-layer perceptron with backpropagation neural network approach was proposed to train the network. Different numbers of hidden neurons, distributions of data sets, learning rate, and momentum were tested in such a way to minimize the error between actual and forecasted output. The network model with 51 hidden neurons using a set of 0.1, 0.9 and 0.3 for learning rate, momentum and initial weight, respectively, produced the best result. Shown with a MAPE value of less than 10%, this developed model shows an excellent accuracy in forecasting the CO_2 emissions for future use. Validation using sensitivity analysis also proved that the model produced negligible impacts on CO_2 emissions due to variations of the six significant indicators.

Keywords: CO_2 emissions, forecast, precast concrete, artificial neural network

1. Introduction

The demand of precast concrete construction is progressively increasing year by year with tendencies toward high rise construction. Despite several advantages that precast concrete can offer, such as precision of measurement for members, improvement of material quality, short period of works, reduction of workforces at site, the increase of precast concrete consumption also leads to one of the biggest environmental problems as an emission contributor (Wimala, et al., 2012). The production of cement itself has been known to be responsible for about 5% to CO_2 man-made emissions across the world (WBCSD, 2015). However, the emissions generated from the whole precast concrete industry remain uncertain until now. The number will certainly be much greater if the amount of emissions from other sources along the concrete life cycle is taken into account (Wimala, et al., 2012). Pre-observations indicated that several individual companies within the concrete industry in Japan have examined their specific emitted carbon emissions.

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Constraints such as no standard or guideline and lack of tools regarding this issue has nonetheless led to the absence of some parties ever quantified the emissions as a whole. As the world is striving toward increased environmental awareness and sustainable development, it is appropriate that the major contributor of the anthropogenic Greenhouse Gases (GHG)'s should be properly quantified.

Although everyone agrees that forecasting the future is hard, yet it is still needed because some plans have to be made. Forecasting is still the only tool to gain insight how something may unfold in time. It is the process by which one party ponders and prepares for the future. It involves forecasting the future outcomes of various decisions, such as project, resource, financial and marketing planning as short, as well as long-term objectives for the greatest benefit. Due to the absence of the forecast model of CO_2 emissions in precast concrete production, this research aims to develop the model using Artificial Neural Network (ANN) by considering significant indicators that are responsible to the emissions.

By knowing the foreseeable relevant information, appropriate preventive as well as improvement measures to promote the reduction of environmental impact can be planned. It helps the parties concerned to prevent losses by making the proper decisions. For example, this model can be used in dealing with the policy such as tax reduction for each precast concrete company that can cut back its emission and permission to transfer the emission reduction requirements across time. Based on the forecast, the company can arrange the best strategy and manage the cash flow for a few years ahead in order to avoid any loss in the future. Aside from its application for future use, the developed CO_2 emissions model can also be used for the benefit of the present for different cases. Whatever it is, the results can be issued by the precast concrete company as emissions report accurately to a third party for public disclosure. This approach is one of the many ways to market companies as a green corporation. The companies will be publicly recognized for their efforts and achievement and as a result, it will enhance the reputation, and improve response to increasing requests from the customers and the socially responsible investment community. In a larger scale, the CO_2 emissions model can be used as one of the tools to help realizing the three flexible mechanisms as stated in the Kyoto Protocol, i.e. Emission Trading (IET), the Clean Development Mechanism (CDM) and Joint Implementation (JI). One country can organize and make some plans to purchase the GHG credits from elsewhere, through financial exchanges, implement some projects in developing countries, etc.

2. Significant Emissions Indicators

A set of questionnaires was carried out to indicate indicators that were responsible for the CO_2 emissions in precast concrete production. The questionnaires were distributed either directly or indirectly to several precast concrete plants and related professional associations. As a result, 12 indicators from 107 plants of precast concrete production all around Japan, categorized as two main groups, i.e. material and energy, were believed to be responsible for generating the CO_2 emissions. However, in order to produce a highly accurate CO_2 emissions model, the best inputs are certainly needed in the development. Using Statistical Package for the Social Sciences (SPSS), Principal Component Analysis (PCA) was performed to determine which ones of the 12 indicators are the significant ones by reducing the dimensionality of the data set (indicators). After following the appropriate procedure of PCA, it was concluded that 6 indicators, i.e. ordinary Portland cement, coarse aggregate, fine aggregate, heavy oil, kerosene and electricity were mostly contributing to the CO_2 emissions in precast concrete production. Hereafter, these 6 indicators were used as inputs for the development of the CO_2 emissions model using ANN.

