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RESEARCH ARTICLE

Prediction of Indoor Air Ventilation Performance in Kindergarten using Nonlinear Autoregressive Neural Network

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Abstract:

Introduction: Indoor air pollution has become one of the major issues that cause health issues for building occupants, especially people from sensitive groups such as the elderly and younger children. However, indoor air pollutants can be reduced by providing adequate ventilation to the building. Effective and adequate ventilation can help to dilute and remove pollutants, providing healthier air for the building occupants to breathe. The adequacy of ventilation can be determined by measuring the concentration of carbon dioxide (CO_2) in the building, as CO_2 is widely used as an indicator for ventilation. **Method:** To determine the ventilation performance, a method of forecasting through a modelling process using a nonlinear autoregressive neural network (NARNN) is developed. The CO_2 concentration data that was collected from kindergarten is used to construct and find the best-fitted model with a suitable number of neurons and hidden layers. This model can help predict the future concentration trend of CO_2 in kindergarten and determine the ventilation performance of the building. **Result:** The concentration of CO_2 in the building is decreasing through the operation hours, indicating it has adequate ventilation. The dataset of CO_2 concentration is used to develop a prediction model that consists of an artificial neural network (ANN) structure. A model with a 1-9-1 structure with a data division of 80:20 is the best-fit model for forecasting as it has high accuracy and is highly relevant to be used for prediction as it has the nearest R-value near one. **Conclusion:** Indoor air quality needs special attention from multiple authorities and organisations, especially in buildings that have younger children as occupants. Poor indoor air quality can pose a health risk to the occupants and disrupt their comfort while doing their activities in the building. The modelling technique is one of the most relevant and advanced methods to forecast the quality of a building, as it can help determine the future concentration of pollutants in the indoor environment.

Keywords: Indoor Air Quality, Modelling, Ventilation

1. INTRODUCTION

Air pollution is defined as the release of pollutants into the air that are detrimental to human health, and the World Health Organisation (WHO) stated that nine out of ten people currently breathe air that exceeds the WHO's guidelines for pollutants, especially people from low- and middle-income countries (Jillian et al., 2021). Indoor air pollution contributes greatly to human wellbeing, as most people tend to spend around 90% of their time indoors, mainly at home or in the workplace (Tran et al., 2020). Indoor Air Quality (IAQ) is the air quality within and around any building or structure, especially as it relates to the health and comfort of building occupants. Controlling the common pollutants indoors can help reduce the risk of indoor health concerns (USEPA, 2014). Indoor air pollution is a condition where the presence of chemical, biological, and physical contamination in the air of an indoor environment results in adverse health effects (OECD Statistics Directorate, 2022). With the increasing incidence of respiratory illness, health experts warn about the indoor air pollution hazard, as several studies show that indoor air pollution levels are much higher than those in an urban outdoor environment (Bureau, 2017). Generally, indoor air pollution is generated from various sources, including tobacco smoke, building materials, fixtures, cleaning and hygiene products, air fresheners, computers, printers, cooking, and other indoor activities, and humans themselves are one of the sources of pollutants (Abu Mansor et al., 2020). Poor indoor air quality can lead to multiple diseases and health problems such as chest pain, asthma, fatigue, throat irritation, headache, loss of coordination and decreased in lung function (Tran et al., 2020). Indoor air pollution is a leading risk of people die prematurely and 4.1% of global deaths are attributed by indoor air pollution (Ritchie & Roser, 2013).

To provide a good quality of air in the environment, ventilation is the most important way to maintain and improve indoor air quality. According to DOSH (2010), as stated in the Industry Code of Practice on Indoor Air Quality (ICOP IAQ) 2010, ventilation means the process of supplying air or removing air from space for the purpose of controlling air contaminant levels, humidity, or temperature within the space. In a poorly ventilated classroom, students are likely to be less attentive and to concentrate less well on instruction given by the teachers, and the magnitude of the negative effect of inadequate ventilation was even higher for tasks that require more complex skills such as spatial working memory and verbal ability to recognise words and non-words (Bakó-Biró et al., 2012).

