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Prediction and correlation analysis of ventilation performance in a residential building using artificial neural network models based on data-driven analysis

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A R T I C L E I N F O

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A B S T R A C T

This study investigates approaches to evaluate prediction and correlation how significantly mechanical and natural ventilation rate and local weather conditions affect the actual ventilation performance of a residential building using Artificial Neural Network (ANN) algorithms: Feedforward networks and Layer recurrent neural networks. In order to evaluate the ventilation performance in a residential building, an impact factor was determined for these measured datasets. This study selected two residential apartments in Switzerland and measured indoor carbon dioxide concentration and volatile organic compound levels, façade opening ratio, mechanical ventilation rates, and indoor temperature and humidity ratio between July 2019 and June 2020. The results described that ANN models illustrate performance in predicting ventilation performance and indoor air quality using mechanical and natural ventilation systems in a residential apartment. Both algorithms have presented relatively lower average error rates, 3.36– 6.12 % in the analysis results. The results presented that the two ANN models using the Levenberg-Marquardt Back Propagation (LMBP) algorithm have good agreements with actual data measured. The accuracy differences were 0.18-1.89 for the average error rates, 0.13–0.78 for the Coefficient of Variation of the Root Mean Square Error (CVRMSE) and 0.07–0.35 for the Normalized Mean Bias Error (NMBE). Through impact factor analysis, mechanical ventilation system mainly dominates the impact of indoor ventilation performance, and other surrounding environments also had significantly affected the residential building. However, the natural ventilation system has limitations to largely influence the ventilation performance in the building because occupants have difficulties adjusting ventilation rates in extreme weather conditions or early morning and nighttime. And these elements could not affect indoor air quality independently. These ANN methods are helpful in analyzing input parameters how each element factor can influence indoor air quality in a residential building. The proposed ANN methods can utilize to predict the performance as reliable approaches.

1. Introduction

Natural ventilation (NV) effectively saves energy using a passive design strategy as a natural air conditioning system and improves indoor air quality to supply fresh outdoor air in moderate weather conditions without thermal and mechanical energy demands (Tantasavasdi et al., 2001). However, this strategy has limitations in that the passive system performance is significantly affected by surrounding environmental conditions. Therefore, its utilization is limited in extreme hot or cold weather, polluted air, or high environmental noise (Kim et al., 2018; Ren et al., 2022). And occupants also have difficulties adjusting a favorable amount of airflow using window airing in variable outdoor environmental conditions. Due to these applicable limitations, many buildings have preferred to use Mechanical Ventilation (MV) systems. MV system has been widely used in commercial and residential buildings to improve indoor air quality and thermal comfort (Kang et al.,

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2022; Liu et al., 2021a, 2021b). In moderate conditions such as intermediate seasons, this system can use an economizer to save Heating, Ventilation and Air Condition (HVAC) demand. Many works of literature (Baldini et al., 2014; Fu et al., 2021a; Kim & Baldini, 2016; Park & Jeong, 2017) have presented the ventilation performance using NV and MV systems in buildings. And they also described the effect of airflow rate, surrounding weather conditions on the actual ventilation performance and indoor air quality in buildings.

Using Artificial Neural Network (ANN) modeling, some studies (Cao & Ren, 2018; Masood & Ahmad, 2021; Ren & Cao, 2020; Tian et al., 2021) have presented methods to predict ventilation performance in buildings. In ventilation performance and indoor air quality prediction, the main issue involves establishing a data-driven mathematical model for the prediction. Ventilation performance and indoor air quality in buildings are influenced by many factors such as temperature and humidity ratio difference between indoor and outdoor environment, windows and doors opening ratio, outdoor wind speed, and airflow ratio of MV system. In a building using an MV system such as a constant air volume (CAV) system, the supply airflow rate is generally fixed, and therefore, the surrounding outdoor environment does not significantly affect the actual indoor ventilation performance. However, using the NV system, the façade opening ratio, and local weather parameters can influence the natural ventilation performance and indoor air quality. This study presents ventilation performance and indoor air quality of two case studies in residential buildings: one uses both MV and NV systems, and the other uses only NV systems. And this study, as a sensitivity analysis explores the prediction of how significantly the elements, MV system, windows and doors opening ratio, and local environments impact the ventilation performance and indoor air quality in a residential building. Variable data-driven algorithms, as ANNs have been proposed for predicting energy consumption and indoor air quality. Current studies have proposed variable predicting methodologies of developing algorithms, such as regression, statistical methods, support vector machines (SVM), a multilayer neural network. Compared to conventional statistical methods, ANN algorithms' results have presented better prediction performance and accuracy and brought forward the analyzing effectively (Liu et al., 2021b; Shao et al., 2020).

In particular, the ANN methods are some of the main algorithms currently used to predict electricity consumption in buildings (Carrera et al., 2021; Gellert et al., 2022; Kim et al., 2019a, 2020b; Ye & Kim, 2018; Li et al., 2022a, 2022b). ANNs provide the function and structure of biochemical reactions in human brains by performing nonlinear processing. ANNs are self-learning systems and can constantly adjust their approach to adapt to variable environments when processing many types of information (Hsu, 2015; Kalogirou, 2000; Kumar et al., 2013; Werbos, 1975). Therefore, ANNs have been widely used in pattern recognition to forecast changes in processes, improve accuracy, optimize decision making, and other tasks. One of the main advantages of neural network algorithms is that they can memorize training information and self-learning, optimizing the information and knowledge factors that impact the testing results. Self-adaptability is the most crucial factor of ANN algorithms to influence the results' accuracy compared to conventional algorithms (Ahmad et al., 2017; Hao et al., 2013; Neto & Fiorelli, 2008; Zorzetto et al., 2000). Therefore, recently ANNs have illustrated a significant methodology in predicting IAQ and air ventilation performance in buildings (Ashtiani et al., 2014; Li et al., 2022a; Martínez-Comesaña et al., 2021; Tian et al., 2021).

Previous studies have described indoor air quality using ANNs algorithms; however, this study newly proposes the prediction of novel ventilation performance using ANNs in a residential building, and illustrates how the actual elements, windows and doors opening ratio, local weather condition, indoor thermal condition, and airflow rate from MV system are correlated with indoor air quality and ventilation performance. And how each parameter significantly affects indoor air quality in a residential building located in Switzerland. As a sensitivity analysis, the proposed predictive control strategy is based on two ANNs, a layered recurrent neural network, and feed-forward neural network algorithms. We explored the utilization of impact factors demonstrated with ANNs' training and outputs using input parameters, i.e., airflow rate from MV system, windows and doors opening ratio, and weather parameters such as temperature, humidity ratio, wind speed, and predicted the actual indoor air quality of a residential building with these two ANN approaches.

The four main objectives of this research are:

- Analysis of the variation in airflow rate from MV system, windows and doors opening ratio, indoor thermal condition and local weather data based on experimental data in a residential building.
- Prediction of indoor air quality in a residential building using two ANN algorithms: a feed-forward neural network algorithms and layered recurrent neural network as a comparative analysis.
- Investigation of the impact of parameters' correlation of airflow rates from MV system, windows and doors opening ratio, indoor thermal condition, and weather conditions which are temperature, humidity ratio, and wind speed on ventilation performance and indoor air quality with sensitivity analysis.
- Application of the predictive analysis in the natural and mechanical ventilation systems.

2. Ventilation performance and indoor air quality prediction models

ANN models are widely used in experimental data-driven analysis and prediction modeling in built environment research areas because it is derived by the human brain (Hsu, 2015; Singh et al., 2007; Xu et al., 2015). And this study selected two algorithms: a feed-forward perception neural network and recurrent neural network. Currently a popular model is a feed-forward perception neural network that is trained using error back-propagation algorithms. However, to reduce local minima, improve training speed, minimize overfitting problems, and design optimal network structure, other algorithms such as genetic algorithms recurrent and conjugate gradient algorithms are also suggested (Brezak et al., 2012; Karim & Rivera, 1992; Moore et al., 1991; Taver et al., 2015). These algorithms have their advantages and disadvantages for training and predicting results. Feed-forward back propagation modeling has illustrated good accuracy; however, the performance can be affected by recurrence pattern and reusing inputs and outputs. Therefore, the two neural networks have been performed for these reasons.

2.1. Feed-forward neural networks (FFNN)

A feed-forward neural network comprises three layers, respectively: the input, hidden, and output layers (Amber et al., 2015; Li et al., 2015; Moore et al., 1991; Ye & Kim, 2018). Each layer connects at least one neuron operating in parallel and responds independently to each layer. Fig. 1 shows an example of the feed-forward neural network models.

As presented in Fig. 1, X_1, X_2,…, X_n are the input elements in the input layer that can impact ventilation performance and indoor air quality in a building, such as an airflow rate of MV system, windows, and doors opening ratio, indoor temperature, indoor humidity ratio, and outdoor weather parameters. Y_1, Y_2, … Y_n are the output nodes corresponding to the algorithm using input and hidden nodes to predict indoor air quality.

The output node of the hidden vector is as follows (Brezak et al., 2012; Lek & Guégan, 1999; Yu et al., 2008):

$$o_j = f\left(\sum_{i=1}^{n} w_{ij}x_i + w_{N+1,j}\right) j = 1, 2, \ldots, l \quad (1)$$

where f is a function, w_{ij} is the weight in the hidden layer, and n is the number of input nodes, and d is the threshold of each node

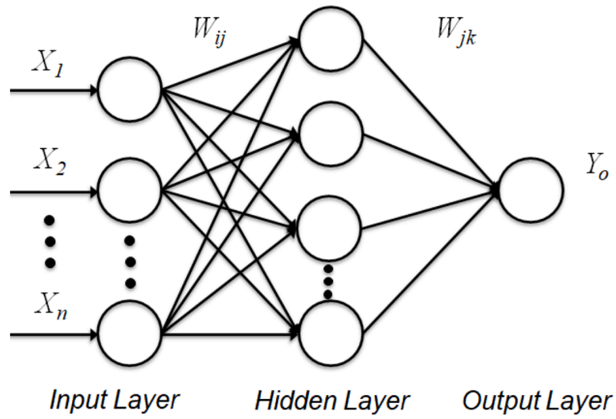

Fig. 1. Feed-forward neural network structure.

