DATA-DRIVEN PREDICTION MODEL OF INDOOR AIR QUALITY

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ABSTRACT

People mostly spend their time indoors for their daily activities. However, indoor air pollutant concentrations are found to be higher than outdoors. Generally, this is caused by the ventilation performance that is not able to dilute indoor air pollutants adequately. The presence of indoor CO_2 at certain concentration level is an indicator of indoor air quality and requires field measurements to evaluate it. On the other hand, the consequence of field measurements is not only time consuming but also costly. In order to minimize that problems, this study aimed to predict the model of indoor air quality by referring to previous data. It was achieved by several stages such as input, process, and output. A number of previous data regarding indoor air quality namely indoor CO_2, indoor temperature, number of occupants, and air conditioner usage duration were assigned as input. Subsequently, the process stage in this study adopted feed-forward neural networks that divided the data into training data and testing data. Additionally, several activation functions in neural network such as ReLU, tanh, logistic, and identity were involved in the process phase in order to imitate the actual model precisely. Ultimately, the outputs were evaluated using mean square error, mean absolute percentage error, and coefficient of determination. The findings indicated that the application of logistic as activation function was prominently reliable to predict the targeted data. This activation function can improve learning performance which is characterized by their value of mean square error, mean absolute percentage error, and coefficient of determination. In addition, a number of discrepancies of each activation functions were also presented to identify their behavior in terms of imitating the given data. Finally, this approach can be used as a tool to predict the concentration level of indoor CO_2 in a concise time and leads to cost efficiency.

***Key words**: prediction model, indoor air quality, artificial neural network, activation functions*

INTRODUCTION

Indoor air is the most critical part in human life since people almost spend 90 % on average per day to live at indoor. It needs a number of measurement in order to obtain the existing condition of indoor air to determine its quality. The number of parameters involved are classified into two groups, the first one is indoor air which is based on several factors such as air velocity, temperature, and relative humidity. The other group is indoor air pollutants by considering to the existing concentration of Particulate Matter (PM) and Carbon Dioxide (CO_2). The concentration of indoor air pollutants are resulted from the interaction between those two groups in which the sufficient condition of indoor air parameters leads to the better quality of indoor air by diminishing the concentration of PM and CO_2. Generally, in order to dilute indoor air pollutant is carried out by increasing the rate of ventilation. However, it leads to the excessive consumption of household electricity. Clearly, this problem attracts majority of researchers to provide effective solution.

Furthermore, the monitoring stage of indoor air quality is not only time consuming but also costly. For instance, it needs an amount of time to prepare a number of equipment. Besides, for the areas which are less covered by a number of equipment, an approach of interpolation is needed to obtain missing data between measurement points. Therefore, it really important to come up with another approach of estimating the indoor air quality in a precise fashion.

Multilayer Perceptron (MLP) neural networks of Artificial Neural Networks (ANN) have been used to predict CO_2 concentrations instead of implementing a set of data to new algorithms in order to assess their behavior in the scope of simulations (Khazaei, Shiehbeigi, and Haji Molla Ali Kani 2019). This approach was considered as a useful way to monitor indoor air condition. Moreover, Buratti and Palladino (Buratti and Palladino 2020) have stated that ANN was prominently to estimate the concentration of CO_2 in the room even though it uses a few inputs. In addition, MLP neural networks also adopted by Segala *et al.,* (Segala et al. 2021). They varied a number of data involved in the calculation starting from a week to a month to evaluate the discrepancy with actual measurement. Obviously, the number of data used affects to the degree of discrepancy.
This study uses feed-forward neural networks by considering the concentration of several parameters such as inlet airflow, temperature, and indoor CO_2 concentrations. Subsequently, a set of verification tools namely mean absolute percentage error (MAPE), R^2, and mean squared error (MSE) are presented to assess the results of prediction in order to select the precise model.