3. Development of CO_2 Emissions Model

Over the past two decades, ANN has gained immense popularity due to their ability to learn from past examples and derive explicit relationships that are difficult to formulate using traditional methods of computing (Chandwani, et al., 2015). ANN, also called as artificial neural nets or neural nets, is the first successful attempt that closes to a computational system that can mimic the human brain. Unlike conventional computers which employ specific algorithms to solve particular problems, ANN operates by learning the experiences and examples. It is analogous to human who often learns by trial and error and therefore a network must be trained by repeatedly fed input data and output data. After sufficient number of training iterations, the network learns to recognize patterns in the data (between input and output data). In effect, it creates an internal model of the process governing the data. Then, the internal model can be used to forecast the new input conditions. For that reasons, ANN has the capability to handle problems involving data that are imprecise or noisy as well as that are highly non-linear and complex (Bhagat, 1990). Hence, it can provide a relatively easy way to model and forecast non-linear systems (Goonatilake and Treleaven, 1995). In general, ANN models are specified by network topology, node characteristics, and training or learning rules.

In supervised learning, the input connections of the artificial neurons are summed up to determine the strength of their output, which is the result of the sum being fed into an activation function (Matulja, et al., 2010; Choundhary and Mirja, 2014). The resultant of this function is then passed as the input to other neurons through more connections, each of which are weighted and these weights determine the behavior of the network (Nissen, 2005; Goyal, and Goyal, 2012). Initially, all the weights in the network are set to random values, the network learns by adjusting the weight in such a way as to reduce the difference between the network's calculation of what the output value should be and the actual value (Gyang, et al, 2015).

In this research, a fully connected three-layer perceptron (1 input layer, 1 hidden layer and 1 output layer) with backpropagation algorithm was applied in the ANN. The objective is to correlate the indicators which responsible in producing the CO_2 emissions in precast concrete production. As mentioned earlier, the 6 indicators produced from the previous analysis were used as the inputs. The amount of CO_2 emissions was used as the output of this ANN forecast model. The input data were normalized between the interval of (0,1) before they were applied to the neural network mode due to the different range of magnitude of the 6 indicators. Rows of input matrices with large magnitude variation can dominate the value of the output. These make the inputs with small magnitude difference seem to be irrelevant to the forecasting process.

The activation function can be adjusted for each layer to which it will propagate. For a three-layer perceptron, it meant in hidden and output layer. In the hidden layer, sigmoid function was chosen here due to the fact that it has been very useful for most of the neural network applications (Bahkary, 2001; Gomes, et al., 2010; Zadeh, et al., 2010; Zainun, 2012). It was needed to introduce non-linearity into the network, thus making the neural network more powerful than just plain perceptron. Meanwhile in the output layer, the linear function was applied because it has been proved more useful when the output is a continuous variable with unknown bounds, as opposed to several outputs which represent categories for example (Jordan, 1995).

The influences of different combinations of number of hidden neurons and distribution of data sets to ANN performance were further investigated to produce the best forecasting model of CO_2 emissions. A trial and error approach was taken to formulate the most reliable network architecture. Here, the data were divided into three sets: training, test, and production sets. Table 1 shows the list of parameters, i.e. number of hidden neurons, distribution of data sets, and learning rate and momentum which were adjusted in developing the model. Combinations between these three parameters were then tested. The initial weight was set to be 0.3, representing a range of values from -0.3 to +0.3 and used in randomized order. The simulation stopped after reaching 40,000 epochs, or when the desired error reached a value of 0.001 between the actual and forecasted values. By these criteria, the developed network deemed to have fulfilled all the requirements before it can be used to forecast the CO_2 emissions.