The output node of the output vector is as follows (Ekici & Aksoy, 2009; Neto & Fiorelli, 2008):

$$Y_k = f\left(\sum_{j=1}^{l} o_j w_{jk} + w_{N+1,k}\right) \quad k = 1, 2, \ldots, m \tag{2}$$

w_{jk} is the weight in the output layer, l is the number of the hidden layers, and m is the number of output nodes.

Each connection between neurons has a weight value associated with it.

2.2. Recurrent neural network (RNN)

Compared to a feed-forward neural network, recurrent neural network (RNN), the connection of each neuron is allowed to feedback between the layers for the training process. Therefore, it has the potential for data pattern recognition and compression. The feedback process refines inputs to improve the accuracy of the result outputs using estimated outputs to refine the input data (Brezak et al., 2012; Cossu et al., 2021; Karim & Rivera, 1992; Kurnaz & Demir, 2022; Moore et al., 1991).

The equations presenting an RNN algorithm are shown as follows (Karim & Rivera, 1992; Moore et al., 1991):

$$y^t = g(h^t) \tag{3}$$

$$h^t = f\left(x^t, h^{t-1}\right) \tag{4}$$

x,y, and *h* are the input, output, and hidden layer at time step *t*, respectively.

Fig. 2 illustrates an example of the recurrent neural network models

The Levenberg-Marquardt Back-propagation (LMBP) algorithm was selected to design functions using feed-forward and recurrent neural network training methods. Recently it has been well known alternative approach to the Gauss-Newton method for creating the minimum of squares of nonlinear functions (Bocheng Zhong et al., 2015; Ye & Kim, 2018).

Compared to other algorithms such as the conjugate gradient method, and Quasi-Newton method in the nonlinear training, LMBP algorithm is one of the quick training functions. Some studies have reported that LMBP has better maintained performance and stability in neural networks, and the network converges effectively; however, it requires more hardware memories and system performance than other algorithms (Kim et al., 2020a; Lek & Guégan, 1999; Wong et al., 2010). The two neural network training and prediction processes applied in this study are illustrated in Fig. 3.

This study collected data of the indoor air quality, windows and doors opening ratio, temperature, humidity ratio, and wind speed at a residential building in Büren, Switzerland. The multi-family apartment was built in 2017. And the building consists of four layers: two floors, an attic, and a basement. The first and second floor has two apartments, of which the left apartment have 80 m^2 surface area, and the right-side apartment has 113 m^2 surface area.

Fig. 4 shows different family sizes occupying the two monitored apartments. Fig. 5 illustrates the technical installations of the ventilation system and sensors to check the airing ratio. A single person occupied the top left apartment, and two people occupied the bottom left apartment. The top apartment is ventilated by only natural ventilation. The bottom apartment is mechanically ventilated with a Zehnder balanced ventilation unit, type ComfoAir Q350 which is equipped with an enthalpy exchanger that can transfer heat and moisture between the incoming and the outgoing air stream. The bottom apartment is constantly ventilated, and fresh air is supplied into each living room and bedroom by individual air ducts. The airflow rate of the MV system is 110 m^3/h. The MV system data were monitored via a KNK system following standards (EN 50090, ISO/IEC 14543) connected to the ComfoAir Q unit. This system (Model: Wisey AllSense, accuracy: $\pm 0.1\ ^{o}C$, $\pm$ 1.5% RH, $\pm$ 1hPa) analyzes airflow rate, temperature, humidity ratio of all supply and exhaust air streams with sensors. CO_2 and volatile organic compounds (VOCs) sensors (Model: Senseair Sunrise, accuracy: $\pm$ 30 ppm, Model: BME680, accuracy status: Index for Air Quality, 0-3) analyzed the indoor air quality. Sensors are placed in each room. Moreover, the windows and doors opening ratio is monitored with the sensors (Model: DT35-B15251, accuracy: $\pm$ *10 mm*) positioned at the envelope of the apartment.

This study selected a residential apartment using both NV and MV system and collected a full year data (except for a few days) within 5 minutes for the building's opening ratio, mechanical ventilation rates, indoor and outdoor temperature and humidity ratio, wind speed indoor air quality (CO_2 and VOCs level) between July 8, 2019, and June 30, 2020. The experimental data were categorized into two groups: working days and non-working days because on non-working days, occupant ratio and behavior patterns are not regulated compared to the occupant patterns on working days; however, we used only the working days' data to predict the indoor air quality because the non-working days' data

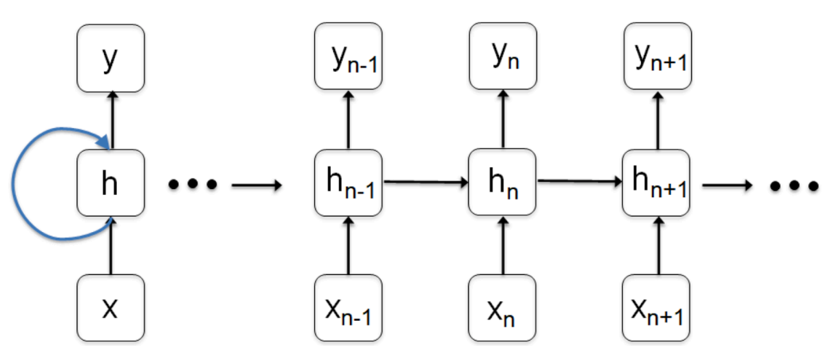

Fig. 2. Recurrent neural network structure.

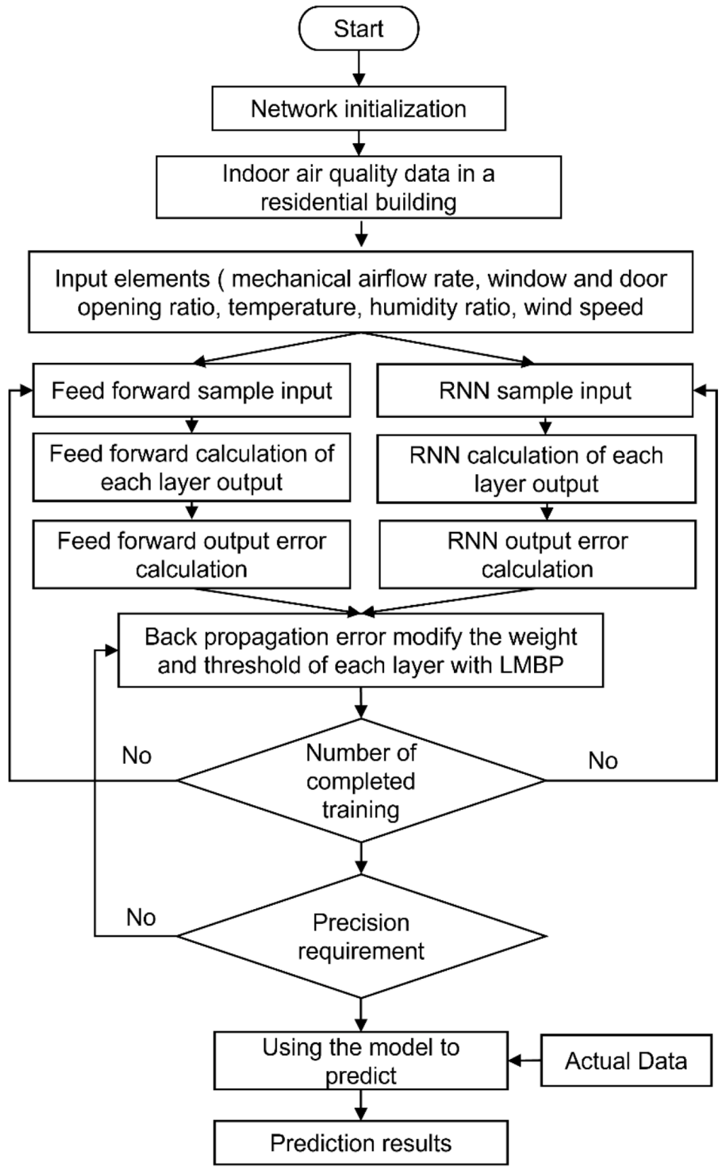

Fig. 3. Training process for the artificial neural networks.

were relatively insufficient for training and testing. Data driven-ANNs analysis needs sufficient training data for learning which normally accounts for 70-90% of total data collected (Giovanni & John, 2010; Kamlesh Shah et al., 2020; Lazrak et al., 2016; Lorenzo et al., 2015). Low training data numbers and fluctuated data can significantly increase error rates and the insufficient numbers' data could not validate the results.