Artificial Neural Networks (ANNs)

ANNs are generated from a computational approach to neuroscience facilitated with algorithm and architecture to be extracted from neurobiological scheme (Daponte and Grimaldi 1998). Besides, it is an imitation of human brain which has capability to memorize a number of experiences and able to recall it. In principle, this approach resembles the human brains in two aspects, which are knowledge recognizing by the network through learning process and storing it by interneuron connection strengths as synaptic weights(Haykin 1994). Fundamentally, a construction of ANN is consisted of one or more hidden layer between input and output layers. Mathematically, it is depicted by a function of:

$$a = f(n) \tag{1}$$

Where,
f = activation function

Commonly, a structure of ANN requires several processes to work successfully:

- Node(s)
- Weight
- Input and Output

Based on those three requirements, a structure of ANN is depicted as figure below:

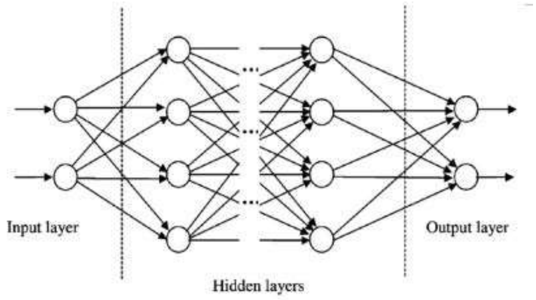

Figure 1. Schematic diagram of a multilayer feed forward neural network (Kalogirou 2003)

As refer to the Figure 1. It shows that the first step of ANN is input stage, then it followed by hidden layer(s) and output as a final stage. According to Kalogirou (Kalogirou 2003), each of neuron is associated with the others through adaptable synaptic weights. In practical, knowledge is applied as a set of connection weights and requires a learning method to improve it. Subsequently, a value lies in input and output layers is assigned in network with its proper weight. Therefore, the networks able to generate the desired output.

Furthermore, the communication mechanism of each neuron is presented as in Figure 2.

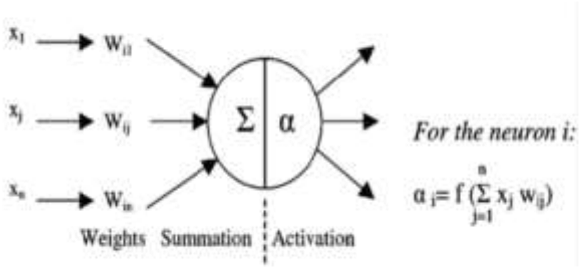

Figure 2. Information processing in a neural network unit (Kalogirou 2003)

Figure 2 indicates that each of node receives weighted activation of other nodes over its input network connection. Originally, the weights of other nodes are gradually added to the expected nodes. Once it completed, the following step is passing its result to the next nodes by using activation function(Kalogirou 2003).

The activation function is needed to activate the process of propagation in the forward direction to compute the hidden layers. Generally, it adopts a nonlinear activation function to its weighted sum. Subsequently, a loss function to obtain error information occurs once the forward propagation is done. By implementing this error, the weights are updated in the backward pass(Yüksel, Soydaner, and Bahtiyar 2021).

Several activation functions involved in artificial neural networks are denoted as follows:

Hardlimit function: (2)

a = $\{1 \ if \ n \ \geq 0\}$
$\{0 \ if \ n \ \leq 0\}$

Linear function: (3)
a = n

Sigmoid function: (4)
$a = 1/(1+e^{-n})$

Rectified Linear Unit (ReLU) (5)
f(z) = max (o,z)

tanh (6)
$f(z) = e^{z} - e^{-z} / (e^{z} + e^{-z})$

In terms of updating the weights, perceptron experiences a series of learning process which are systematically elaborated as follows:

- The initial weight is initiated with small value in order to maintain the proportional difference with the target.
- The initial weight is randomly chosen within the range of -0.5 to 0.5
- Output stage is a process of multiplying between input and weight
- If the difference between output and target happens, then the consequence is to update the weight in order to match with the target.

To evaluate the difference in terms of value between output and target is by applying this equation as below:

e(k) = a(k) – t(k) (7)

Where,
e(k) = error
a(k) = output neuron
t(k) = expected target

To assign an update weight in learning process, an equation used as follow:
w(k+1) = w(k) + Δw(k) (8)

Where,
Δw(k) = learning speed x input x error

In addition, to improve the performance by minimizing an error occurs from one hidden layer, a multiple hidden layers are introduced by learning more complicated functions of the input. In this study, the structure of ANN was adopted to predict the indoor CO_2 concentration by considering the existence of relative humidity and inlet airflow.

METHOD

Source of Data

The data involved in this study were temperature, inlet airflow speed, and indoor CO_2 concentrations. These data were obtained from field measurements during 5 (five) days in the office within working hours and were measured by using two equipments namely davis anemometer and yes plus LGA meter. The davis anemometer was used to measure inlet airflow speed and the yes plus LGA meter was utilized to measure indoor CO_2 concentrations.