Table 1 - Different Parameters Tested in ANN

No. of Hidden Neurons	Distribution of Data Sets		Learning Rate and Momentum	
1 to 60	Set I	10 10 80*	Comb. I	0.1 and 0.9
	Set II	15 15 70*	Comb. II	0.3 and 0.7
	Set III	20 20 60*	Comb. III	0.5 and 0.5
			Comb. IV	0.7 and 0.4
			Comb. V	0.9 and 0.1

*The sequence of numbers indicates the percentage of data numbers as training, testing and production data, respectively

3.1 Performance Analysis

As the network training progressed, the total error, that is the sum of the errors over all the training sets, will get smaller (Chesshireeng, 2003). Once the network reduces the total error to the limit set, training may stop. As the result, the network can be applied using the weights and thresholds as trained. In this research, coefficient of multiple determinations (R^2) was used to assess the forecasting performance of the neural network model. A perfect fit would result in an R^2 value of 1, a very good fit near 1, and a very poor fit less than 0 (Wardsystems, 2008; Toraman and Ural, 2014). With as y actual/desired/target values, $\hat{y}$ as the forecasted value of y, and $\bar{y}$ as the mean/average of y values, the R^2 is formulated as following:

$$R^2 = 1 - \frac{\Sigma\left(y-\hat{y}\right)^2}{\Sigma\left(y-\bar{y}\right)^2} \tag{1}$$

3.2 Validation/Forecast Accuracy

To compare the performance of ANN models, it is necessary to ascertain the developed models on unseen data, i.e. production data set. This situation tends to be closest to the actual forecast situation. As the most common method for validation, Mean Absolute Percentage Error (MAPE) was applied to measure the forecasting ability or accuracy among various ANN models. It basically measures the deviation between actual and forecast outputs. The smaller the MAPE value, the closer the predictive value is to the actual value. MAPE is usually expressed in percentage and defined by a relationship between actual/desired/target value (y), forecasted value ($\hat{y}$) and number of forecasts (n) with the following equation:

$$MAPE = \frac{\left| \frac{(y - \hat{y})}{y} \times 100\% \right|}{n} \tag{2}$$

4. Sensitivity Analysis

At different times, it is likely that the data will vary from the ones obtained for this study. Sensitivity analysis was conducted to investigate how different values of a set of 6 significant indicators affect the CO_2 emissions forecast under certain specific conditions. In performing the analysis, 3 sets of 80 randomly selected data were separated from the previous 107 data, trained and tested based on several parameters as stated in Table 1. The sensitivity value was obtained by comparing the R^2 results for different sets of data. In this case, the distribution of each data set was only differentiated into 10 10 80 and 20 20 60.

5. Results

After thousand series of trial and error using different combinations of parameters as shown in Table 1, the highest R^2 values for various distributions of data sets, as well as learning rates and momentums are shown in Figure 1. The results show that high-performance networks have been produced in this research, marked with R^2 values of above 0.9. The difference between the highest and lowest R^2 was only 0.19%. The highest R^2, 0.9984, was shared by a 10 10 80 network using a learning rate of 0.1 and momentum of 0.9, a 10 10 80 network using a learning rate and momentum of 0.5 each, and a 15 15 70 network using learning rate of 0.7 and momentum of 0.4.

