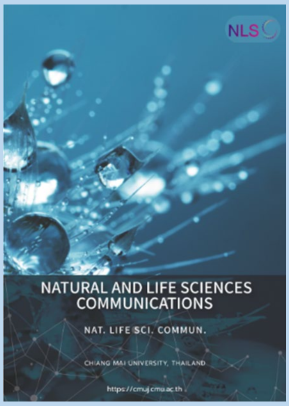
Research article



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Physio-Chemical Indoor Air Quality Analysis and CO_2 Ventilation Forecasting Using Artificial Neural Networks in Boat Manufacturing

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ABSTRACT

This study presents a comprehensive analysis of indoor air quality within a boat manufacturing facility, focusing on the physio-chemical parameters and forecasting of CO_2 levels using artificial neural networks (ANN). The investigation involved measuring key physical, chemical, and ventilation performance factors, including total volatile organic compounds (TVOC), particulate matter (PM_{10}, $PM_{2.5}$, PM_1), formaldehyde (HCHO), carbon monoxide (CO), temperature, relative humidity (RH), and air movement. The ANN model, employing a multilayer perceptron (MLP) architecture optimized with the Levenberg-Marquardt algorithm, was developed to predict CO_2 concentrations based on these inputs. The results revealed that indoor activities such as sanding, cutting, painting, and adhesive application significantly elevated levels of TVOC, particulate matter, and formaldehyde, often exceeding acceptable limits. The ANN model demonstrated high predictive accuracy, with correlation coefficients (R) ranging from 0.7556 to 0.8725 during training and 0.6798 to 0.8163 during validation and mean squared error (MSE) values as low as 0.0048 ppm. The optimal model architecture was identified as 8:15:1, providing a reliable forecast of CO_2 levels with an accuracy of up to 87.25%. This study underscores the importance of monitoring indoor air quality in industrial environments and highlights the potential of ANN-based models for enhancing ventilation strategies. By enabling real-time prediction of CO_2 concentrations, the model offers a practical approach to maintaining healthier indoor conditions and improving worker safety. The findings suggest that such predictive tools could be effectively implemented in similar industrial settings to mitigate air quality issues and ensure compliance with health standards.

Keywords: Indoor air quality, Boat manufacturing, Artificial neural network, Carbon dioxide

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INTRODUCTION

Air pollution in the Malaysian Peninsula has increased because of more vehicles on the roads and rapid urban development (Usmani et al., 2020). These changes have degraded air quality, endangering health, especially for those who are most vulnerable (Douglass, 2020). While most people concentrate on outdoor air quality, indoor air pollutants are also well-acknowledged to have negative impacts on individuals, particularly on vulnerable populations like children, the elderly, and those suffering from cardiovascular disease (Rafiq et al., 2021). This claim was supported by a prior study that showed how stressors related to poor indoor air quality might negatively impact a person's early development, particularly a child's growth (Garcia et al., 2021). Cardiovascular illnesses, lung cancer, early mortality, asthma, and bronchitis were among the detrimental effects of poor indoor air quality (IAQ), particularly for vulnerable populations (Chen et al., 2022). The majority of the day is spent by the occupants carrying out their everyday tasks inside the building. Consequently, early-life exposures that may raise lifetime illness risk depend on workplace indoor air quality (IAQ) (Lolli et al., 2022). Studies conducted on workers have shown that while prolonged exposure to PM_{10}, NO_2, and SO_2 may affect workers' lung development in later life (Lytras et al., 2020), higher building carbon dioxide (CO_2) concentrations short-term reduced workers' attendance (Laurent et al., 2021). More importantly, air pollution may have a significant impact on the central nervous system during vulnerable times (Sîrbu et al., 2022), which could have an impact on behavior and productivity at work. To give employees a comfortable, safe, and productive environment, a workplace with good IAQ is essential. As a result, the indoor environment needs special consideration because it poses a risk to public health.