Carbon dioxide (CO_2) is one of the gases that are present in indoor environments, and the presence of a high concentration of CO_2 indicates that the indoor environment is not properly ventilated. According to DOSH (2010) in ICOP IAQ 2010, the acceptable limits of CO_2 for indoor environments are 1000 ppm, where the value is the ceiling limit that shall not be exceeded at any time, and the readings above the value are indications of inadequate ventilation. The use of CO_2 for steering the ventilation system, as there are no pollutants, is more dominant than CO_2 for the indoor environment (De Gids, 2010). A study conducted by Ramalho et al. in 2015 found that CO_2 concentration has correlation coefficients with CO2, and both formaldehyde and benzene were found in rural nurseries and schools. It is also found that CO_2 is often considered a surrogate of ventilation rate. The study also found that even with good ventilation, the reduction of pollution remained necessary to achieve satisfactory indoor air. This study also found that measurement of CO_2 (for mitigation purposes) is still recommended as an indicator for air stiffness.

The concentration trend of CO_2 in the indoor environment can be determine through the modelling process. Air pollution modelling is the term used to describe using mathematical theory to understand or predict the way pollutant behave in the environment or atmosphere. Modelling is the activity of using mathematical models while using simple description of a system process to make calculations or predict what might happen (Cambridge Dictionary, 2022). Previous research on modelling the CO_2 concentration perfectly predicted the CO_2 concentration in most parts with three different approaches, which are open-loop, closed-loop, and multi-step prediction, and this study is able to be used in demand-controlled ventilation systems (Khazaei et al., 2018). Alavi et al. (2022) in their study developed and compared an algorithm that can predict in real-time whether or not the CO_2 level in an office will exceed the threshold solely on the basis of the previous measurement of CO_2 in the same office. Artificial neural networks (ANN) are computer systems developed to imitate learning, which is one of the most basic features of the human brain, and to automatically perform abilities such as deriving, creating, and discovering new information without any assistance (Kurnaz & Demir, 2022). Network learning takes place as the weights are adjusted along the layers according to the relationship between the inputs and the desired outputs. One of the most basic models is the multilayer preceptron (MLP) network, which is widely used in the approximation of nonlinear functions that describe complex relationships between independent and dependent variables in many applications (Benrhmach et al., 2020).

There are two models that can be used to determine the concentration of CO: linear regression (Zhou et al., 2021) and non-linear regression (Ben Cheikh et al., 2021). Linear regression is the relationship between two variables (X and Y) in a straight line (y= mx + b), while non-linear regression relates two variables in a non-linear (curved) relationship (Will Kenton, 2021). A non-linear autoregressive neural network (NARNN) consists of an input layer, an output layer, and hidden layers in between. It has been observed that only one hidden layer is enough for most applications, provided it has an adequate number of neurons (Ahmed & Khalid, 2017). The nonlinear autoregressive neural network (NAR), as shown in Figure 2.1, can be trained to predict a time series from that series past values ***Y (t -1, Y (t -2), …, Y (t - d),*** called feedback delays, where d is the time delay parameter. The network is created and trained in an open loop, using the real target values as a response and making sure that the quality is very close to the true number in training. After training, the network is converted into a closed loop, and the predicted values are used to supply new response inputs to the network. (Benrhmach et al., 2020). Figure 1 below shows the architecture of a non-linear autoregressive neural network (NARNN), and Figure 2 shows the multiple layers in the neural network.

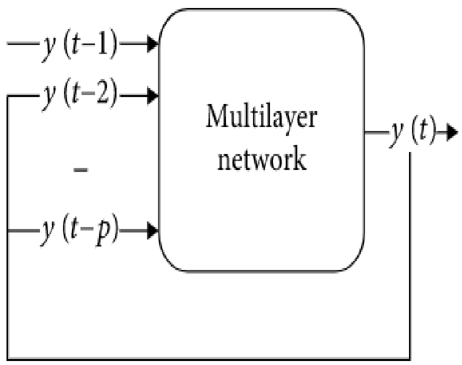

Figure 1: Architecture of non-linear autoregressive neural network (NARNN)

