The Prediction of CO_2 in Office Room Using Artificial Neural Network

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Abstract. The investigation of indoor air quality had attracted a number of researchers since the findings showed that the condition of indoor air quality was more polluted as compared to outdoor air quality. However, the approaches of investigation mostly completed through experiment and it required not only time but also cost. This paper aims to predict the condition of CO_2 as one of indoor air quality indicator through artificial neural network. It carried out by using the historical data from five days measurement consecutively. In which, the measurement took eight hours per day by using Yes Plus LGA Meter to capture the CO_2 existing. Once the measurement completely done, then it used to predict the further condition of CO_2 through artificial neural network approaches. The results indicated a good agreement between prediction data and validation data which were used to predict further condition of indoor air quality. Additionally, the use of back propagation method to conduct artificial neural network also gave good correlation between input data and target data. Finally, it can be concluded that beside the preparation of input data, the selection of training method was very impacted to the result of the data prediction.

Keywords: Indoor Air Quality; Artificial Neural Network; Back Propagation; Particulate Matter; CO_2

1. Introduction

The existence of indoor air quality (IAQ) was investigated continuously since a number of researchers had found that the level of IAQ is more polluted than outdoor air quality[1]–[5]. Challoner and Gill [1], they found that either naturally or mechanically ventilated was not effective to diminish indoor air pollution that comes from outdoor air. Subsequently, as a concern regarding the potential of adverse effect to the indoor occupant, Goyal and Khare [6] had investigated several parameters that existed at indoor environment which are particulate matter (PM) and Carbon dioxide (CO_2). It found that, the polluted air that comes from outdoors affects the occupant's health, especially their respiratory condition.

Besides, the importance indicators that frequently used for assessing IAQ level are the existence of PM and CO_2. In which the characterization of PM $\geq$ 0.3 µm and PM 10 µm are used to determine the IAQ level, due to these two particles dimension are lead to the adverse effect of building's occupant respiratory. However, the existence of CO_2 in certain level is not only to determine the condition of IAQ level as represented by a number of sick building syndrome (SBS) symptoms that occur to reduce the working performance of workers but also assess the performance of ventilation to dilute indoor air pollutants.

Furthermore, Apte et al., [7] had analyzed statistically an association between indoor CO_2 concentrations and SBS in U.S. office and found that average CO_2 levels of 800 ppm was the threshold for the occurrence of SBS symptoms. Its occurrence is characterized by a minimum number of 20% of buildings' occupant experiencing the symptoms such as itchy or watery eyes, blocked or stuffy nose, runny nose, dry throat, lethargy or tiredness, headache, irritated skin [8]. Yet, that symptoms will leave once the occupant leave the building [9]. Therefore, the existence of CO_2 at indoor is more important to be further investigated due to its adverse effect that can be occur in certain level.

A number of investigation that has been previously conducted regarding the existence of indoor CO_2, was commonly carried out either by monitoring [10]–[12] or experiment [10]. However, the main obstacles for conducting research either by monitoring or experiment approach is time required that leads to the additional cost of research. The measurement of CO_2 in entire building for 24 hours will generate a complete data that useful for determine building's IAQ. Nevertheless, it is very expensive way.

However, Mba [13] had predicted indoor environmental quality (IEQ) in terms of relative humidity and temperature parameters using artificial neural network (ANN). This approach is achieved by measuring the data of relative humidity and temperature for certain time and divide it into input data and target data. The input data will be trained in order to recognize some certain patterns as characterized by target data. Once it done, the input data is expected to recognize the certain pattern of target data in order to predict the upcoming data. Xie et al., [14] used previous data from BASE to predict IAQ using ANN. A number of comfort and IAQ parameters such as air temperature, relative humidity, air velocity, CO_2, $PM_{2.5}$, and fungi were involved. In addition, Azid et al., [15] had combined principal component analysis (PCA) and ANN to identify source of air pollutants and to predict air pollutant index (API).

Based on the description of ANN application in several cases regarding IAQ prediction as above, it is described that the application of ANN is capable to be adopted for data prediction especially in IAQ. Moreover, the advantage of ANN application is due to it more efficient in terms of cost as compared to experiment approaches. Therefore, it had motivated the author to study ANN to predict IAQ.

2. **ARTIFICIAL NEURAL NETWORKS**

ANN is a network of a group of unit's small processors are modeled based on human neural tissue. According to Kalogirou [16], The ANNs are good for task involving incomplete data sets, fuzzy or incomplete information, and for highly complex and ill-defined problems, where humans usually decide on an intuitional basis. Besides, the ANNs application can learn from example and solve non-linear problem. These are some characteristics of ANN that is pointed from Kalogirou [16],

1. Function approximation. Mapping of a multiple input to a single input is established. Unlike most statistical techniques, this can be done with adaptive model free estimation of parameters.

2. Pattern recognition and pattern association. This is a problem of pattern classification. ANNs can be effectively used to solve difficult problems in this field, for instance in sound, image,

or video recognition. This task can even be made without an a priori definition of the pattern. In such cases the network learns to identify totally new patterns.