Using ANN simulations as sensitivity analysis, this study investigated the impact of airflow rate of MV system, windows and doors opening ratio, temperature and humidity ratio, and local weather elements conditions on the indoor air quality. Moreover, the collected data (340 days or 8160 hours) were randomly separated into training (200 working days or 4800 hours) and test data (15 working days or 360 hours). In the prediction methodology, this study provided the input nodes that influenced indoor air quality (CO_2 and VOCs level) such as airflow rate of MV system, windows and doors opening ratio, the temperature difference between indoor and outdoor (^{o} C), humidity ratio difference between indoor and outdoor (g/kg), and wind speed (m/s). The collected data are presented in Figs. 6–10. In order to ascertain the number of hidden layers and nodes, this analysis used references (Amber et al., 2015; Tang Zhong, 2012; Ye & Kim, 2018). Figs. 6 and 7 presents the annual outdoor temperature and humidity ratio at Büren in Switzerland. The summer season's temperatures and humidity ratios were around 10-35 °C and 5-15 g/kg and the winter season's data were about -5-12 °C and 2-7 g/kg. Fig. 8 illustrates the airflow rate of MV system. The ventilation system was designed as constant air volume control with a heat recovery unit. The actual supplied airflow rates were oscillated near 110 m^3/h. Fig. 9 presents façade (windows and doors) opening ratios of two apartments. The opening ratios were affected by seasonal changes. In the summer season, the occupants relatively increased the opening ratios, but in the cold winter season, the occupants decreased the opening ratios due to strong stack and buoyancy effect by high temperature difference between the indoor and outdoor condition. Especially the top apartment had constantly used the natural ventilation with the façade openings; however, the bottom apartment mainly used the mechanical ventilation, so that the numbers of façade opening usage were less than those of the top apartment. And Fig. 10 shows the outdoor wind velocity, and the values were around 0-12 m/s. These collected data can influence the indoor CO_2 concentration, and VOCs levels in Figs. 11 and 12.

Figs. 11 and 12 show two apartments' indoor air quality performance. CO_2 concentration level evaluates indoor air quality as a good

Fig. 4. A multi-family apartment in Büren (left) and plan view of the two apartments (right).

Fig. 5. Technical installations of the building for heating and ventilation (left), a photoelectronic laser senor to detect windows and doors opening ratio (middle), a façade contact sensor.

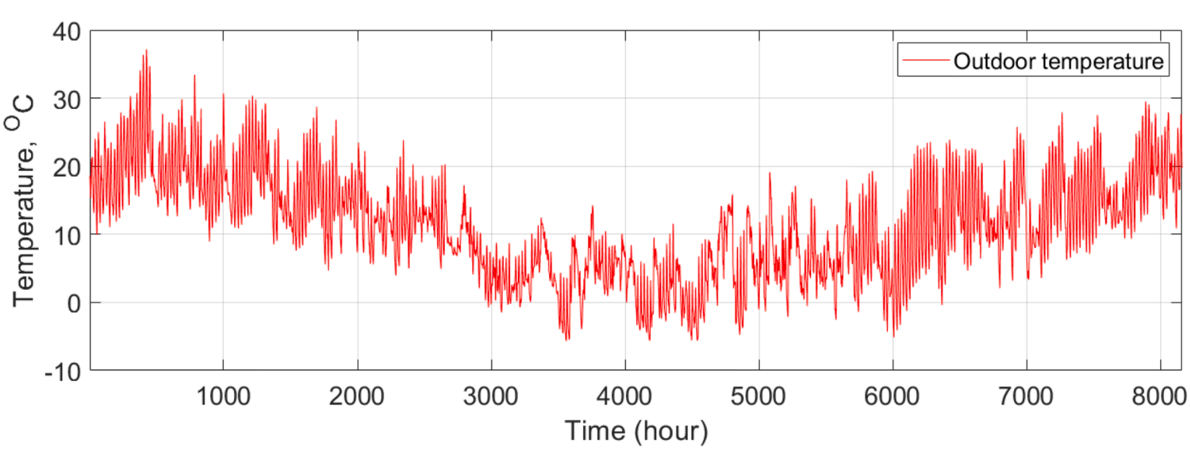

Fig. 6. Collected data: Outdoor temperature (340 days, July 2019, to June 2020).

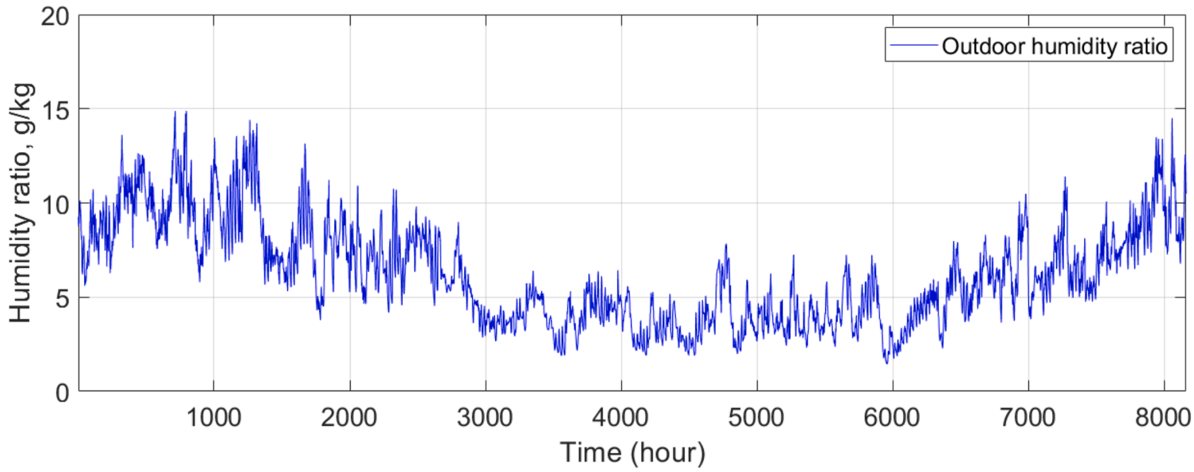

Fig. 7. Collected data: Outdoor humidity ratio (340 days, July 2019, to June 2020).

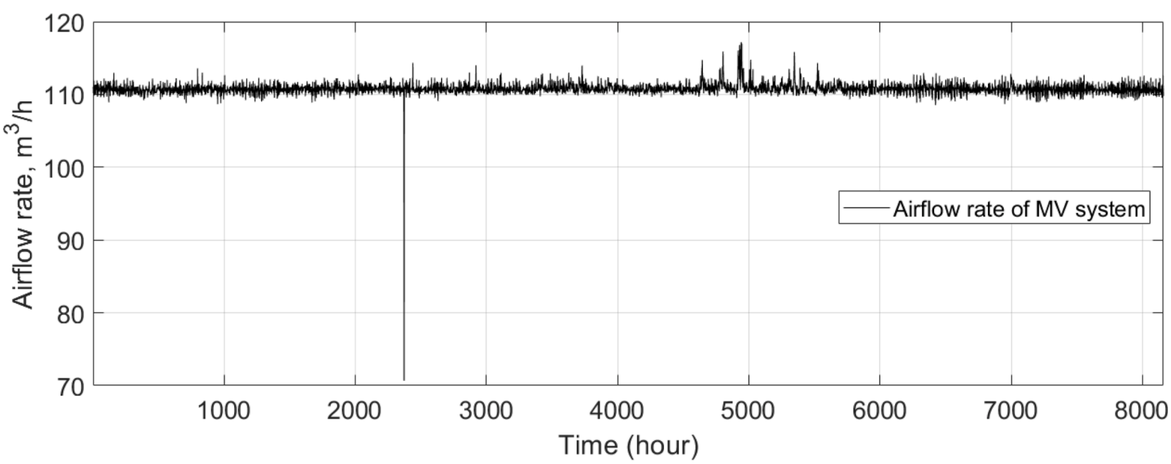

Fig. 8. Collected data: Supply airflow rate of MV system (340 days, July 2019, to June 2020).

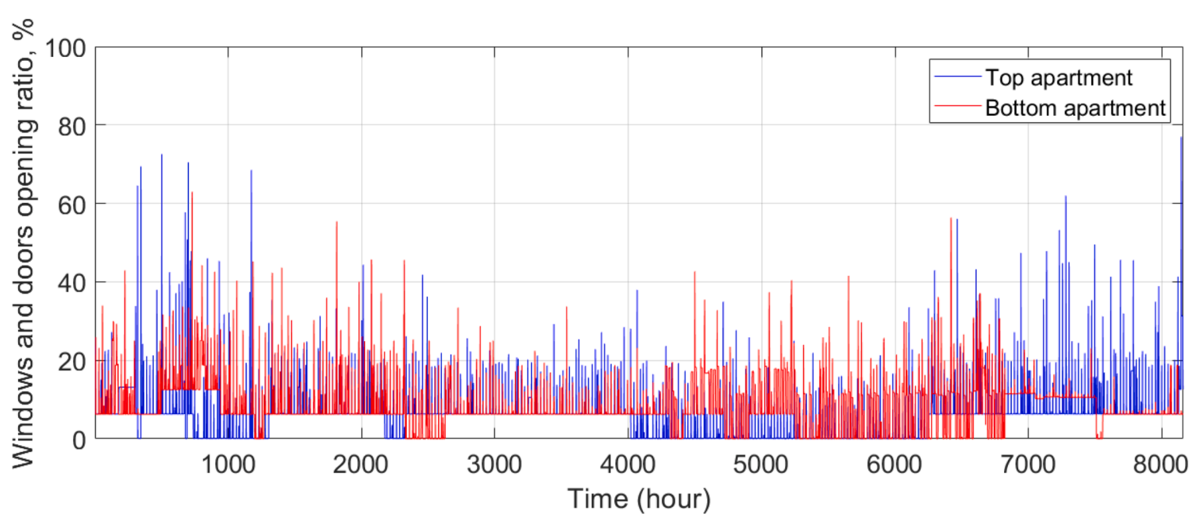

Fig. 9. Collected data: Windows and doors opening ratio of two apartments (340 days, July 2019, to June 2020).

indicator and is not the main air pollutant to influence human health in an indoor space (CEN 2004; ASTM Standard D6245-12, 2012). However, recent works of literature have described that CO_2 could be a direct air pollutant and a small CO_2 level increase affect occupants' cognitive decision-making (Allen et al., 2016; Fu et al., 2021a, 2021b; Kim et al., 2020a; Kim and Choi, 2019b; Satish et al., 2012; William et al., 2013). And VOCs as an internal air pollutant source in buildings have contributed to poor air quality and negatively impacted human health (Caron et al., 2020). Even small VOC concentrations can lead to dizziness, tiredness, and skin irritations (Caron et al., 2020; Yoon et al.,