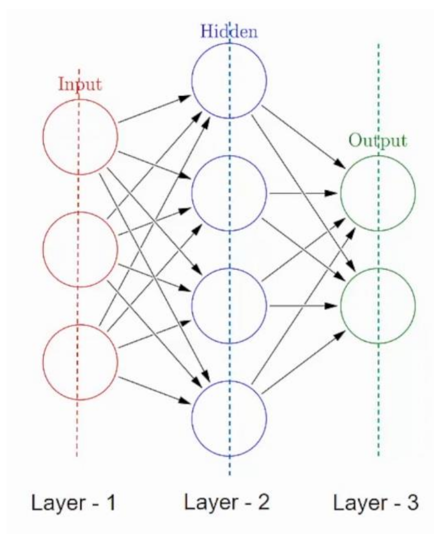

Figure 2: Multiple layers in the neural network

The ANN models gave better results than other models, especially for the ANN models that were built with non-constant variance (Feng et al., 2015). Gardner and Dorling (1998) gave an informative review of the applications of ANN in the atmospheric sciences. They pointed out the advantages of ANN when handling non-linear systems, especially when theoretical models are difficult to construct. There are disadvantages related to linear regression in air pollution modelling. Syafei et al. (2015) stated that a linear equation is not enough to capture the true air quality because of its high complexity, and it is also related to the high fluctuation of the concentration due to the short time interval.

From the model, forecasting process can be done to determine the trend of CO_2. Forecast is projection, prediction or estimate some future activity, event and occurrence.

2. MATERIALS AND METHODS

This study is carried out at Tadika Cahaya Elit located in Kampung Duyung, Kuala Terengganu, Terengganu, Malaysia (Plate 1). The sampling process was carried out for three days with a four hours period for each day starting from 0800 hours to 1200 hours in accordance with the operational time for the kindergarten. According to Department of Safety and Health (DOSH, 2010), carbon dioxide monitoring should be measure by real time monitoring to can be used to provide information on the variation of contaminants level throughout the day.

A sampling point is chosen based on the layout of the kindergarten and 4 hours of reading will be carried out at each sampling point. The location of the sampling point is selected and being determined based on guideline from ICOP-IAQ (2010). The air sampling instrument is suggested to be placed 1.1 meter from the floor, have minimal disturbance from the work activities in the area, at least 0.5 meters from the wall, indirectly in front of air supply diffuser, floor fans or heaters and preferably not on passageways. Since the building occupants are children, the sampling points is determine based on several factors including to avoid disturbance on the instruments by the children during the sampling periods. For this study, Q-Trak Multifunction Indoor Air Quality Monitoring Model 7575 is used to collect the reading of CO_2 at kindergarten. Q-Trak Multifunction Indoor Air Quality Monitoring Model 7575 has a high accuracy in measuring CO_2, temperature, carbon monoxide, and relative humidity. ICOP-IAQ (2010) stated that a valid sampling program must have equipment that have appropriate detection limit and it cover the assessment objective.

Plate 1: Location of Taska Permata Keluarga

This study was designed to predict the ventilation performance at the kindergarten by using Nonlinear Autoregressive Neural Network (NARNN). This study is carried-out by collecting CO_2 data from a kindergarten through real-time monitoring. Prediction of CO_2 concentration trend in the kindergarten will be carried out following Figure 3 below:

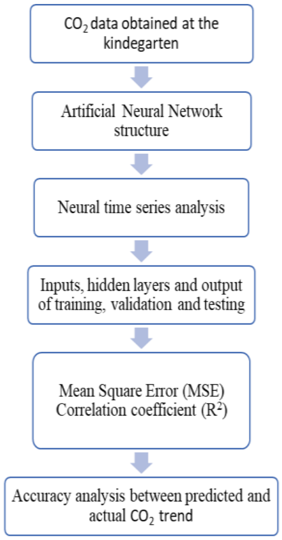

Figure 3: Flowchart of CO_2 trend prediction process

The method for data analysis in computational method. The data collected from sampling process undergo modelling process by using Nonlinear Autoregression Neural Network (NARNN). The data of the real time sampling can be used to validate the predicted data. This artificial neural network (ANN) is a neural model that is mainly based on the perceived work of human intelligence or known as model of the brain and it is particularly beneficial for forecasting the future using historical data (Shahabi et al., 2012). The analysis model will be simulated by using MATLAB version R2017b. ANNs are capable for mapping between input and output it consist of the network that is a data-driven mathematical tool and is composed of neurons that are organized in layers which are capable of learning the situation and making up the association process's input and output (Singh & Chakrapani, 2015). A prediction model for CO_2. The set of input and output will assist the constructing a complex non-linear structure for CO_2 modelling. The accuracy of the model can be assessed by its evaluating criteria including min square error (MSE) and correlation coefficient (R^2).