Table 1. The specification of Davis Anemometer

Wind Direction	
Display Resolution	16 points (22.5°) on compass rose, 1° in digital display
Accuracy	±3°
	Wind Speed
Range	1 to 200 mph, 1 to 322 kph, 1 to 173 knots, 0.5 to 89 m/s
Accuracy	± 2 mph (3 kph, 2k ts, 1 m/s)

Table 2. The specification of Yes Plus LGA Meter

Enclosure	Column A (t)
Dimensions	Width: 254 mm
	Height: 89 mm
	Length: 178 mm
Right	18 mm
Weight	1.7 kg
Construction	Ruged,
	ABS/Polycarbonate
	Portable instrument
	Enclosure UL94
	rating.

Enclosure	Column A (t)
Power	
Standard	Rechargeable NiMH
Standard	Up to 18 to 24 hours
	(full charge)
Continuous	Plug-in, 12 VDC,
	Class-2, 2.5 Amp
	Max. Wall adapter.
	Adapter input 100 to
	240 VAC, 50 to 60
	HZ/ 700 mA.
Monitoring mode	Internal, automatic
	sample pump for
	"Active" sampling of
	Target environment.
Operating ranges	
Temperature	5°C to 50°C
RH	0 to 99%
CO_2	0 to 5000 ppm

Variable of Research

Main object of this study was the existing condition of indoor CO_2 concentrations which has been measured and it will be estimated by comparing through ANN developed in this study.

Analysis of ANN

The feed-forward neural network method was implemented to generate ANN model in order to predict the output of indoor CO_2. If the error value caused from output and target is still high, the network will update the weight and the bias gradually to minimize its error value.

The Optimum Model of ANN

The model selection of ANN is based on several parameters such as coefficient of determination (R^2), Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE). The R^2 is an indicator of how well the regression able to predict the real data points. While, the MAPE is widely used as a loss function for regression issues and model evaluation because of its intuitive interpretation in terms of relative error.

$$R^2 = 1 - \frac{SS_e}{SS_{yy}} \tag{9}$$

$$MSE = \frac{\left(\sum_k^p y\ actual - \sum_{k=1}^p z\ j\ W\ jk\left(\frac{1}{1+exp^{-z(nj)}}\right)^{\wedge}2\right)}{n} \tag{10}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|xi-pi|}{xi} \text{ X } 100 \tag{11}$$

Where, xi is the actual value and pi is the predicted value of i^{th} data point, n is the total number of data samples.

RESULTS AND DISCUSSION

Data–Driven Prediction Model of Indoor CO_2 by ANN

To generate an optimum model of ANN, it needs an optimization processes by selecting proper configuration of hidden layers (net structure). In addition, activation function is required to adjust a number of input to work in non-linear mechanism and prepare it to learn and to perform in solving complex issues. Furthermore, the proper selection of hidden layer construction and activation function is identified by several indicators such as MSE, MAPE, and R^2. This study proposed a number of perturbation composition of hidden layers and activation function to assess its effect to the performance of ANN model.

Table 3. Composition of ANN constructions

No.	Net Structure	Activation Function	Learning Initial Rate
1	15	logistic	0.2
2	15	tanh	0.2
3	15	identity	0.2
4	15	ReLU	0.2
5	15 - 5	logistic	0.2
6	15 - 5	tanh	0.2
7	15 - 5	identity	0.2
8	15 -5	ReLU	0.2
9	15 – 5 - 2	logistic	0.2
10	15 – 5 - 2	tanh	0.2
11	15 - 5 -2	identity	0.2
12	15 – 5 - 2	ReLU	0.2

As showed in Table 1. The variations of hidden layers were divided into three layers in which the first layer was consisted of fifteen nodes, it followed by the second layer was comprised of five nodes, and ultimately the third layer was configured of two nodes. Besides, several activation functions involved to this study were logistic, tanh, identity, and ReLU.