3. Associative memories. This is the problem of recalling a pattern when given only a subset clue. In such applications, the network structures used are usually complicated, composed of many interacting dynamical neurons.

2.1 The theoretical background of ANN

Based on Daponte and Grimaldi [17], the ANNs are derived from a computational approach to neuroscience equipped with algorithms and architecture to be extracted from neurobiological system. Additionally, this approach is imitating a human brain which has capability to memorize a number of experiences and can recall it as well. Technically, it resembles the human brains in two things which are recognizing of knowledge by the network through learning process and storing the knowledge by interneuron connections strengths as synaptic weights [18].

Subsequently, a schematic diagram of multilayer perceptron neural network is depicted as in Figure 1.

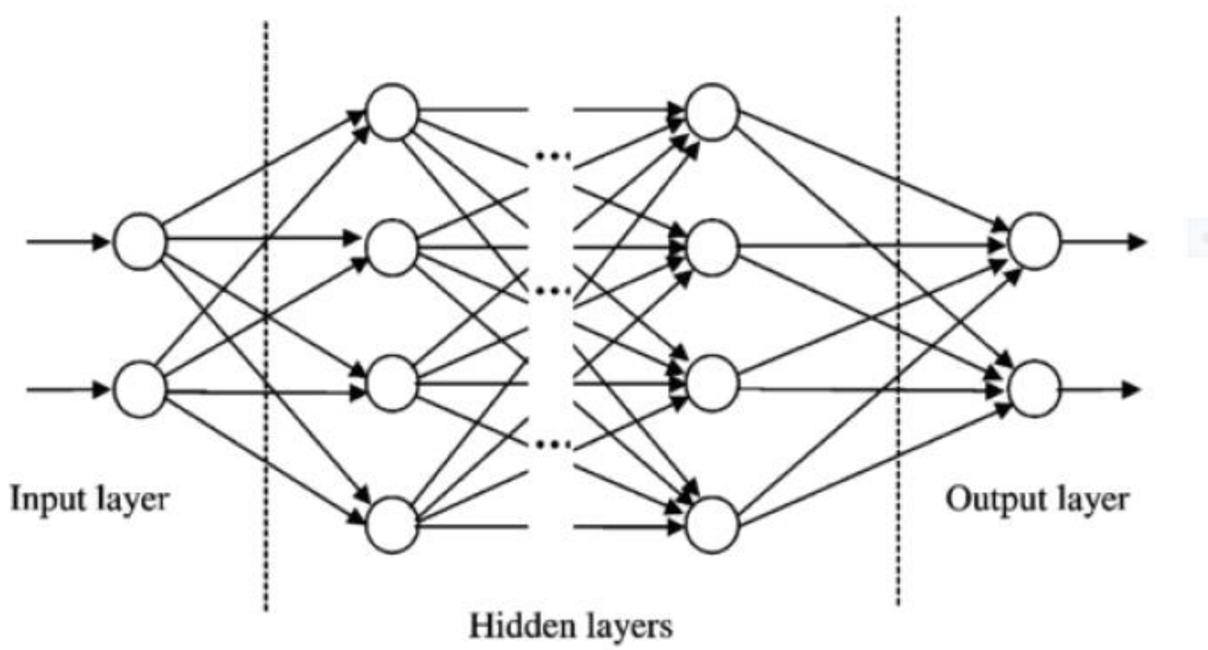

FIGURE 1. Schematic diagram of a multilayer feedforward neural network [19]

Based on Figure 1, the network structure is consisted of input layer, hidden layers, and output layer. Every single of neuron is connected to other neurons of a previous layer through adaptable synaptic weights [19]. Generally, knowledge is implemented as a set of connection weights. In order to modify the connection weights in training stage, it involves a learning method.

Subsequently, a data input and data target are required to be presented to network and the weights are conformed, then the network can generate the desired output.

Subsequently, the communication process of every single neuron is presented as in Figure 2.