In this study, a NARNN model with input of CO_2 data collected from the kindergarten will be developed to predict the trend of CO_2 at the building by filling data with time series regression model. The data set will undergo three process which are training, validation and testing and this model will be operated in the close and open loop. The equation this NARNN model is:

$$y(t) = b_0 + b_1\, y(t-1) + b_2\, y(t-2) + ... + b_n\, y(t-n)$$

From the equation, $y(t)$ is the output at time t and b is the coefficient. Figure 4 shows the structure of NARRN that will be used for this study.

The outcomes from the NARNN can help to predict the trend of CO_2. The result from the outcome sis analysed using descriptive analysis. The number of hidden layers is adjusted to determine the best ANN time series model. From the outcome computed through this whole process, the CO_2 trend can be determined and can help to predict the indoor air ventilation performance of the buildings.

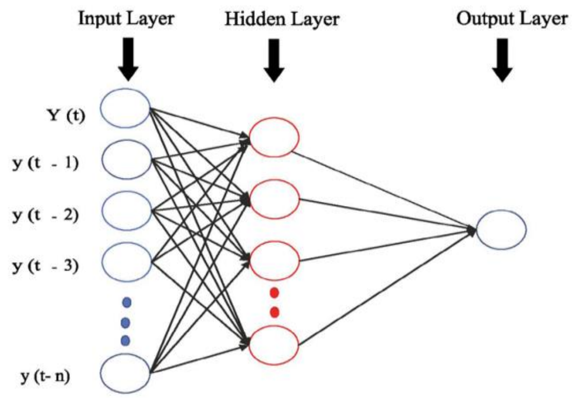

Figure 4: The NARNN Structure

3. RESULTS AND DISCUSSION

3.1. Trend of CO_2 in Kindergarten

The data obtained was analysed using a Microsoft Excel spreadsheet. Descriptive statistical analysis in terms of graphs was plotted to determine the trend of CO_2 concentration at the kindergarten. A box plot was constructed to represent the trend of CO_2 concentration at the kindergarten.

The averaging data show a decreasing trend of CO_2 through the operation hours, as shown in Figure 5. From 9.00 a.m., the CO_2 concentrations slightly decreased as the mean value of CO_2 concentration at 9.00 a.m., 347 ppm, increased to 534.19 ppm at 10.00 a.m. Then, the mean value of CO_2 concentration continues to decrease to 487.42 ppm at 11 a.m. and 463.11 ppm at 12 p.m. This indicates that the trend of CO_2 is decreasing through the kindergarten operation hours.

The high mean value of CO_2 concentration, which is 537 ppm at 9.00 a.m. and 534.19 at 10.00 a.m., is due to intensive learning sessions such as singing and spelling lessons that involve all of the students that are available at the kindergarten. These types of activities surely increase the respiration rates of the children, which contribute to the production of CO2, and children are known to have a higher respiratory rate compared to adults. A study found that CO_2

that is stored in younger children is smaller than that stored in teenagers, as children have lower levels of haemoglobin than adults (Cooper et al., 1987). Young children also have a significantly higher metabolic rate than adults and therefore have a higher oxygen demand, which in turn results in higher respiratory rates (The Royal Children's Hospital Melbourne, 2016). During exercise or activity, the body uses more oxygen to provide energy and produces more CO_2 as the waste product created when producing energy during physical activities (Breath, 2016).

After 10 a.m. until 12 p.m., the concentration of CO_2 decreases to a mean value of 463.11 ppm. The decreasing trend of CO_2 indicates that the kindergarten building has a proper ventilation system to dilute excess CO_2 produced in the previous hour, while CO_2 also represents an indicator for ventilation. This means that the facility has enough ventilation to circulate and dilute the pollutants that are present in the indoor environment. Ventilation is intended to dilute and remove pollutants to acceptable levels for the health and comfort of building occupants, and it must be sufficient to maintain the building's integrity (Olli Seppänen & Jarek Kurnitski, 2023). Ventilation is important since it provides oxygen for metabolism and helps to dilute metabolic pollutants such as CO_2, removing and diluting other pollutants that emit within the space, and it is a major contributor to the health and comfort of building occupants (Maria Kapsalaki, 2013). Good ventilation system not only provide thermal comfort but also distribute adequate fresh air for the building occupants and remove the pollutants (Clements-Croome et al., 2008). It indicates that this premise is well-ventilated as the CO_2 concentration decrease through the time and it is important to keep removing the pollutants continuously from the indoor environment. Even the concentration of hazardous pollutants is below permissible limit, it also can contribute to health and satisfaction of children and as well as their performance of schoolwork and learning (Cabovská et al., 2022).