ReLU is utilized to extract non-linearity patterns from data (Segala et al. 2021) and the result is more biologically accurate. It has the output 0 if its input is less than or equal to 0. Subsequently, Logistic function is a form of sigmoidal nonlinearity and its value lies in the range of $0 \leq y_j \leq 1$ (Simon Haykin 2009). Another activation function is tanh which widely used in the form of sigmoidal nonlinearity (Simon Haykin 2009). It has wider input within the range of -1 to 1. This function gives an output which is zero-centered. Consequently, large negative values are classified into negative outputs. Ultimately, Identity function or commonly known as linear activation function is the simplest function of activation. It employs identity operation on your data and feature data is proportional to the input data. These four activation functions aim to propose non-linearity in an ANN. It facilitates us to model a class label that varies non-linearly with independent variables. The term of non-linearity is defined that the output cannot be imitated from a linear combination of inputs, this authorizes the model to learn complex mapping from the available data.

Table 4. The results of perturbing ANN constructions

No	MAPE	MAPE (train)	MSE	MSE (train)	R^2
1	3.584	3.354	2326.549	2038.951	0.854
2	5.249	5.076	4670.782	4344.298	0.707
3	7.177	7.125	8385.698	8142.088	0.474
4	5.227	5.210	4507.246	4527.944	0.717
5	3.651	3.461	2208.783	2016.671	0.861
6	10.757	10.708	15956.756	15709.633	-0.000127
7	7.287	7.231	8074.533	8006.150	0.493
8	5.393	5.402	4929.409	5041.982	0.691
9	10.743	10.696	15955.180	15710.167	$-2.877.10^{-5}$
10	10.743	10.696	15955.161	15710.189	$-2.756.10^{-5}$
11	7.488	7.457	8395.501	8282.155	0.473
12	5.584	5.621	4871.269	4942.777	0.694

Table 4 presented that the highest of determination coefficient was 0.861, while 2.877x10-5 was recorded as vice versa. Moreover, the value of R2 impacted to the behavior of MAPE and MSE. It was indicated that the highest value of R^2 led MAPE to decrease and conversely. This scheme occurred the same in MSE behavior as well.

Furthermore, the discrepancy results between actual conditions and prediction were tabulated as in Table 5 to Table 16. These tables were categorized into three different groups, the first group was started from Table 5 to Table 8, the following group was from Table 9 to Table 12, and the final group was from Table 13 to Table 16. The first group was assigned to predict indoor CO_2 concentration by using one hidden layer and four different activation functions.

Table 5. Discrepancies of logistic function in one hidden layer

No	Prediction (ppm)	Actual (ppm)	Discrepancy (%)
1	1093.735	1193	8.320
2	867.405	840	-3.262
3	880.971	854	-3.158
4	867.404	859	-0.978
5	935.397	1006	7.018
6	941.443	979	3.836
7	956.769	954	-0.290
8	957.759	999	4.128
9	1059.492	1131	6.322
10	926.51	956	3.084

Table 6. Discrepancies of tanh function in one hidden layer

No	Prediction (ppm)	Actual (ppm)	Discrepancy (%)
1	1099.455	1193	7.841
2	836.569	840	0.408
3	886.648	854	-3.822
4	836.569	859	2.611
5	967.713	1006	3.805
6	970.145	979	0.904
7	995.5	954	-4.350
8	963.398	999	3.563
9	1106.839	1131	2.136
10	970.144	956	-1.479

Table 7. Discrepancies of identity function in one hidden layer

No	Prediction (ppm)	Actual (ppm)	Discrepancy (%)
1	993.222	1193	16.745
2	868.972	840	-3.449
3	920.063	854	-7.735
4	867.043	859	-0.936
5	1017.17	1006	-1.110
6	900.833	979	7.984
7	893.886	954	6.301
8	983.065	999	1.595
9	1114.067	1131	1.497
10	943.493	956	1.308

Table 8. Discrepancies of ReLU function in one hidden layer

No	Prediction (ppm)	Actual (ppm)	Discrepancy (%)
1	1079.952	1193	9.475
2	838.437	840	0.186
3	913.489	854	-6.965
4	841.887	859	1.992
5	962.139	1006	4.359
6	923.365	979	5.682
7	958.808	954	-0.503
8	964.787	999	3.424
9	1063.599	1131	5.959
10	953.325	956	0.279

Based on Table 5 to Table 8, it can be seen that the percentage of discrepancy from logistic function was lesser as compared to the other three activation functions.