People spend over 90% of their working hours indoors, which is becoming increasingly significant and receiving attention as a result of spending more time indoors, whether in homes or offices (Awada et al., 2020). Prior investigations have demonstrated that indoor air is more polluted than outdoor air (Stratigou et al., 2022). The assessment of indoor air quality (IAQ) has gained significant attention due to the high concentration of indoor contaminants that might increase health hazards, especially with longer exposure times. Formaldehyde (HCHO), particle matter (PM), often referred to as respirable particulates, volatile organic compounds (VOCs), carbon monoxide (CO), carbon dioxide (CO_2), and ozone (O_3) were the most frequently observed indoor air pollutants (Zhang et al., 2020). In general, assessments of indoor air quality (IAQ) were carried out for several reasons, including to identify the sources of pollutants that are prevalent in indoor environments, and to learn about potential negative effects (Bakri et al., 2018; Mansor et al., 2024), and to ascertain whether building constructors and occupants intended to meet standard limit values.

High CO_2 concentrations are often a sign of inadequate ventilation, which can lead to a buildup of indoor pollutants and negatively impact worker health and comfort. Consequently, accurate forecasting of CO_2 levels is crucial for effective ventilation management and ensuring a safe working environment (Kallio et al., 2021). Traditional methods of predicting CO_2 levels based on physical models or empirical relationships often fall short due to their inability to capture the complex, non-linear interactions between various environmental parameters. Artificial Neural Networks (ANNs), particularly Multilayer Perceptrons (MLPs), offer a promising alternative. ANNs are capable of learning intricate patterns and relationships from historical data, making them well-suited for modeling the non-linear dependencies between indoor air quality parameters and CO_2 concentrations. By leveraging the power of ANNs, it is possible to develop predictive models that provide accurate forecasts of CO_2 levels, thereby facilitating more effective control of ventilation systems.

MATERIAL AND METHODS

Study area

MSET Inflatable Composite Corporation, located at coordinates 103°4'46.21"E, 5°22'45.13"N in Kuala Terengganu, Malaysia (Figure 1(a)), is a long-established and respected entity in the boat and shipbuilding industry. Founded on April 30, 2005, MSET Inflatable Composite Corporation has grown to become a key player in the manufacturing sector. The company's latest financial highlights reveal significant growth, with net sales revenue increasing by 135.02% in 2021. However, during the same period, the company's total assets decreased by 48.81% (MSET, 2021).

The focus of this study is on the fabric and woodwork workshop area of the company, which represents a critical part of its manufacturing operations. The importance of maintaining a comfortable and healthy working environment is emphasized due to the nature of the indoor settings in which employees operate. The workshop is equipped with a mechanical ventilation and air conditioning (MVAC) system, designed to regulate the indoor climate and ensure that air quality is managed effectively.

In today's economic and industrial context, prioritizing employee well-being is essential. A comfortable indoor environment not only enhances productivity but also helps in preventing health issues and discomfort among workers. Factors such as lighting, temperature, humidity, air quality, and interior design all play significant roles in shaping the indoor environment. Proper management and balance of these factors are crucial for creating a healthy and conducive workspace. Ensuring optimal conditions can help maintain high standards of employee comfort and health, ultimately contributing to the overall success of the business (Ali et al., 2019).

(a)