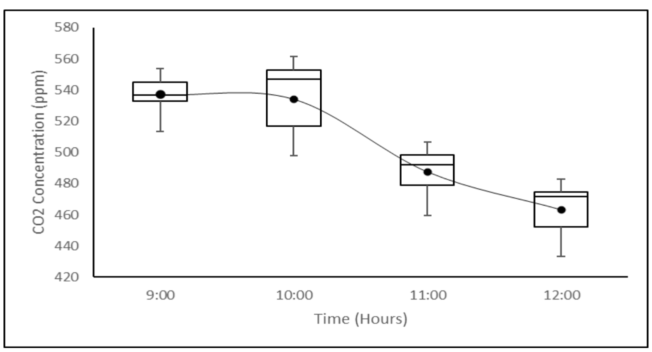

Figure 5: Box and Whiskers Graph of CO^2 Trend at the Kindergarten from 8.00 am until 12.00 pm.

Besides, ventilation can help reduce the probability of children getting infected by airborne diseases such as COVID-19, influenza, and measles. According to the CDC (2020), good ventilation is a step that can reduce the number of virus particles in the air and reduce the likelihood of spreading diseases. Exposure of children to pollutants can pose a threat to their health as they are more vulnerable compared to adults. Children are sensitive to environmental pollutants due to the immaturity of their immune systems (Cabovská et al., 2022). Children are vulnerable to the effects of air pollution since they breathe more rapidly due to the limited space for the exchange of oxygen (O_2) and CO_2 in their lungs, and their respiratory system is still developing through their ages.

Through the descriptive analysis, the average maximum value of CO_2 concentration is 586 ppm and the mean value of average CO_2 concentration is 503.896 ppm, which indicates that the CO_2 concentration at the kindergarten is about half of the ceiling limit, which is 1000 ppm, as stated in the Industry Code of Practice on Indoor Air Quality (ICOP IAQ) 2010 by the Department of Safety and Health (DOSH). The concentration of CO_2 is still at the acceptable limit since the kindergarten is occupied with natural ventilation such as windows and mechanical ventilation such as fans. The descriptive statistical analysis of CO_2 concentration in kindergarten is shown in Table 1.

Descriptive Statistical	CO_2 Concentration (ppm)
Mean	503.896
Median	506
Standard Deviation	39.514
Variance	1561.329
Kurtosis	0.050
Skewness	-0.362
Minimum	398
Maximum	586

Table 1: Descriptive Data of CO_2 Concentration at the Kindergarten

3.2. NAR Models Development for CO_2 Prediction

Prediction model used in this study is a non-linear autoregressive (NAR) model using MATLAB version R2017b which constructed with an input of CO_2 concentration at the kindergarten via a time series model. The NAR model has been tested using CO_2 concentration data that are collected from 0800 hours to 1200 hours for 3 days of sampling and the model is operated in closed loop and open loop. Overall, there were 144 data (n=144) used for the training, validation, and testing process. The proportion of data were divided as in Table 2 for each section.

Data Division	Training	Validation	Testing
60:40	60% involving 86 target timesteps	20% involving 29 target timesteps	20% involving 29 target timesteps
70:30	70% involving 100 target timesteps	15% involving 22 target timesteps	15% involving 22 target timesteps
80:20	80% involving 116 target timesteps	10% involving 14 target timesteps	10% involving 14 target timesteps
90:10	90% involving 130 target timesteps	5% involving 7 target timesteps	5% involving 7 target timesteps

Table 2: Data Division for Training, Validation and Testing

The NAR models used the training algorithm of Levenberg-Marquardt (LM), a type of training algorithm that automatically stop when the generalization stops improving as, indicated by an increase in the mean square error of the validation samples. The best ANN model structure for each CO_2 concentration data were selected by the correlation coefficient (R^2) and the value close to one indicate a close relationship and the suitability of the model for forecasting CO_2 trend at the kindergarten. The best model also has low mean square error (MSE) value which indicates the model has low statistical error when assessing the average squared difference between the observed and predicted data.