Table 9. Discrepancies of logistic function in two hidden layers

No	Prediction (ppm)	Actual (ppm)	Discrepancy (%)
1	1115.031	1193	6.535
2	893.471	840	-6.365
3	869.119	854	-1.770
4	893.471	859	-4.012
5	924.689	1006	8.082
6	934.319	979	4.563
7	978.61	954	-2.579
8	929.069	999	7.000
9	1094.929	1131	3.189
10	951.548	956	0.465

Table 10. Discrepancies of tanh function in two hidden layers

No	Prediction (ppm)	Actual (ppm)	Discrepancy (%)
1	992.768	1193	16.783
2	992.768	840	-18.186
3	992.768	854	-16.249

No	Prediction (ppm)	Actual (ppm)	Discrepancy (%)
4	992.768	859	-15.572
5	992.768	1006	1.315
6	992.768	979	-1.406
7	992.768	954	-4.063
8	992.768	999	0.623
9	992.768	1131	12.222
10	992.768	956	-3.846

Table 11. Discrepancies of identity function in two hidden layers

No	Prediction (ppm)	Actual (ppm)	Discrepancy (%)
1	952.073	1193	20.195
2	844.590	840	-0.546
3	933.302	854	-9.285
4	841.389	859	2.050
5	984.281	1006	2.158
6	880.375	979	10.074
7	865.785	954	9.246
8	1009.796	999	-1.080
9	1096.915	1131	3.013
10	954.508	956	0.156

Table 12. Discrepancies of ReLU function in two hidden layers

No	Prediction (ppm)	Actual (ppm)	Discrepancy (%)
1	1041.892	1193	12.666
2	825.027	840	1.782
3	887.454	854	-3.917
4	826.973	859	3.728
5	907.539	1006	9.787
6	908.067	979	7.245
7	953.896	954	0.010
8	947.614	999	5.143
9	1017.242	1131	10.058
10	937.650	956	1.919

Table 9 to Table 12 showed a number of percentage discrepancies for the four different activation functions in the two hidden layers. It indicated that the accuracy of the logistic function in imitating the actual model improved as hidden layers increased from one layer to two hidden layers

Table 13. Discrepancies of logistic function in three hidden layers

No	Prediction (ppm)	Actual (ppm)	Discrepancy (%)
1	992.025	1193	16.846
2	992.025	840	-18.098
3	992.025	854	-16.162
4	992.025	859	-15.486
5	992.025	1006	1.389
6	992.025	979	-1.33
7	992.025	954	-3.985
8	992.025	999	0.698
9	992.025	1131	12.287
10	992.025	956	-3.768

Table 14. Discrepancies of tanh function in three hidden layers

No	Prediction (ppm)	Actual (ppm)	Discrepancy (%)
1	992.011	1193	16.847
2	992.011	840	-18.096
3	992.011	854	-16.160
4	992.011	859	-15.484
5	992.011	1006	1.390
6	992.011	979	-1.329
7	992.011	954	-3.984
8	992.011	999	0.699
9	992.011	1131	12.289
10	992.011	956	-3.766

Table 15. Discrepancies of identity function in three hidden layers

No	Prediction (ppm)	Actual (ppm)	Discrepancy (%)
1	969.298	1193	18.751
2	834.148	840	0.696
3	920.262	854	-7.759
4	831.294	859	3.225
5	1017.694	1006	-1.162
6	912.668	979	6.775
7	870.391	954	8.764
8	1046.745	999	-4.779
9	1141.214	1131	-0.903
10	967.689	956	-1.222

Table 16. Discrepancies of ReLU function in three hidden layers

No	Prediction (ppm)	Actual (ppm)	Discrepancy (%)
1	1076.107	1193	9.798
2	864.188	840	-2.879
3	947.734	854	-10.975
4	866.355	859	-0.856
5	976.207	1006	2.961
6	908.936	979	7.156
7	966.875	954	-1.349
8	961.008	999	3.803
9	1055.319	1131	6.691
10	962.594	956	-0.689

Surprisingly, when the number of hidden layers increased to three hidden layers of logistic activation function. The results indicated that accuracy in predicting actual model decreased significantly.

From those table above, it can be concluded that the majority of models were in the tolerable range of results. According to Chowdhury *et al.,*(Chowdhury, Rasul, and Khan 2008) and Judkoff *et al.,* (Judkoff et al. 2008), a percentage difference is considered as tolerable value if the value lies within the range of 6 % to 10%. Another interesting finding was presented to identify the behaviors between the testing data and training data. It involved the results between MSE and MAPE of four different activation functions as presented in Figure 3 to Figure 10.