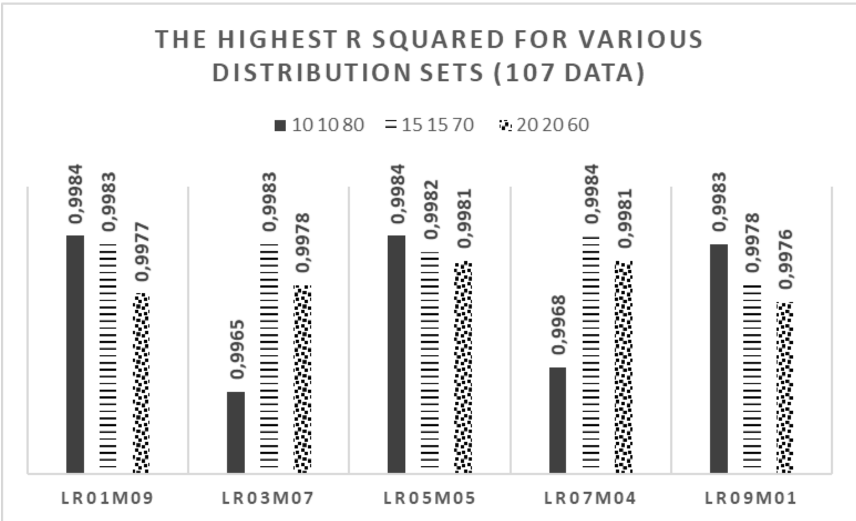

Fig. 1 - R^2 values of the best networks for three types of data distributions with different combinations of learning rates and momentums

Figure 2 resumes the results regarding the R^2 and MAPE values for each distribution of data set. It indicates that the first distribution of data set (10 10 80) produced 0.9984 of R^2 and 1.31% of MAPE value. The second distribution of data set (15 15 70) generated 0.9984 of R^2 but higher MAPE value than the one of 10 10 80, which was 5.26%. Meanwhile, the third distribution of data set (20 20 60) produced the highest R^2 of 0.9981 and 5.6% of MAPE value. As the main finding in this research, based on 107 data, the best ANN model for forecasting the CO_2 emissions was produced by distributing the data into 80% of training data, 10% of test data and another 10% of production data, using 6 neurons in input layer, 51 neurons in hidden layer, and 1 neuron in output layer, trained with learning rate of 0.1 and momentum of 0.9.

Figure 3 presents the resume of the highest R^2 and MAPE values for various sets of data with two different distributions of data set. The R^2 values between different sets of data, as well as different distributions of data sets did not show much differences. The results of 10 10 80 were slightly higher than those of 20 20 60. It proved that with the greater amount of training data set, better result would be obtained. The values of MAPE illustrated good results for various data sets, with various distributions. The lowest accuracy of a network was shown by the highest MAPE value of 10.24%. In the contrary, the best network with the highest accuracy was indicated by the lowest MAPE value of 0.21%. Only two of the networks had the MAPE values of more than 10%, however, they were still considered to be accurate forecasts. The rests were regarded to be very accurate.

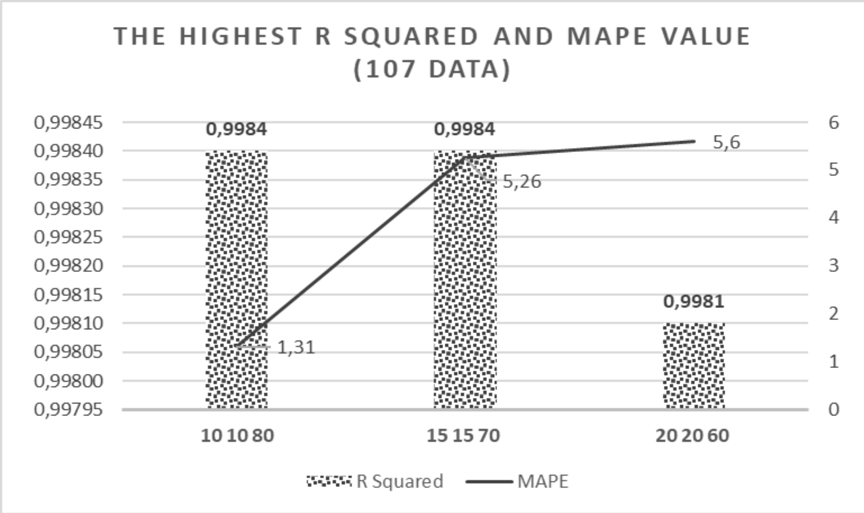

Fig. 2 - R^2 and MAPE values of the best networks for each distribution of data set