The development of the NAR model was based on the error and trial method, where the number of neurons was added one after another, as in previous studies that adapted the NAR model (Pawlus et al. 2013). The best network structure was accomplished by the neuron testing process from 1 to 15 and trained with three layers: an input layer, an output layer, and a hidden layer. A model with different data divisions was tested with this method, and the ANN structure was 'learned' from the past target data and underwent testing (Atikah et al., 2022). Each of the data divisions was tested 15 times by modifying the number of hidden layers (1 until 15) for each testing process, and the best dataset for each data division was selected. There are four ANN structures of the model selected for each data division, labelled Model 1, Model 2, Model 3, and Model 4, as shown in Table 3.

Model	Optimum Neuron	Data Division	ANN Architecture	Predicted Equation	R-values			MSE Value
					Training	Validation	Testing	
1	4	60:40	1-4-1	y= 0.75(x) + 1.3E2	0.80529	0.72971	0.88999	1252.65
2	3	70:30	1-3-1	y= 0.63(x) + 1.8E2	0.82952	0.67013	0.87817	1299.05
3	9	80:20	1-9-1	y= 0.71(x) + 1.4E2	0.83068	0.79494	0.93427	609.17
4	7	90:10	1-7-1	y= 0.76(x) + 1.1E2	0.82312	0.80348	0.92946	631.79

Table 3: Data separation for prediction model of carbon dioxide using nonlinear autoregressive neural network (NARNN)

Model 1 has 60:40 data division, where 60% represent the 86 datasets for training, 20% represent the 29 datasets for validation, and another 20% represent the 29 datasets for testing. Through the error and trial method for Model 1, the selected ANN structure model is 1-4-1, which consists of 4 neurons with the highest R2, which is 0.88999. The regression graph for Model 1 is shown in Figure 7.

Model 2 has 70:30 of data division where 70% represent the 100 datasets for training, 15% represent the 22 datasets for validation, and another 15% represent the 22 datasets for testing. Through the error and trial method for Model 2, the selected ANN structure model is 1-3-1, which consists of 3 neurons with the highest R2, which is 0.87817. The regression graph for Model 2 is shown in Figure 8.

Model 3 has 80:20 data division, where 80% represent the 116 datasets for training, 10% represent the 14 datasets for validation, and another 10% represent the 14 datasets for testing. Through the error and trial method for Model 3, the selected ANN structure model is 1-9-1, which consists of 3 neurons with the highest R2, which is 0.93427. The regression graph for Model 3 is shown in Figure 9.

Model 4 has a 90:10 data division, where 90% represent the 130 datasets for training, 5% represent the 7 datasets for validation, and another 5% represent the 7 datasets for testing. Through the error and trial method for Model 4, the selected ANN structure model is 1-7-1, which consists of 7 neurons with the highest R2, which is 0.92946. The regression graph for Model 4 is shown in Figure 10.

Among the selected ANN structures for each model, Model 3 with 1-9-1 and a data division of 80:20 is the best fitted model for forecasting as it has high accuracy and is highly relevant to be used for prediction as it has the nearest R-value near one, which is 0.93427, and the lowest value of mean square error (MSE), which is 609.17. The NAR model is a great one as it can capture and process non-linear and complex data, and it has been widely applied in various fields of study such as medicine, environment, and engineering. This model also has the capability of learning and determining the trend of CO_2 concentration as it has the capability to capture non-linear dynamics and high accuracy for the specific study location (Atikah et al., 2022). The trial-and-error method is implemented to achieve the optimal network structure for the developed model (Khan & Gupta, 2020). The trial-and-error method also help to the identification of the best structure and neuron number is in hidden layer that have the best fitness value for the best ANN model (Saemi et al., 2007). Implementation of LM algorithm is crucial which can reduce any bias during training, testing and validation during prediction process in the model (Alsumaiei & Alrashidi, 2020).