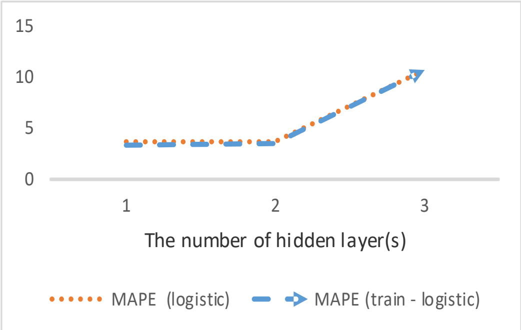

Figure 3. MAPE (logistic) vs. MAPE (train – logistic)

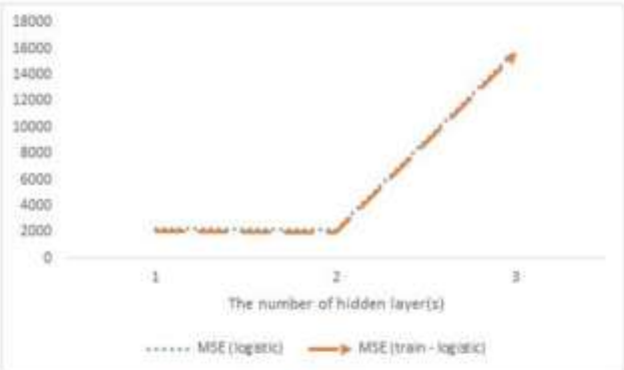

Figure 4. MSE (logistic) vs. MSE (train – logistic)

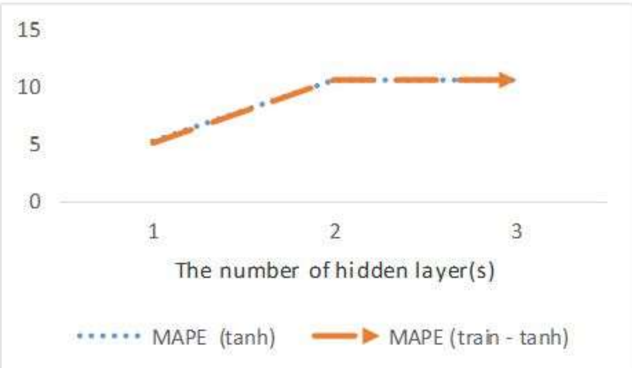

Figure 5. MAPE (tanh) vs. MAPE (train – tanh)

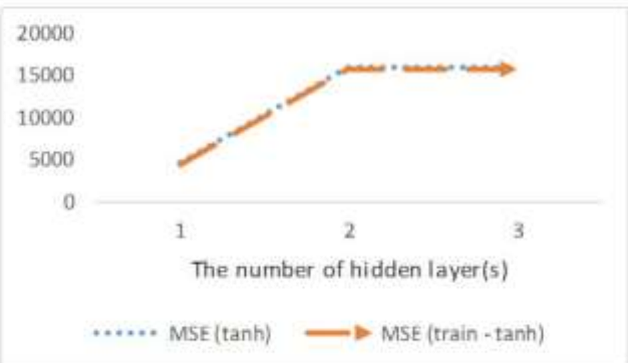

Figure 6. MSE (tanh) vs. MSE (train – tanh)

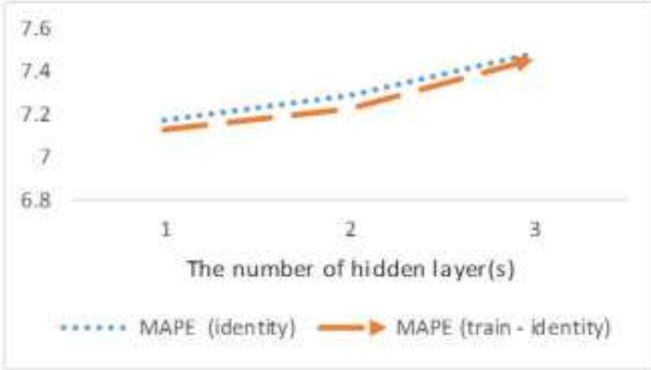

Figure 7. MAPE (identity) vs. MAPE (train – identity)