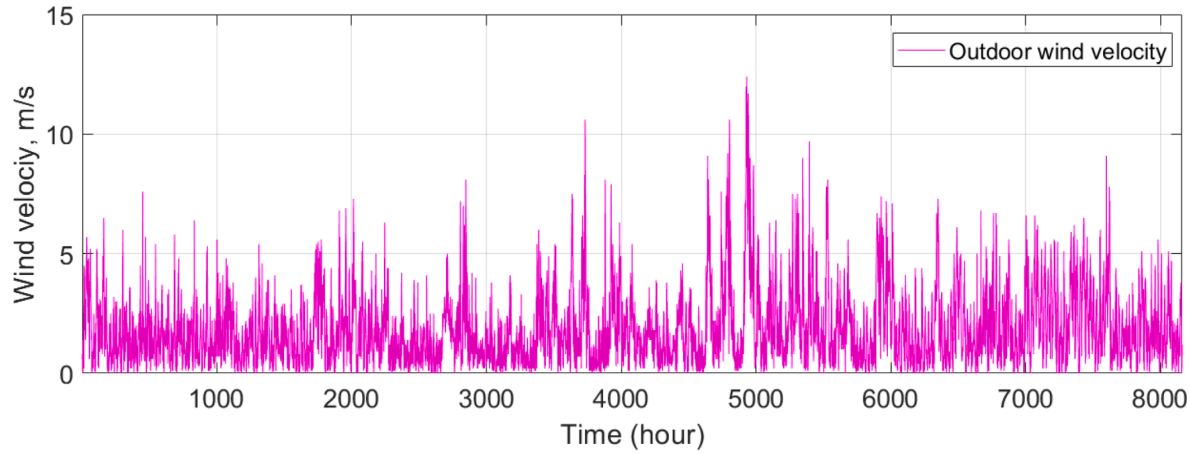

Fig. 10. Weather data: Wind velocity (340 days, July 2019, to June 2020).

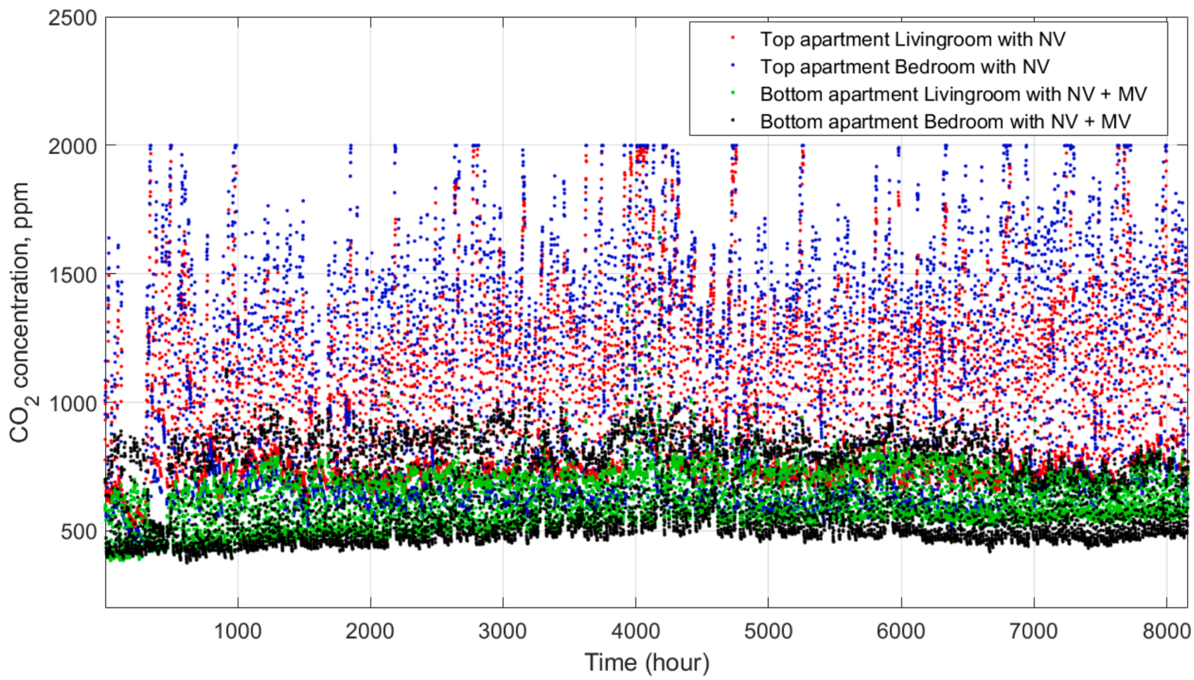

Fig. 11. Collected data: CO_2 concentrations at the living room and bedroom of two apartments (340 days, July 2019, to June 2020).

2010). In Fig. 11, the collected data shows that CO_2 levels of the top apartment using only NV system overall higher air pollution value than those of the bottom apartment using both NV and the MV system. And the maximum CO2 levels were around 2000 ppm. Only a single person had lived in the top apartment and the tenant kept windows open slightly. We estimate that the small amount volume of air infiltration and the apartment space could be enough to dilute the indoor CO_2 concentration level below 2000 ppm. The results show that the MV system significantly impacts the indoor air quality because an NV system is limited to use at nighttime and in challenging weather conditions, especially the cold winter season in Switzerland. Hence, the MV system can maintain constant indoor quality in a building.

2.3. Comparison impact analysis

This study suggests evaluating the correlation performance among the input elements affecting indoor air quality in buildings. This study exploits a methodology using deep learnings to define an impact factor value (IFV). The differences of input elements and the output in the values illustrate the magnitude of impact, and positive and negative values of results present the directivity of the influence (Cha et al., 2021; Kim et al., 2020a, 2020b).

For the calculation of the IFV, the process is illustrated as follows: after the training processes using two ANN algorithms (FFNN and RNN) are completed, each testing input parameter value is adjusted by 10% of its actual test input value to design new testing samples. The testing input value with 10% adjusting evaluated as an impact of each adjusting element since the analyzing impact value estimates a linear relationship between the actual test results and changed results (Cha et al., 2021; Kim et al., 2020a, 2020b, 2020c). The adjusted testing nodes calculate the new prediction results compared to an actual result value of how each element impacts the air quality prediction results. The aim of IFV process is to evaluate how each element influences the results' value. And based on the IFV process, we could categorize into the numerous collected elements for the ANNs analysis, whether it is crucial to predict the result or can be neglected for training.

Finally, the level difference between the predicted and adjusted result values estimates the IFV value, and the results analyze indoor air

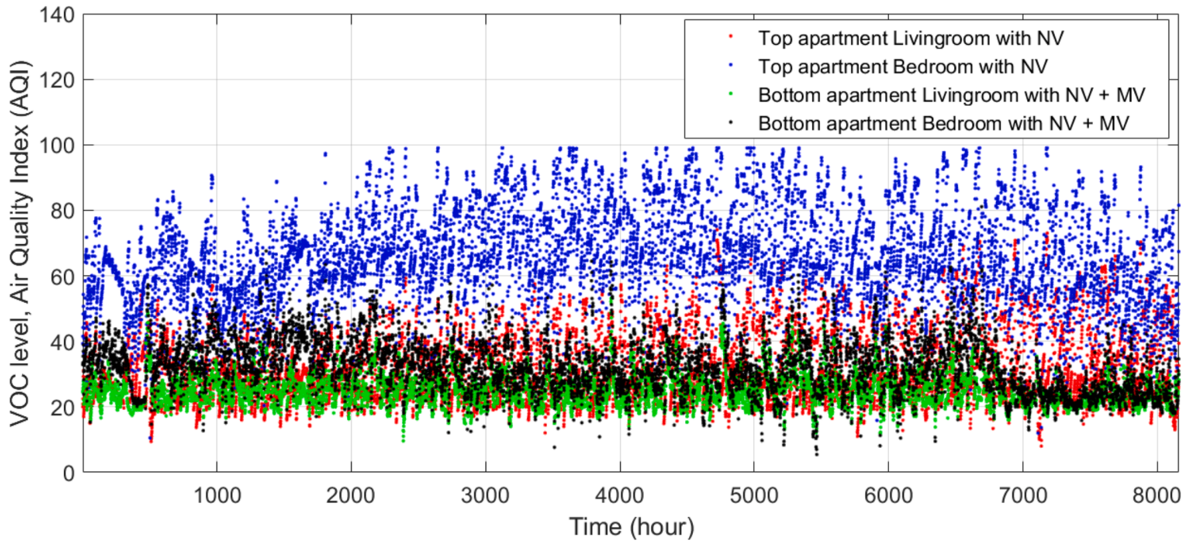

Fig. 12. Collected data: VOC levels at living rooms and bedrooms of two apartments (340 days, July 2019, to June 2020).

quality the performance in buildings (Cha et al., 2021).

$$Impact\ factor\ value\ (IFV) = \frac{\frac{y_{test\ results\ with\ adding\ or\ subtracting\ 10\%\ of\ sample} - y_{test\ results}}{y_{test\ result}}}{0.1} \tag{11}$$

This study also suggested the two methods, the coefficient of variation of the root mean square error (CVRMSE), and the normalized mean bias error (NMBE), to indicate an accuracy of the two algorithms. The equations are shown as follows (American Society of Heating, Refrigeration and Air Conditioning Engineers, 2002):

$$CVRMSE\ (\%) = \frac{\left[\frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y}_i)^2\right]^{1/2}}{\overline{y}} \times 100 \tag{12}$$

$$NMBE\ (\%) = \frac{\sum_{i=1}^{n}(y_i - \overline{y}_i)}{N \times \overline{y}} \times 100 \tag{13}$$

3. Results

This study evaluates the indoor air quality of a residential apartment with experimental methods in which the apartment has used both natural and mechanical ventilation systems. And this study also illustrates approaches to evaluate indoor air quality (CO_2 concentration and VOC level) correlation how weather data parameters, temperature, humidity ratio, wind speed, windows and doors opening ratio, and mechanical ventilation rate impact the indoor air quality in residential buildings.