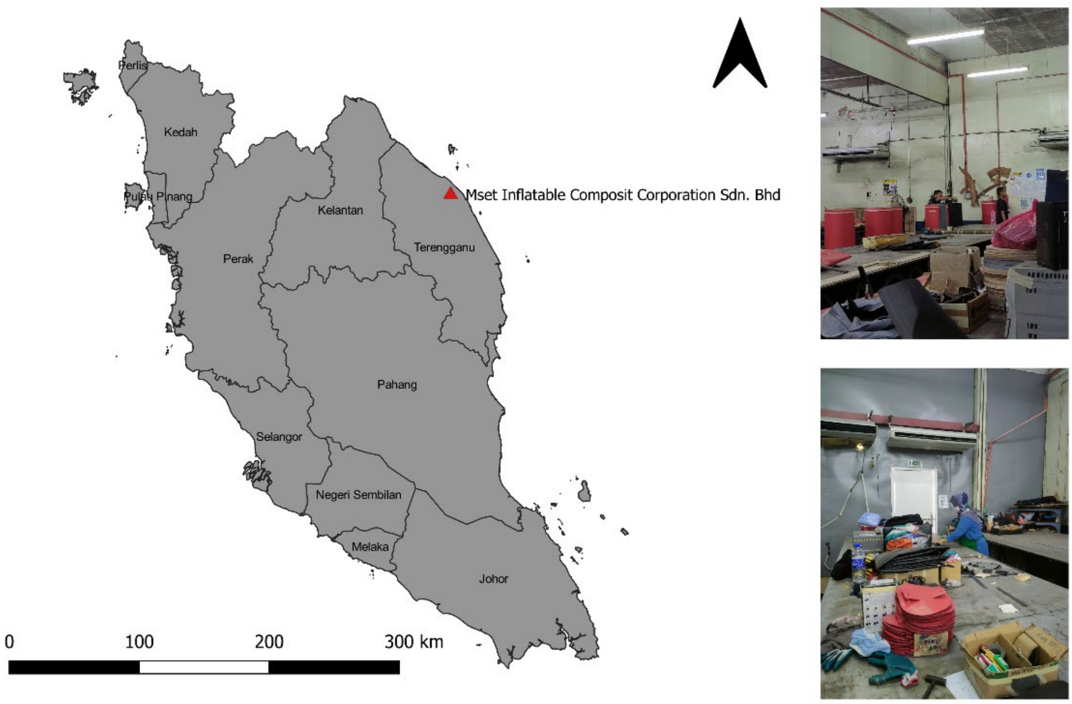


Figure 1. The study site is situated within the MSET Inflatable Composite Corporation (a); The sampling points in the MSET Inflatable Composite Corporation (b).

(b)

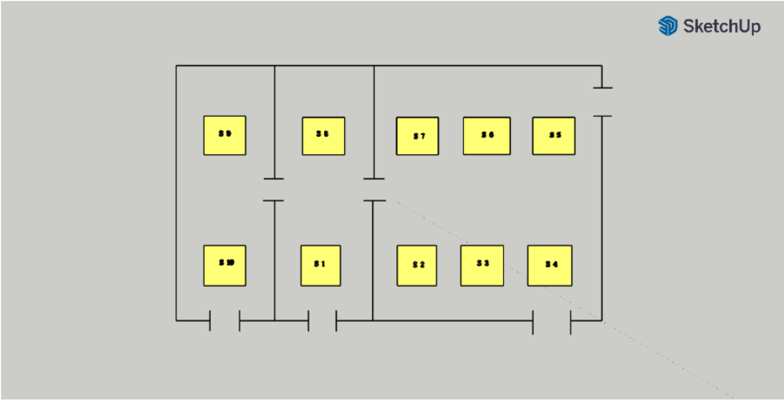


Figure 1. **Continued.**

Sampling campaign

Physical, chemical, and ventilation performance factors were measured for this investigation. The chemical criteria include the following: total volatile organic compound (TVOC) (ppm), respirable suspended particulate (RSP) (mg/m^3), and formaldehyde (HCHO) (ppm). The physical metrics were temperature (T) (°C), air movement (AM) (m/s), relative humidity (RH) (%), and lastly the carbon dioxide (CO_2) (ppm) which indicated the ventilation performance. The study area is located on the first level of a building with a total area of 800 square meters and a volume of 5600 cubic meters. The manufacturing space features 4 windows, 3 doors, 2 industrial fans, and a single air conditioning unit, with the ventilation system relying on an open configuration that likely facilitates natural airflow. The building, constructed over 10 years ago, is primarily made of concrete and is situated in an industrial zone. Traffic around the facility often involves traffic light controls, which could affect air quality due to intermittent vehicle emissions. The facility operates from 7:30 AM to 6:30 PM, accommodating 26 occupants during working hours. The sampling points consisted of a total of 10 locations (Figure 1(b)), all positioned inside the buildings of MSET Inflatable Composite Corporation. Samples were collected at 6-minute intervals, from 0800 to 1700 hours, to capture variations in indoor air quality throughout the workday. The study area encompassed key areas of the facility: the fabric assembly area (S2-S7), fabric cutting area (S1 & S8), and wood workshop (S9 & S10). This distribution of sampling locations was chosen to represent a range of work environments and potential emission sources within the facility. The instruments used to measure these chemical and physical parameters, as well as the indicators of ventilation performance (Abdullah et al., 2019), were listed in Table 1. To ensure the accuracy and relevance of the data, the instruments were positioned according to guidelines from the 2010 Industrial Code of Practice (ICOP-IAQ 2010) (Department of Occupational Safety and Health, 2010). Specifically, they were placed between 75 and 120 cm above the floor, with a preferred height of 110 cm from the floor when possible (Mansor et al., 2024). This positioning helps ensure that measurements are representative of the air quality experienced by occupants in typical working conditions.