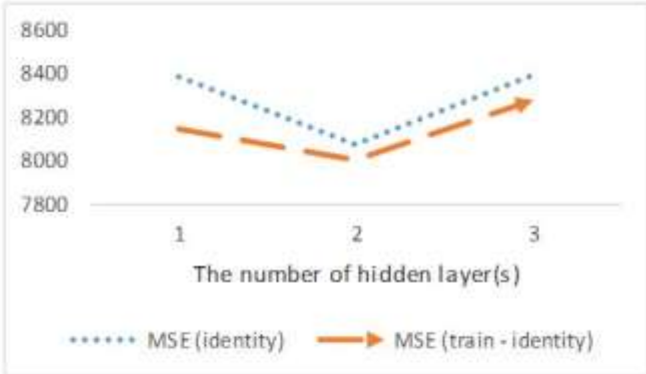

Figure 8. MSE (identity) vs. MSE (train – identity)

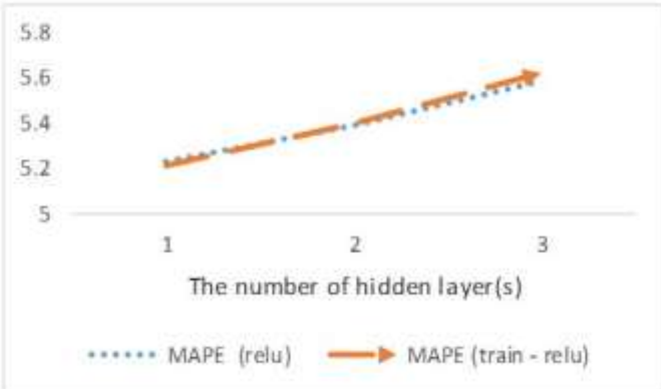

Figure 9. MAPE (RLUu) vs. MAPE (train – ReLU)

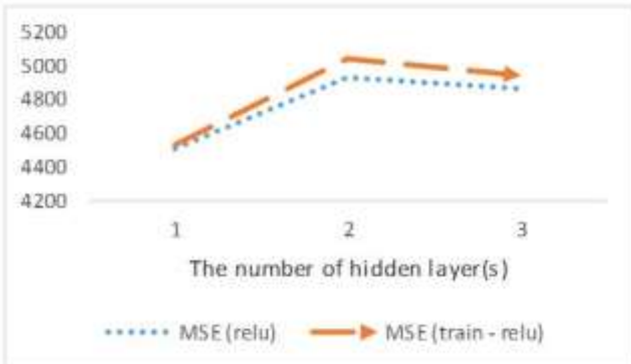

Figure 10. MSE (ReLU) vs. MSE (train – ReLU)

Based on the figures presented in Figure 4 to Figure 10, it showed that, both the testing data and the training data successfully learned the given data. It means that, the varieties of activation function provided a prominent result in terms of imitating the initial data. Furthermore, to explore its effects on each learning processes, the further behavior analysis of discrepancies of three different hidden layers based on four different activation functions such as logistic, tanh, identity, and ReLU was presented as in Figure 11 to Figure 14 respectively.