This study exploits two ANN methods—FFNN and RNN algorithm—to predict the indoor air quality profiles for two residential apartments in Büren, Switzerland. The models trained datasets of the temperature (°C), and humidity ratio (g/kg), wind speed (m/s), windows and doors opening ratio (%), and Mechanical ventilation rate (m^3/h). This study also illustrates the accuracy and error rate of two ANN models (FFNN and RNN). It evaluates how significantly input parameters impact the actual indoor air quality in the building. Moreover, we can predict long-term indoor air quality performance using the ANN methods depending on the variation of weather conditions, the façade opening ratio, and the mechanical air ventilation rate. We evaluated the models' performances with accuracy and error rates for various scenarios; the results are presented in Figs. 13–16, and Table 1.

Overall, the two ANN models performed well for forecasting indoor air quality such as CO_2 and VOC concentration levels of the residential apartment for the working days. Both models represented good performance with higher accuracy and lower error rates to predict CO_2 concentration level and no significant differences. The RNN model presented relatively higher accuracy rates and better accuracy to predict VOC concentration level. However, the overall prediction accuracy rate of CO_2 pollutant levels at the living room is higher than those in the bedroom. This study estimated that other input elements, i.e.,

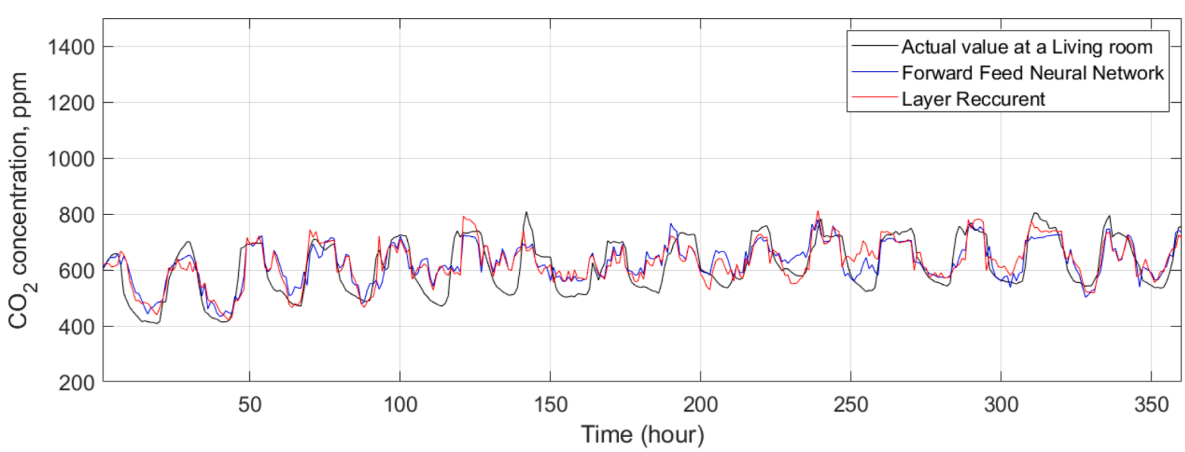

Fig. 13. Prediction of Indoor CO_2 concentration level of the two ANN models at a living room using both NV and MV system compared with actual values measured for working days.

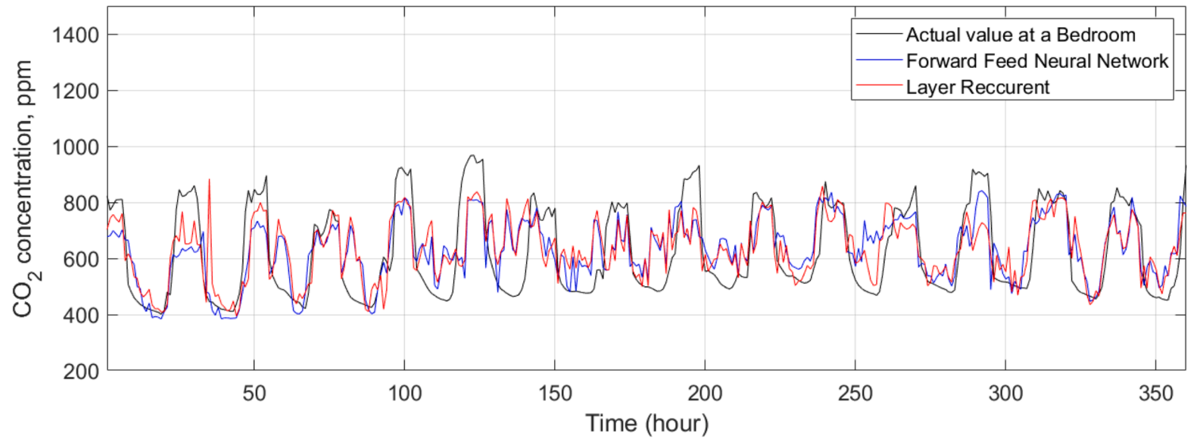

Fig. 14. Prediction of Indoor CO_2 concentration level of the two ANN models at a bedroom using both NV and MV system compared with actual values measured for working days.

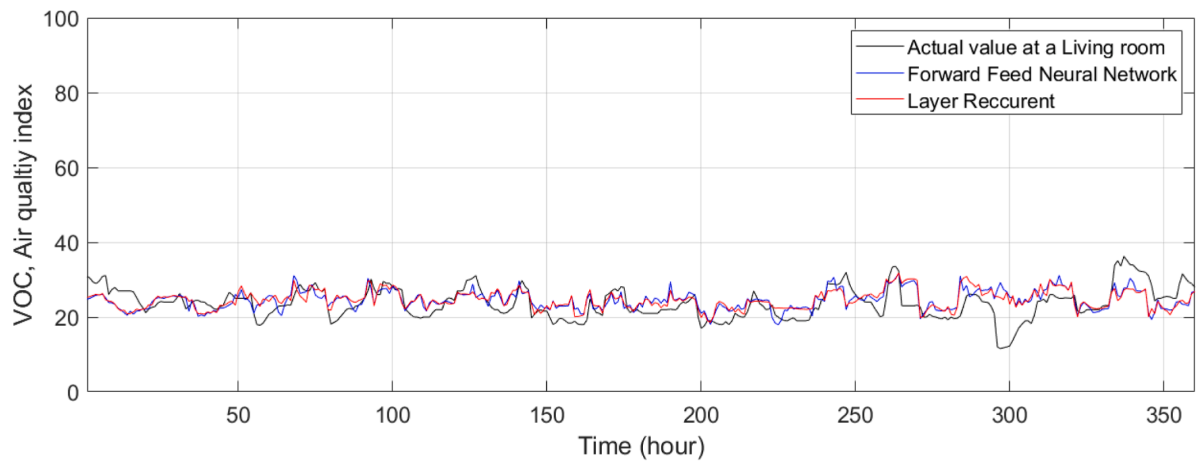

Fig. 15. Prediction of Indoor VOC level of the two ANN models at a living room using both NV and MV system compared with actual values measured for working days.

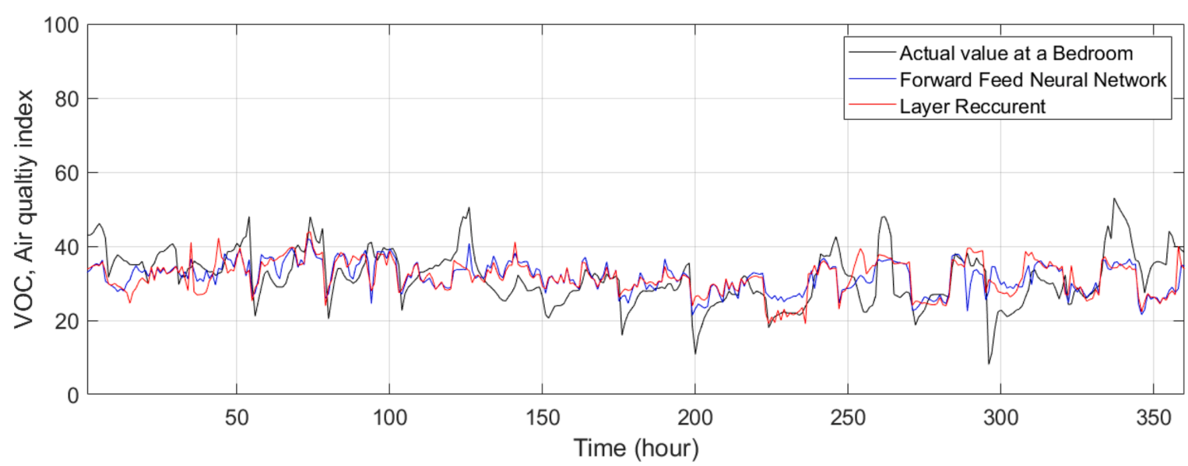

Fig. 16. Prediction of Indoor VOC level of the two ANN models at a bedroom using both NV and MV system compared with actual values measured for working days.

occupancy diversity factors, indoor activity level, room volume, could significantly impact the indoor air quality in the rooms. Accordingly, further study needs to observe the other elements that highly impact indoor air quality in residential buildings.

Table 1 presents the average error rate, CVRMSE, and NMBE results. The results of CVRMSE and NMBE values using the two methods were no significant difference to predict CO_2 concentration level. And at CVRMSE value, the FFNN prediction method predicting CO_2 level has better accuracy and the lower value (0.13-0.53); however, the RNN method has a lower average error rate (3.18-5.49) than those of FFNN methods (3.36- 4.90). The RNN methods have a lower average error rate at VOC levels; however, there are no significant differences between

Table 1
Comparison of Performance of the ANNs.