Table 1. Instruments used for measuring chemical, physical, and ventilation parameters.

Instruments	Range	Accuracy	Parameters
TSI Climomaster Model 9545	Air Velocity: 0.15 to 30 m/s Temperature: 10°C to 60°C 5 to 95%RH	Air Velocity: ±2% or ± 0.03 m/s Temperature: ±0.5°C ±3%RH	Temperature, relative humidity, and air movement
DustTrak DRX Aerosol Monitor 8533RSP	PM_1, $PM_{2.5}$, and PM_{10}: 0.001 to 150 mg/m³	±10% ±0.001 mg/m³	RSP-(PM_{10}, $PM_{2.5}$, PM_1)
Q-Trak Indoor Air Quality Monitor 7575	0 to 5,000 ppm	±30 ppm ±3%	Carbon dioxide
Formaldehyde meter	0.01 to 5.00 ppm	±0.01 ppm or ±5%	Formaldehyde
Portable VOC Monitor MiniRae 30000	0.1 to 10,000ppm	±5% or ±0.1 ppm	TVOC

Correlation analysis

Spearman's correlation coefficient was employed to analyze the measured data, providing insights into both the direction and strength of relationships between different parameters. This statistical method is particularly useful for identifying and quantifying the degree of association between variables, regardless of whether the relationships are linear or non-linear (Kalimeri et al., 2019, Deng et al., 2017). The correlation coefficient (r) can range from -1 to 1, where the sign indicates the direction of the relationship, and the magnitude reflects the strength of the correlation. Values between 0 and 0.30 indicate a weak correlation. This means that there is a slight association between the variables, but the relationship is not strong enough to be considered significant. A weak correlation suggests that changes in one variable are not reliably associated with changes in another. Correlation coefficients that fall between 0.31 and 0.49 are considered moderate. In this range, there is a noticeable association between variables, though it is not particularly strong. Moderate correlations imply that while there is some degree of predictability between the variables, other factors may also be influencing the relationship. When the correlation coefficient is between 0.50 and 1.00, the relationship between the variables is considered strong. A strong correlation indicates a high degree of association, where changes in one variable are closely related to changes in the other. Such strong correlations suggest a significant and potentially causal relationship between the parameters being analyzed. A positive coefficient (ranging from 0 to 1) indicates that as one variable increases, the other variable tends to increase as well, reflecting a direct relationship. A negative coefficient (ranging from -1 to 0) signifies that as one variable increases, the other tends to decrease, indicating an inverse relationship (Walizada, 2021).

ANN models development

The design and training of an Artificial Neural Network (ANN) model for CO_2 forecasting is a multi-step process that involves carefully selecting relevant input parameters, constructing a suitable network architecture, and applying an effective training algorithm. The choice of training algorithm is critical to the model's performance, and in this case, the Levenberg-Marquardt (LM) algorithm has been chosen for its efficiency and reliability in handling non-linear optimization problems (Cho et al., 2021). The first step in designing the ANN model is to identify and select the input parameters that are most relevant to predicting CO_2 concentrations. These parameters typically include a variety of environmental factors that influence indoor air quality. In this model, eight input parameters have been selected as Total Volatile

Organic Compounds (TVOC), Particulate Matter (PM_{10}, $PM_{2.5}$, PM_1), Formaldehyde (HCHO), Temperature, Air Movement, and Relative Humidity. These parameters are fed into the input layer of the ANN, where each parameter is represented by a neuron.