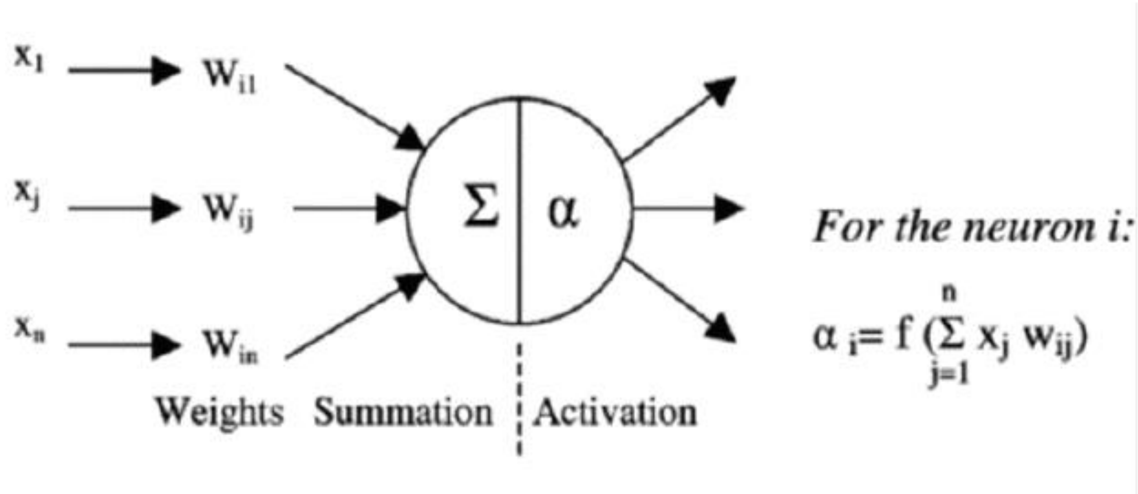

FIGURE 2. Information processing in a neural network unit [19]

The Figure 2 shows that the node receives weighted activation of other nodes through its incoming connections. Initially, the weights of other nodes are added up. Once it done, the result is passed by activation function to activation of the node [19]. Moreover, to every outgoing connections, it needs to multiply this activation value with the specified weight then transfer it to the next mode [19].

Besides, a training set is a number of fitted input and output patterns used to train the network, and it refers to the synaptic weights [16]. When the pattern of data could be recognized, then the network uses the input data to produce output data. To evaluate whether the output data is correct, so it is compared with the training data [16].

3 METHODOLOGY

3.1. Source of Data

The data regarding to indoor air pollutants were generated from the direct measurement during 5 days on office hours.

3.2.Variable of Research

Main object of the research is the existing condition of CO_2 which has been measured and it will be predicted using artificial neural network

3.3.Analysis of Artificial Neural Network

The methodology of back propagation will be adopted to model and predict the output of the CO_2 existing. If the error value resulted from output and target is still consider high, the network will update the weight and bias in order to minimize its error.

3.4.Determine the best model of artificial neural network

The selection of best model is based on the following parameters namely coefficient of determination (R^2) and Mean Absolute Percentage Error (MAPE). R^2 is an indicator of how well the regression predictions approximate the real data points. Meanwhile, MAPE is commonly used as a loss function for regression problems and in model evaluation, because of its very intuitive interpretation in terms of relative error.

4 RESULTS AND DISCUSSION

4.1. ANN Modelling

Feed-forward neural network have been applied in this study. The logistic activation functions were used for the neurons in the hidden layer and output layer respectively. The weights and biases were adjusted based on gradient-descent back-propagation in the training phase. The mean absolute percentage error (MAPE) was chosen as the statistical criteria for measuring of the network performance. The overview of the parameters and their values was shown in Table 1.

Table 1.

Net No.	Net Structure	Activation	Learning Initial Rate	Momentum Constant	MAPE	R^2
1	5 – 15 -1	logistic	0.2	0.9	3.354	0.854

From Table 1, it can be seen that model with network structure of 5-15-1 is the best models for the CO_2 prediction as it yields the lowest values of MAPE and a 85.4% coefficient of determination, R^2. The model shows a good agreement between predicted and measured values based on the value of coefficient of determination, and it presented as in Figure 3.

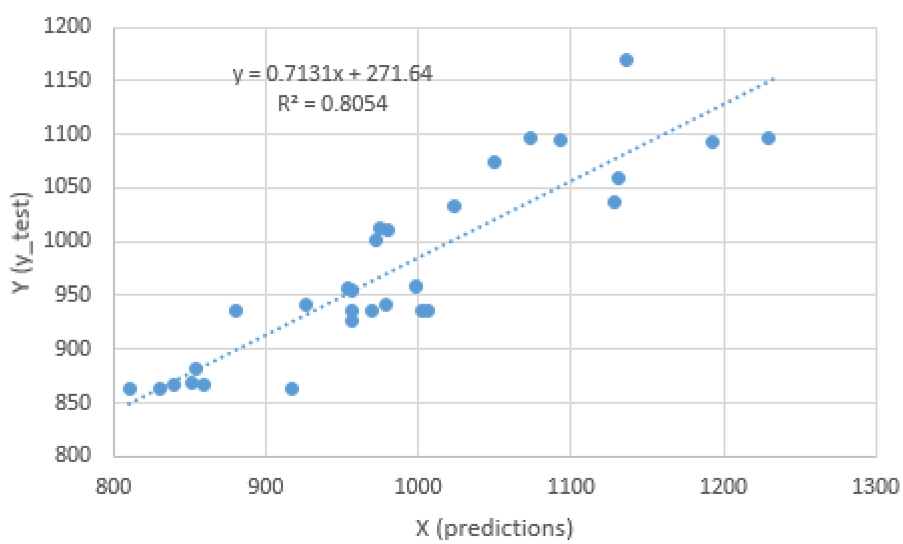

FIGURE 3. The performance between prediction and validation phase

5 CONCLUSION

Based on the analysis conducted, model with neural network structure 5-15-1 produces the best performance in the prediction of CO_2 and it R^2 of 0.854 which indicate a good agreement between the targets and predicted outputs. However, this model still need an improvement to give a better result for CO_2.

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