ANNs models		Average error rate, %		Coefficient of variation of the root mean square error (CVRMSE), %		Normalized mean bias error (NMBE), %	
ANNs models	Air Pollutant	Living room	Bedroom	Living room	Bedroom	Living room	Bedroom
FFNN	CO_2	3.36	4.90	10.06	18.74	2.18	1.58
RNN	CO_2	3.18	5.49	10.19	19.27	2.11	1.95
FFNN	VOC	6.12	6.47	16.70	19.86	3.47	0.19
RNN	VOC	4.72	4.53	16.42	20.64	3.82	0.07

CVRMSE and NMBE values. Thus, both algorithm methods predict indoor air quality in a residential apartment and have good stability when indicating indoor air quality using the elements. However other methods and elements could be included for training and simulation to reduce the error rates.

Figs. 17 and 18 illustrate a correlation and an impact of each average input factor in the two ANN methods, respectively. Mechanical ventilation rates strongly dominated the indoor air quality in both ANN methods. And the four other elements—temperature and humidity ratio difference and windows and doors opening ratio —also affected the actual indoor air quality. The other parameter—wind speed—had a slight impact on the air quality in the residential building.

This study estimates that the natural ventilation system did not significantly impact indoor air quality compared to the MV system because in extreme weather conditions, especially a chilled winter season, occupants did not open the windows and doors. Therefore, other elements, such as temperature, humidity ratio, façade opening ratio and wind speed, did not significantly affect indoor air quality; however, only MV system was largely and independently responsible for the ventilation performance and actual indoor air quality. Figs. 11, and 12 show that the NV system cannot improve indoor air quality in the room by closing windows and doors.

The elements for using the NV system, temperature and humidity level difference, façade opening ratio, and wind speed, also positively impacted the indoor air quality throughout the year, but not as much as the MV system had. Studies have described that each element for the NV system cannot solely or independently engage indoor air quality because each parameter needs to combine other aspects. For example, even though there is a high temperature or humidity level difference between indoor and outdoor thermal conditions, closing windows and doors could not improve indoor air quality. Inversely, in conditions with no temperature and humidity level differences, wide windows and doors opening ratio did not significantly affect the indoor air quality. Additionally, the opening positions are crucial for indoor air quality. Typically, occupants stayed in bedrooms at the nighttime. Small opening ratio in the living room has a limitation to improve the bedroom air quality at night. Therefore, relatively, predicting bedroom air quality has higher error rates compared to those of living room prediction.

We estimate that airflow rates with the MV system significantly dominate ventilation performance and indoor air quality in the residential apartment; thus, the actual impact of NV systems is lower than that of the MV system. If it has no supply airflow rates from the MV system, the elements of NV system could affect much more than the results. The results have good agreement with the experimental data in Figs. 11 and 12.

An interesting finding is that wind speed variation did not significantly impact indoor air quality throughout the year. Still indoor air quality had a high sensitivity to temperature and humidity level difference, façade opening ratio, and mechanical ventilation rates. On this basis, further future studies should consider other input elements that can impact indoor air quality and ventilation performance, such as the occupant ratio, and behaviors, to determine correlations of the elements. This study used constant air volume system for MV system, and the MV system design did not consider the occupant rates and space zoning. The further studies need to provide the more detail effects with variable air ventilation strategies and occupant behavior pattern using a centralized or decentralized mechanical ventilation unit in residential buildings.

The results indicated that the two ANN models could predict indoor air quality using the input elements in a residential apartment with relatively good accuracy and low error rates. The two ANN models using the LM-BP algorithm could predict indoor air quality in a residential building. And the differences in accuracy between the two ANN models are small; thus, the two ANN models could utilize for predicting indoor air quality and ventilation performance. Through impact factor analysis, the MV system was found to dominate the indoor air quality in the building strongly. Other elements, temperature, humidity ratio, windows and doors opening ratio, and wind speed, also affect the results. The MV system has solely and independently influenced the indoor air quality; however, other elements have limitations to influence the results independently because the natural ventilation elements need to combine other sources with improving ventilation performance and indoor air quality. The components for natural ventilation systems steadily influenced the indoor air quality but not as much as the MV system.

4. Discussions

These methods effectively predict how each element impacts indoor

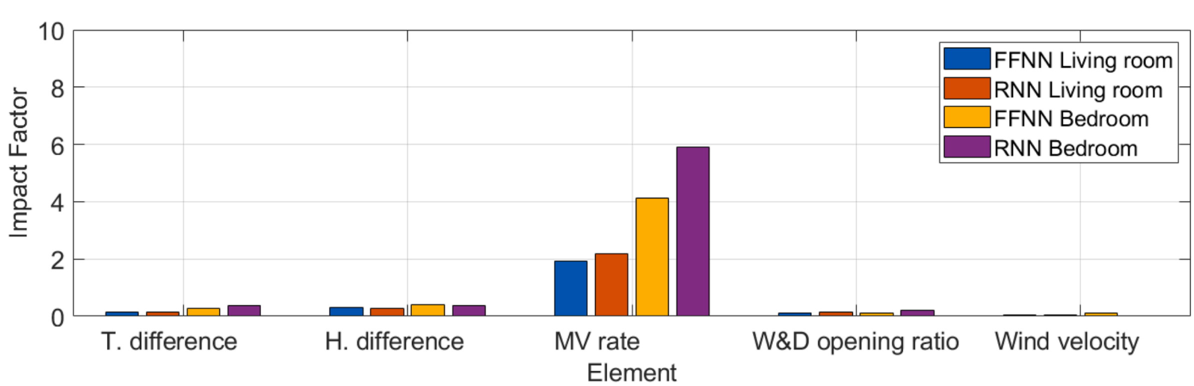

Fig. 17. Average impact factor values of input parameters to affect CO_2 concentration level at a living room and bedroom of the two ANN models (T. difference: temperature difference, H. difference: humidity ratio difference, MV rate: mechanical ventilation rate, W&D opening ratio: windows and doors opening ratio).

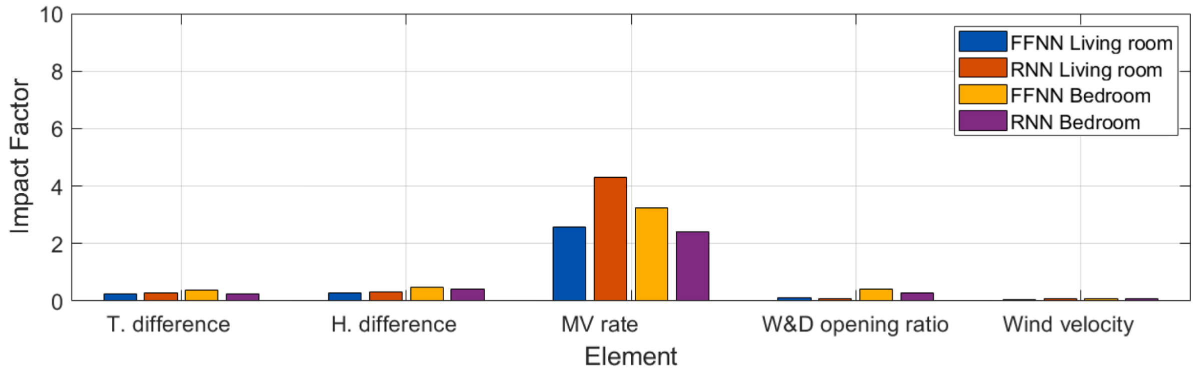

Fig. 18. Average impact factor values of input parameters to affect VOC level at a living room and bedroom of the two ANN models (T. difference: temperature difference, H. difference: humidity ratio difference, MV rate: mechanical ventilation rate, W&D opening ratio: windows and doors opening ratio).

air quality and how the ventilation system adjusts each element for occupants' health and indoor air quality. Thus, these approaches could help understand the ventilation performance regarding short and long-term indoor air quality prediction. For example, ventilation performances in a building could be changed in seasonal variations and climate change. The two deep learning ANN methods are reliable in predicting short and long-term indoor air quality in buildings using the elements. Future works should utilize these proposed ANN models with additional input elements such as occupant ratio and behaviors. Additional ANN models recently developed could be designed to improve the accuracy of the predictions and save simulation time.

We found some limitations to be explored via future research in these results. This study selected a residential apartment to measure indoor air quality, temperature humidity ratio, façade opening ratio, and wind speed for working days. However, the accuracy and error rates of predicting indoor air quality on non-working days may differ because occupancy ratio and behaviors can significantly influence indoor air quality in a residential building. Future studies could consider another deep learning algorithm recently developed such as Generative Adversarial Networks (GANs), Deep Belief Networks (DBNs), or Radial Basis Functional Networks (RBFNs) to compare the prediction accuracy and validations for forecasting indoor air quality. And future studies also would analyze correlations of indoor air quality with different ventilation systems, seasonal changes, climate changes, and energy consumption with ANNs algorithms.

5. Conclusion

This study proposed prediction strategies of ventilation performance in a residential building using two ANN methodologies, feed-forward neural network and recurrent neural network with an LM-BP algorithm. These were designed with input elements, temperature, humidity ratio, windows and doors opening ratio, mechanical ventilation rate and wind speed to predict the indoor air quality. This study evaluated the predicting performance of two ANN methods using a training data set and compared the forecasting results simulated with actual experimental indoor air quality data tested for the residential building. The results illustrated that both ANN models are stable and accurate in predicting indoor air quality and ventilation performance in the building. This study also proposed a novel analysis strategy for how temperature, humidity ratio, windows and doors opening ratio, mechanical ventilation rate, and wind speed are correlated with indoor air quality in a residential apartment. And how these correlations of each element significantly influence indoor air quality.