The architecture of the ANN model refers to the configuration of the network, including the number of layers and the number of neurons in each layer. This architecture is crucial for the model's ability to learn and generalize from the data. The input layer consists of neurons corresponding to each of the selected input parameters. In this case, there would be eight neurons, matching the number of input factors that influence CO_2 levels. The hidden layer is where the network performs its computational tasks, learning the relationships between the input parameters and the output. The complexity of the problem dictates the number of hidden layers and neurons. For CO_2 forecasting, a single hidden layer is often sufficient to capture the necessary patterns in the data. According to Camargo & Yoneyama (2001), the number of neurons in the hidden layer is typically set to a value not more than twice the number of inputs. This guideline helps balance the model's capacity to learn complex patterns while avoiding overfitting. In this case, with eight input parameters, the hidden layer could contain up to 16 neurons, though often a smaller number is selected to reduce computational complexity and improve model generalization. The output layer of the ANN has a single neuron, which represents the predicted CO_2 concentration. The purpose of the model is to forecast a single output value, making this simple output structure appropriate for the task. The output layer neuron uses a linear activation function, suitable for predicting continuous values of CO_2 levels.

To develop a robust and reliable ANN model for CO_2 forecasting, the collected data must be carefully managed and split into distinct sets for training and validation. This ensures that the model not only learns from the data but also generalizes well to new, unseen data. The data is divided into two main subsets: a training set and a validation set. The training set, which constitutes 70% of the total data, is used to train the ANN model. This means that during the training phase, the model is exposed to a wide range of scenarios and variations within the data, allowing it to learn the underlying patterns and relationships between the input parameters (such as TVOC, RSP, HCHO, temperature, air movement, and RH) and the output (CO_2 concentration). The remaining 30% of the data is allocated to the validation set. This subset plays a crucial role in evaluating the model's performance on unseen data. By testing the model on this independent validation set, we can assess how well the model is likely to perform in real-world situations where it encounters data that was not part of the training process. This step is critical for identifying potential overfitting, where the model may perform well on the training data but fails to generalize to new data.

Before the training process begins, it is essential to normalize the data. Normalization adjusts the range of the input parameters so that they all fall within a similar scale, typically between 0 and 1. Without normalization, the training process could be inefficient or lead to suboptimal results, as the model might give undue importance to parameters with larger numeric ranges. Normalizing the data ensures that each input contributes equally to the learning process, improving the overall efficiency and effectiveness of the model training (Raju et al., 2020). After the training process is complete, the model's performance is evaluated using the validation dataset. This step involves measuring how accurately the model predicts CO_2 concentrations when exposed to new data. Two key performance metrics are commonly used for this evaluation: (i) Correlation Coefficient (R) measures the strength and direction of the linear relationship between the observed and predicted CO_2 values. A correlation coefficient close to 1 indicates a strong positive relationship, suggesting that the model's predictions closely match the actual data. This metric helps in understanding how well the model captures the underlying trends in the data, (ii) Mean Squared Error (MSE) quantifies the average squared difference between the predicted and actual CO_2 values. It provides a measure of the model's accuracy, with lower MSE values indicating better performance. MSE is particularly useful because it penalizes larger errors more heavily, ensuring that the model minimizes not just the average error but also the impact of significant deviations (Diez et al., 2022).

RESULTS

Indoor air quality patterns in a boat manufacturing facility

In the research area, air movement was consistently below the normal range of 0.15-0.50 m/s for most of the period between 0800 and 1700 hours. This low air movement can significantly impact indoor air quality, especially when various activities are being carried out. Specifically, activities such as sanding foam and wood, applying adhesive foam, cutting foam and wood, painting, and housekeeping were conducted during this time. These activities contributed to elevated levels of chemical pollutants, which exceeded acceptable limits. Most of these activities began around 0900 hours. Table 2 and Figure 2 a) to e) illustrate that, at this time, there was a marked increase in the concentrations of chemical parameters, air pollutants, and the ventilation performance indicators. The presence of only one functional air conditioner in the study area further exacerbated the situation. This single unit was insufficient to effectively manage the indoor environment, leading to suboptimal air quality.