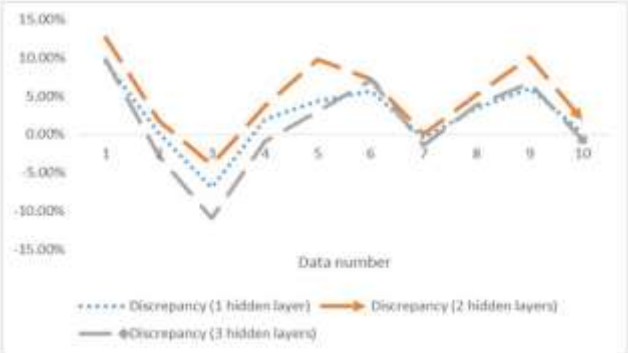

Figure 11. Discrepancies behavior of logistic function

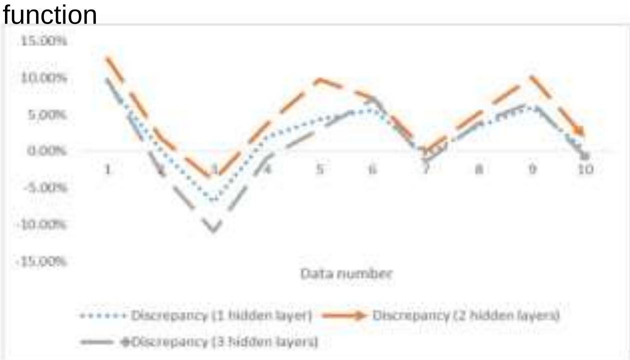

Figure 12. Discrepancies behavior of tanh function

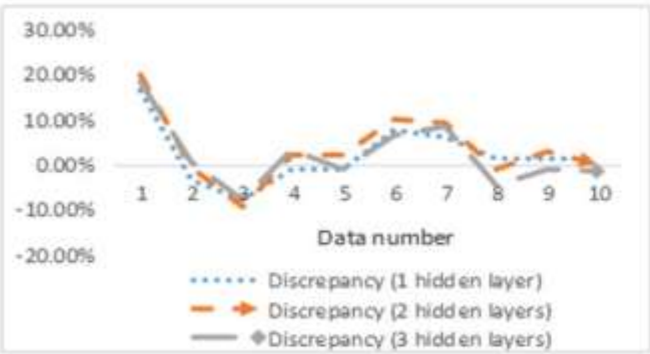

Figure 13. Discrepancies behavior of identity function

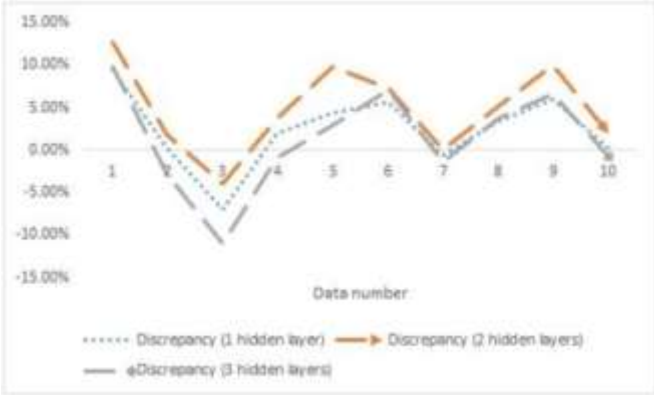

Figure 14. Discrepancies behavior of ReLU function

As refer to the figures presented in Figure 11 to Figure 14, the discrepancies were displayed clearly in terms of the distances between each hidden layers in the same activation function. For instance, in the Figure 13 showed that the difference value of discrepancies amongst hidden layers were quite small and it impacted to the coefficient of determination that more less same. Besides, from the Figures of logistic function and tanh function, these two functions provided a difference on their percentage of discrepancies. This behavior facilitated an opportunity of each hidden layers to enhance the performance of ANN model. Therefore, regarding to this study an optimization of prediction performance was contributed from the selection of proper activation function. Additionally, the structure of hidden layers was identified that it did not necessarily enhance the performance of ANN model.
According to Sharma *et al.,*(Sharma et al. 2020) the number of samples play significant role in determining the accuracy of output model. It was characterized by their value of root mean square error. Furthermore, Shatnawai and Abu-Qdais(Shatnawi 2021) stated that the construction of hidden layers was the important part of ANN development model. The selection of activation functions was also key point to generate the data with good accuracy.

Based on the results of this study, the model was at optimum performance by using two hidden layers of 15 – 5 and using logistic activation function. This selection was based on the implementation of logistic activation function that has succeeded in increasing the value of coefficient determination from 0.854 to 0.861. Additionally, the output of mean square error reduced from 2038.951 to 2016.671. This indicated that the approach successfully reduced the discrepancy between predicted and actual models.

However, another interesting result from this study was the behavior of hidden layers when it was applied with three different hidden layers to model the indoor CO_2. The model performance declined as characterized by a declining value of determination coefficient. Moreover, the output of mean square error was significantly increased to 15710.167.

The addition finding from this study shown that the selection of proper activation functions and number of hidden layers was subjected to the data provided in input stage. This is in line with the because the activation functions only activates its function if exceed the threshold value(Arif et al. 2018).

CONCLUSION

This study was accomplished by implementing feed-forward neural networks and different hidden layers designated with four different activation functions. These approaches were implemented to the measured data of indoor environment which were consisted of indoor temperature and indoor CO_2 concentrations within five days during office hours.

Our findings show that the proper selection of activation function can generate an optimum model of ANN that successfully predicted the target data. Although the model was developed from a week data of indoor environment, it was seen that the model was reliable due to its R^2 value. Consequently, the ANN can be used as a tool to predict indoor CO2 in concise time and leads to cost efficiency.

As further study, we propose to extend our strategy by build some algorithm that interaction comprehensively and it will determine the better behavior to enhance the performance of the targeted model.

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