This study evaluated the predicting performance of two ANN algorithms using a training dataset process and test set process. The predicting results were analyzed and compared with actual measured indoor air quality values, CO_2 concentration, and VOC levels. The results presented that the two ANN models using the LMBP algorithm have good agreements with actual data measured. The accuracy differences were small at 0.18-1.89 for the average error rates, 0.13–0.78 for the CVRMSE, and 0.07–0.35 for the NMBE. By analyzing the impact factor of the five input elements, this study indicated that the mechanical ventilation rates strongly dominated the actual indoor air quality, CO_2 concentration level, and VOC levels in the residential building. And other natural ventilation factors, temperature and humidity ratio, windows and doors opening ratio, and wind speed considerably impact the results, but the impacts are relatively smaller than the MV system had. MV system factor can significantly dominate indoor air quality solely and independently; however, the other factors need to combine to influence the indoor air quality. Thus, the elements for using natural ventilation systems have a limitation to independently improving indoor air quality. We briefly recommended setting up an MV system to effectively improve indoor air quality in a residential building because other elements need to consider surrounding boundary conditions.

Authors' contribution

All authors contributed equally to the preparation of this manuscript.

Declaration of Competing Interest

The author(s) declared no potential conflicts of interest with respect of the research, authorship, and/or publication of this article

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References

Ahmad, M. W., Mourshed, M., & Rezgui, Y. (2017). Trees vs Neurons: Comparison between random forest and ANN for high-resolution prediction of building energy consumption. *Energy and Buildings, 147*(Supplement C), 77–89. https://doi.org/10.1016/j.enbuild.2017.04.038

Allen, J. G., MacNaughton, P., Satish, U., Santanam, S., Vallarino, J., & Spengler, J. D. (2016). Associations of cognitive function scores with carbon dioxide, ventilation, and volatile organic compound exposures in office workers: A controlled exposure study of green and conventional office environments. *Environmental Health Perspectives, 124*(6), 805–812. https://doi.org/10.1289/ehp.1510037

Amber, K. P., Aslam, M. W., & Hussain, S. K. (2015). Electricity consumption forecasting models for administration buildings of the UK higher education sector. *Energy and Buildings, 90*, 127–136. https://doi.org/10.1016/j.enbuild.2015.01.008

American Society of Heating, Refrigeration and Air Conditioning Engineers. (2002). *ASHRAE guideline 14-2002 for measurement of energy and demand savings*. Atlanta, GA, USA: American Society of Heating, Refrigeration and Air Conditioning Engineers.

Ashtiani, A., Mirzaei, P. A., & Haghighat, F. (2014). Indoor thermal condition in urban heat island: Comparison of the artificial neural network and regression methods

prediction. *Energy and Buildings, 76*, 597–604. https://doi.org/10.1016/j.enbuild.2014.03.018
ASTM Standard D6245-12. (2012). Standard guide for using indoor carbon dioxide concentrations to evaluate indoor air quality and ventilation. *ASTM Standard D6245-12, Standard Guide for Using Indoor Carbon Dioxide Concentrations to Evaluate Indoor Air Quality and Ventilation*. West Conshohocken, PA: ASTM International.
Baldini, L., Kim, M. K., & Leibundgut, H. (2014). Decentralized cooling and dehumidification with a 3 stage LowEx heat exchanger for free reheating. *Energy and Buildings, 76*, 270–277. <Go to ISI>://WOS:000336779000026.
Bocheng Zhong, K. L., Dinghao, Lv, Jing, Luo, & Xuan, Fang (2015). Short-term prediction of building energy consumption based on GALM neural network. In *International Conference on Advances in Mechanical Engineering and Industrial Informatics*.
Brezak, D., Bacek, T., Majetic, D., Kasac, J., & Novakovic, B. (2012). A comparison of feed-forward and recurrent neural networks in time series forecasting. In *Proceedings of the IEEE conference on computational intelligence for financial engineering & economics*. (CIFEr).
Cao, S.-J., & Ren, C. (2018). Ventilation control strategy using low-dimensional linear ventilation models and artificial neural network. *Building and Environment, 144*, 316–333. https://doi.org/10.1016/j.buildenv.2018.08.032
Caron, F., Guichard, R., Robert, L., Verriele, M., & Thevenet, F. (2020). Behaviour of individual VOCs in indoor environments: How ventilation affects emission from materials. *Atmospheric Environment, 243*. https://doi.org/ARTN 117713 10.1016/j.atmosenv.2020.117713.
Carrera, B., Peyrard, S., & Kim, K. (2021). Meta-regression framework for energy consumption prediction in a smart city: A case study of Songdo in South Korea [Article]. *Sustainable Cities and Society, 72*. https://doi.org/10.1016/j.scs.2021.103025. Article 103025.
CEN. (2004). *EN 13779, Ventilation for Non-Residential Buildings - Performance Requirements for Ventilation and Room-Conditioning Systems*. Brussels, Belgium: European Committee for Standardization.
Cha, J., Kim, M. K., Lee, S., & Kim, K. S. (2021). Investigation of applicability of impact factors to estimate solar irradiance: Comparative analysis using machine learning algorithms. *Applied Sciences, 11*(18). https://doi.org/10.3390/app11188533
Cossu, A., Carta, A., Lomonaco, V., & Bacciu, D. (2021). Continual learning for recurrent neural networks: An empirical evaluation. *Neural Networks, 143*, 607–627. https://doi.org/10.1016/j.neunet.2021.07.021
Ekici, B. B., & Aksoy, U. T. (2009). Prediction of building energy consumption by using artificial neural networks. *Advances in Engineering Software, 40*(5), 356–362. https://doi.org/10.1016/j.advengsoft.2008.05.003
Fu, N., Kim, M. K., Chen, B., & Sharples, S. (2021a). Investigation of outdoor air pollutant, PM2.5 affecting the indoor air quality in a high-rise building. *Indoor and Built Environment*. https://doi.org/10.1177/1420326X211038279, 1420326X211038279.
Fu, N. D., Kim, M. K., Chen, B., & Sharples, S. (2021b). Comparative modelling analysis of air pollutants, PM2.5 and energy efficiency using three ventilation strategies in a high-rise building: A case study in Suzhou, China. *Sustainability, 13*(15). https://doi.org/ARTN 8453 10.3390/su13158453.
Gellert, A., Fiore, U., Florea, A., Chis, R., & Palmieri, F. (2022). Forecasting electricity consumption and production in smart homes through statistical methods [Article]. *Sustainable Cities and Society, 76*, Article 103426. https://doi.org/10.1016/j.scs.2021.103426
Giovanni, S., & John, E. (2010). *Ensemble Methods in Data Mining: Improving Accuracy Through Combining Predictions*. Morgan & Claypool. http://ieeexplore.ieee.org/document/6813170.
Hao, Y., Li, H., & Wang, H. (2013). Analysis of energy consumption and energy-saving of residential buildings based on LM-BP algorithm [Article]. *International Journal of Applied Mathematics and Statistics, 51*(24), 348–356. https://www.scopus.com/inward/record.uri?eid=2-s2.0-84901647577&partnerID=40&md5=7cf1090c253f22a656d355474e0fd6b5.
Hsu, D. (2015). Comparison of integrated clustering methods for accurate and stable prediction of building energy consumption data. *Applied Energy, 160*(Supplement C), 153–163. https://doi.org/10.1016/j.apenergy.2015.08.126
Kalogirou, S. A. (2000). Applications of artificial neural-networks for energy systems. *Applied Energy, 67*(1), 17–35, 10.1016/S0306-2619(00)00005-2.
Kamlesh Shah, S., Mishra, R., & Samprit Ray, L. (2020). Solution and validation of inverse kinematics using deep artificial neural network. *Materials Today: Proceedings, 26*, 1250–1254. https://doi.org/10.1016/j.matpr.2020.02.250
Kang, I., McCreery, A., Azimi, P., Gramigna, A., Baca, G., Abromitis, K., Wang, M., Zeng, Y., Scheu, R., Crowder, T., Evens, A., & Stephens, B. (2022). Indoor air quality impacts of residential mechanical ventilation system retrofits in existing homes in Chicago, IL. *Science of The Total Environment, 804*, Article 150129. https://doi.org/10.1016/j.scitotenv.2021.150129
Karim, M. N., & Rivera, S. L. (1992). Comparison of feed-forward and recurrent neural networks for bioprocess state estimation. *Computers & Chemical Engineering, 16*, S369–S377, 10.1016/S0098-1354(09)80044-6.
Kim, M. K., & Baldini, L. (2016). Energy analysis of a decentralized ventilation system compared with centralized ventilation systems in European climates: Based on review of analyses. *Energy and Buildings, 111*, 424–433. https://doi.org/10.1016/j.enbuild.2015.11.044
Kim, M. K., Baldini, L., Leibundgut, H., & Wurzbacher, J. A. (2020a). Evaluation of the humidity performance of a carbon dioxide (CO_2) capture device as a novel ventilation strategy in buildings. *Applied Energy, 259*, Article 112869. https://doi.org/10.1016/j.apenergy.2019.03.074
Kim, M. K., Cha, J., Lee, E., Pham, V. H., Lee, S., & Theera-Umpon, N. (2019a). Simplified neural network model design with sensitivity analysis and electricity consumption prediction in a commercial building. *Energies, 12*(7). https://doi.org/10.3390/en12071201
Kim, M. K., & Choi, J. H. (2019b). Can increased outdoor CO_2 concentrations impact on the ventilation and energy in buildings? A case study in Shanghai, China. *Atmospheric Environment, 210*, 220–230. https://doi.org/10.1016/j.atmosenv.2019.04.015
Kim, M. K., Kim, Y. S., & Srebric, J. (2020b). Predictions of electricity consumption in a campus building using occupant rates and weather elements with sensitivity analysis: Artificial neural network vs. linear regression. *Sustainable Cities and Society, 62*, Article 102385. https://doi.org/10.1016/j.scs.2020.102385
Kim, M. K., Kim, Y. S., & Srebric, J. (2020c). Impact of correlation of plug load data, occupancy rates and local weather conditions on electricity consumption in a building using four back-propagation neural network models. *Sustainable Cities and Society, 62*. https://doi.org/ARTN 102321 10.1016/j.scs.2020.102321.
Kim, M. K., Liu, J. Y., & Cao, S. J. (2018). Energy analysis of a hybrid radiant cooling system under hot and humid climates: A case study at Shanghai in China. *Building and Environment, 137*, 208–214. https://doi.org/10.1016/j.buildenv.2018.04.006
Kumar, R., Aggarwal, R. K., & Sharma, J. D. (2013). Energy analysis of a building using artificial neural network: A review. *Energy and Buildings, 65*, 352–358. https://doi.org/10.1016/j.enbuild.2013.06.007
Kurnaz, G., & Demir, A. S. (2022). Prediction of SO2 and PM10 air pollutants using a deep learning-based recurrent neural network: Case of industrial city Sakarya. *Urban Climate, 41*, Article 101051. https://doi.org/10.1016/j.uclim.2021.101051
Lazrak, A., Boudehenn, F., Bonnot, S., Fraisse, G., Leconte, A., Papillon, P., & Souyri, B. (2016). Development of a dynamic artificial neural network model of an absorption chiller and its experimental validation. *Renewable Energy, 86*, 1009–1022. https://doi.org/10.1016/j.renene.2015.09.023
Lek, S., & Guégan, J. F. (1999). Artificial neural networks as a tool in ecological modelling, an introduction. *Ecological Modelling, 120*(2), 65–73, 10.1016/S0304-3800(99)00092-7.
Li, K. J., Hu, C. L., Liu, G. H., & Xue, W. P. (2015). Building's electricity consumption prediction using optimized artificial neural networks and principal component analysis. *Energy and Buildings, 108*, 106–113. https://doi.org/10.1016/j.enbuild.2015.09.002
Li, L., Zhang, Y., Fung, J. C. H., Qu, H., & Lau, A. K. H. (2022a). A coupled computational fluid dynamics and back-propagation neural network-based particle swarm optimizer algorithm for predicting and optimizing indoor air quality. *Building and Environment, 207*, Article 108533. https://doi.org/10.1016/j.buildenv.2021.108533
Li, Y., Tong, Z., Tong, S., & Westerdahl, D. (2022b). A data-driven interval forecasting model for building energy prediction using attention-based LSTM and fuzzy information granulation [Article]. *Sustainable Cities and Society, 76*, Article 103481. https://doi.org/10.1016/j.scs.2021.103481
Liu, J., Kim, M. K., & Srebric, J. (2021a). Numerical analysis of cooling potential and indoor thermal comfort with a novel hybrid radiant cooling system in hot and humid climates. *Indoor and Built Environment*. https://doi.org/10.1177/1420326X211040853, 1420326X211040853.
Liu, X., Ding, Y., Tang, H., Fan, L., & Lv, J. (2021b). Investigating the effects of key drivers on energy consumption of nonresidential buildings: A data-driven approach integrating regularization and quantile regression. *Energy, 122720*. https://doi.org/10.1016/j.energy.2021.122720
Lorenzo, T., Levi, W., Curtis, H., & Giovanni, P. (2015). Bayesian nonparametric cross-study validation of prediction methods. *The Annals of Applied Statistics, 9*(1), 402–428. https://doi.org/10.1214/14-AOAS798
Martínez-Comesaña, M., Ogando-Martínez, A., Troncoso-Pastoriza, F., López-Gómez, J., Febrero-Garrido, L., & Granada-Álvarez, E. (2021). Use of optimised MLP neural networks for spatiotemporal estimation of indoor environmental conditions of existing buildings. *Building and Environment, 205*, Article 108243. https://doi.org/10.1016/j.buildenv.2021.108243
Masood, A., & Ahmad, K. (2021). A review on emerging artificial intelligence (AI) techniques for air pollution forecasting: Fundamentals, application and performance. *Journal of Cleaner Production, 322*, Article 129072. https://doi.org/10.1016/j.jclepro.2021.129072
Moore, J. E., Kim, M., Seo, J. G., Wu, Y., & Kalaba, R. (1991). Linear-programming, recurrent associative memories, and feedforward neural networks. *Computers & Mathematics with Applications, 22*(11), 71–90. https://doi.org/Doi 10.1016/0898-1221(91)90036-4.
Neto, A. H., & Fiorelli, F. A. S. (2008). Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption. *Energy and Buildings, 40*(12), 2169–2176. https://doi.org/10.1016/j.enbuild.2008.06.013
Park, J. S., & Jeong, J.-W. (2017). Mass loading of particles in the supply ducts of mechanical ventilation systems in homes. *Building and Environment, 126*, 348–354. https://doi.org/10.1016/j.buildenv.2017.10.015
Ren, C., & Cao, S.-J. (2020). Implementation and visualization of artificial intelligent ventilation control system using fast prediction models and limited monitoring data. *Sustainable Cities and Society, 52*, Article 101860. https://doi.org/10.1016/j.scs.2019.101860
Ren, J., Liu, J., Zhou, S., Kim, M. K., & Song, S. (2022). Experimental study on control strategies of radiant floor cooling system with direct-ground cooling source and displacement ventilation system: A case study in an office building. *Energy, 239*, Article 122410. https://doi.org/10.1016/j.energy.2021.122410
Satish, U., Mendell, M. J., Shekhar, K., Hotchi, T., Sullivan, D., Streufert, S., & Fisk, W. J. (2012). Is CO_2 an indoor pollutant? Direct effects of low-to-moderate CO_2 concentrations on human decision-making performance. *Environmental Health Perspectives, 120*(12), 1671–1677. https://doi.org/10.1289/ehp.1104789