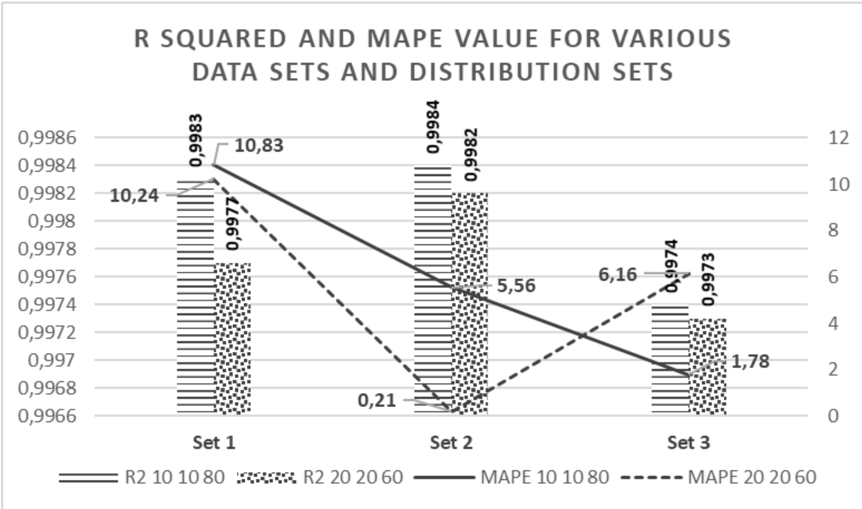

Fig. 3 - R^2 and MAPE values of the best networks for each data set

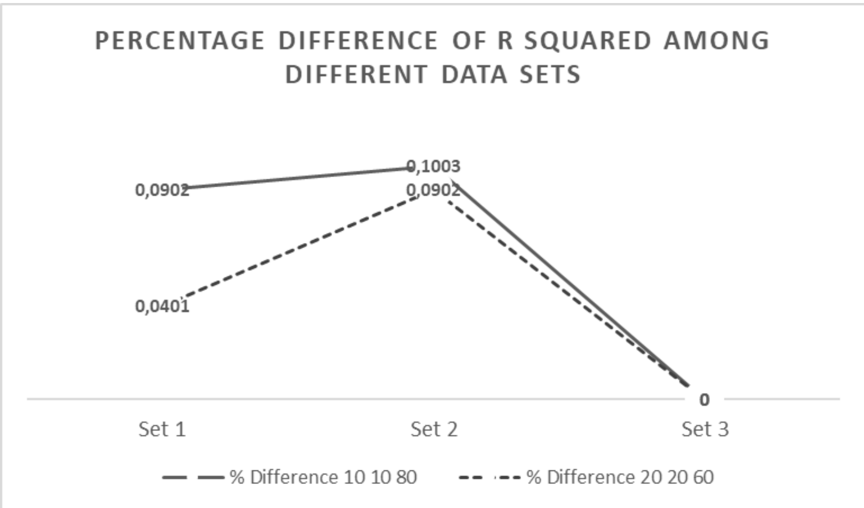

Fig. 4 - Sensitivity analysis of three different sets of data

6. Conclusions

The results of this research add to growing yet limited research on ANN-based model, especially in civil engineering field. It is proved once again that this method could produce a very good result for forecasting purpose. Several conclusions can be drawn from this research, which are as follows:

- Up to now, the CO_2 emission models are focused mostly on the emissions generated by the cement industry. However, this research investigated more specifically on CO_2 emissions resulting from the production of the precast concrete itself, and therefore the CO_2 emission model can be used directly by the precast concrete company.
- Adding to the existing literature, due to the limitation of ANN, it was also proposed here to use other analysis, i.e. PCA to reduce the variability of the data sets to save training time and efforts on producing the result. Instead of trying different combinations of parameters as inputs, only the significant indicators resulting from the PCA were used to develop the ANN model.
- Based on 107 data, the best ANN model for forecasting the CO_2 emissions was produced by distributing the data into 80% of training data, 10% of test data and another 10% of production data, using 6 neurons in input layer, 51 neurons in hidden layer, and 1 neuron in output layer, trained with learning rate of 0.1 and momentum of 0.9. ANN is capable of forecasting the amount of CO_2 emissions in precast concrete production with reliable accuracy based on MAPE value less than 10%.

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