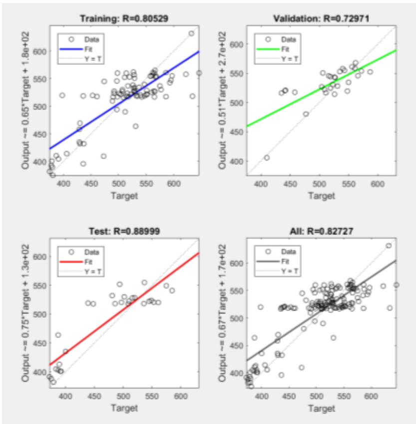

Figure 7: Regression Graph Model 1

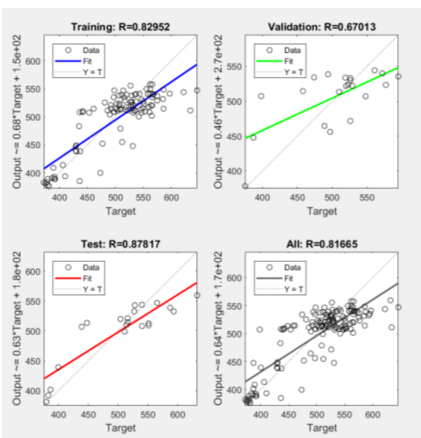

Figure 8: Regression Graph Model 2

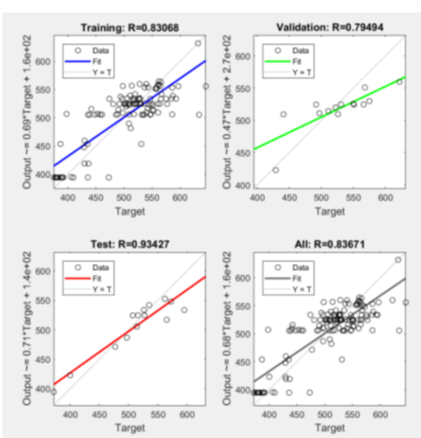

Figure 9: Regression Graph Model 3

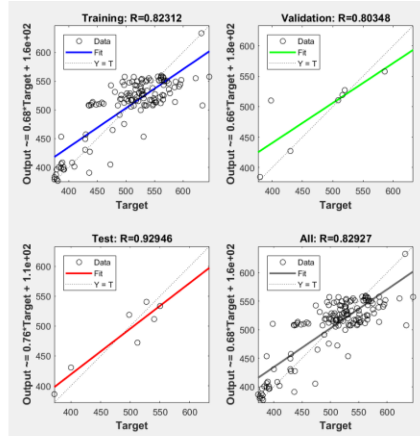

Figure 10: Regression Graph Model 4

Furthermore, the prediction model made by using the nonlinear autoregressive (NAR) model can help the authorities or researchers determine the ventilation performance for the indoor environment by measuring CO_2 concentration, as indoor air quality is necessary to the health and welfare of the building occupants. This is because the NAR model and time series have high accuracy for the R-value, are flexible, and yield good results from the datasets (Ali & Ahmad, 2019). The modelling approach can help to provide information as to realistic daily and longer-term exposure, and thereby it can feed into debates surrounding new indoor air quality legislation (Challoner et al., 2015).

The modelling process can be done before the operation or development of kindergarten premises, as it can help predict the condition of indoor air. It should also be regulated, as it is important to the health and welfare of building occupants. This is because modelling is critical for determining relative contributions from different sources, monitoring compliance with air quality regulations, and making policy decisions (USEPA, 2020). A "performance-based" approach where the achieved indoor air quality (IAQ) is checked at the design stage of the building is still lacking in regulation and standards and needs to be developed for building ventilation (Poirier et al., 2021). Thus, this ANN time series model is applicable for the long-term prediction of the ventilation performance of kindergartens by using the CO_2 concentration in the building. The modelling process surely can help to ensure that building occupants, especially children and people who are sensitive to pollutants that are present in the indoor environment, have a healthy and comfortable indoor environment, as modelling can predict the future condition of air in the indoor environment. A continuum model found that insufficient ventilation leads to the worsening of not only long-range airborne transmission but also short-range airborne transmission (Li et al., 2021). Furthermore, good IAQ can help create a favourable environment for the students and children, improve the performance of teachers and staff, and foster a sense of comfort and well-being, which can assist the school in its core mission (USEPA, 2015). The statement indicates that healthy indoor air can boost and improve the learning process of children and teachers when they are not affected by the pollutants in the indoor environment.

4. CONCLUSION

In conclusion, maintaining the quality of indoor air in the building is an important aspect that is needed to be taken care of, especially in buildings that occupy people from sensitive groups, such as children. Ventilation has been the best approach to maintaining the quality of the indoor air, whether the building is occupied with mechanical or natural ventilation. If the circulation of inside and outside air still occurs, it can help to refresh the indoor air, dilute the presence of pollutants in the indoor environment, and prevent the occupants from facing building-related illness (BRI). Through this study, CO_2 datasets taken from the kindergarten can help develop a prediction model that can be used to predict the trend of CO_2 in the kindergarten. Thus, it can help to determine the ventilation performance of the building, as CO_2 is a reliable indicator to measure the ventilation performance of a building.

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