Shao, M., Wang, X., Bu, Z., Chen, X., & Wang, Y. (2020). Prediction of energy consumption in hotel buildings via support vector machines. *Sustainable Cities and Society, 57*, Article 102128. https://doi.org/10.1016/j.scs.2020.102128

Singh, V., Gupta, I., & Gupta, H. O. (2007). ANN-based estimator for distillation using Levenberg-Marquardt approach. *Engineering Applications of Artificial Intelligence, 20* (2), 249–259. https://doi.org/10.1016/j.engappai.2006.06.017

Tang Zhong, X. T. (2012). Application and simulation of matlab neural network tool NNTool. *Computer and Modernization, 12*.

Tantasavasdi, C., Srebric, J., & Chen, Q. (2001). Natural ventilation design for houses in Thailand. *Energy and Buildings, 33*(8), 815–824, 10.1016/S0378-7788(01)00073-1.

Taver, V., Johannet, A., Borrell-Estupina, V., & Pistre, S. (2015). Feed-forward vs recurrent neural network models for non-stationarity modelling using data assimilation and adaptivity. *Hydrological Sciences Journal, 60*(7-8), 1242–1265. https://doi.org/10.1080/02626667.2014.967696

Tian, X., Cheng, Y., & Lin, Z. (2021). Modelling indoor environment indicators using artificial neural network in the stratified environments. *Building and Environment*. , Article 108581. https://doi.org/10.1016/j.buildenv.2021.108581

Werbos, P. J. (1975). Experimental implications of reinterpretation of quantum-mechanics. *Nuovo Cimento Della Societa Italiana Di Fisica B-General Physics Relativity Astronomy and Mathematical Physics and Methods, 29*(1), 169–177. https://doi.org/ Doi 10.1007/Bf02732237.

William, J. F., Usha, S., Mark, J. M., Toshifumi, H., & Douglas, P. S. (2013). Is CO_2an indoor pollutant? Higher levels of CO_2May diminish decision making performance. *Ashrae Journal, 55*, 84–85.

Wong, S. L., Wan, K. K. W., & Lam, T. N. T. (2010). Artificial neural networks for energy analysis of office buildings with daylighting. *Applied Energy, 87*(2), 551–557. https://doi.org/10.1016/j.apenergy.2009.06.028

Xu, B., Zhang, H., Wang, Z., Wang, H., & Zhang, Y. (2015). Model and algorithm of BP neural network based on expanded multichain quantum optimization [Article]. *Mathematical Problems in Engineering, 2015*, Article 362150. https://doi.org/10.1155/2015/362150

Ye, Z. Y., & Kim, M. K. (2018). Predicting electricity consumption in a building using an optimized back-propagation and Levenberg-Marquardt back-propagation neural network: Case study of a shopping mall in China. *Sustainable Cities and Society, 42*, 176–183. https://doi.org/10.1016/j.scs.2018.05.050

Yoon, H. I., Hong, Y. C., Cho, S. H., Kim, H., Kim, Y. H., Sohn, J. R., Kwon, M., Park, S. H., Cho, M. H., & Cheong, H. K. (2010). Exposure to volatile organic compounds and loss of pulmonary function in the elderly. *European Respiratory Journal, 36*(6), 1270–1276. https://doi.org/10.1183/09031936.00153509

Yu, S., Zhu, K., & Diao, F. (2008). A dynamic all parameters adaptive BP neural networks model and its application on oil reservoir prediction. *Applied Mathematics and Computation, 195*(1), 66–75. https://doi.org/10.1016/j.amc.2007.04.088

Zorzetto, L. F. M., Filho, R. M., & Wolf-Maciel, M. R. (2000). Processing modelling development through artificial neural networks and hybrid models. *Computers & Chemical Engineering, 24*(2), 1355–1360, 10.1016/S0098-1354(00)00419-1.