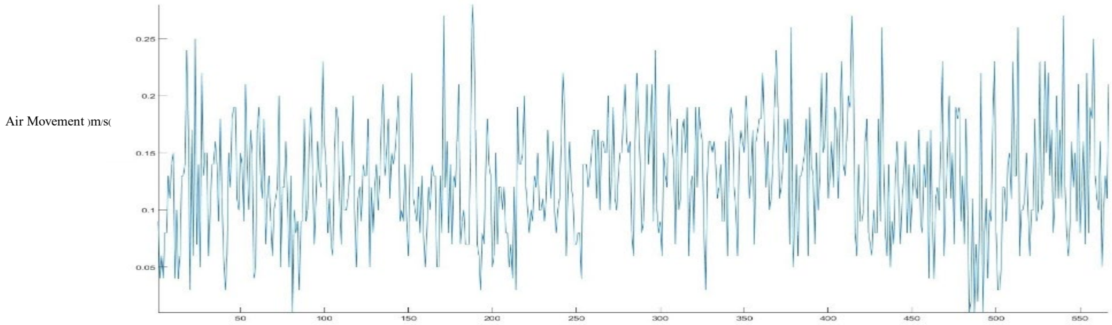
According to Table 2, the mean temperature in the research area exceeded the recommended range of 27.22°C to 31.47°C as specified by the ICOP-IAQ 2010 standards. Figure 2a) shows that temperature trends were inversely related to relative humidity levels, meaning as temperatures increased, relative humidity decreased. This inverse correlation suggests that as the temperature rose, the capacity of the air to hold moisture decreased, which could affect comfort and air quality. Furthermore, the concentration of particulate matter was notably high, with hourly mean values surpassing the standard limit. Specifically, PM_{10} levels ranged from 0.47 to 0.52 mg/m³, $PM_{2.5}$ ranged from 0.44 to 0.48 mg/m³, and PM_1 ranged from 0.43 to 0.47 mg/m³. These elevated levels were attributed to the dust and particles generated by indoor activities like sanding and cutting wood and foam.

Additionally, chemical parameters such as Total Volatile Organic Compounds (TVOC) also exceeded standard limits. This was due to the use of solvents like ethyl acetate, toluene, and glue, which were employed in foam production, boat building, and cleaning processes. These substances release significant amounts of VOCs into the air, further degrading air quality. The reduced air movement, with mean values between 0.12 and 0.14 m/s, compounded the issue. The limited air circulation, coupled with the inefficacy of the single functioning air conditioner, resulted in poor dispersion of air pollutants. This concentration of pollutants made it challenging to maintain acceptable indoor air quality, highlighting the need for improved ventilation and air management strategies in the study area.

Table 2. Trend of indoor air quality (IAQ) parameters and compliance with Malaysian standards.

MEAN	8:00	9:00	11:00	12:00	14:00	15:00	16:00	STANDARD
AT (^{0}C)	26.24	27.22	29.27	30.40	31.34	31.47	30.78	23.00-26.00
AM (m/s)	0.12	0.12	0.13	0.14	0.12	0.13	0.12	0.15-0.50
RH (%)	79.97	75.27	67.62	64.62	62.52	63.86	63.65	40.00-70.00
PM_{10} (mg/m^3)	0.47	0.48	0.51	0.52	0.46	0.52	0.50	0.15
$PM_{2.5}$(mg/m^3)	0.44	0.45	0.47	0.47	0.43	0.48	0.47	0.15
PM_1 (mg/m^3)	0.44	0.45	0.47	0.47	0.43	0.47	0.47	0.15
HCHO (ppm)	0.02	0.03	0.03	0.04	0.03	0.04	0.04	0.10
TVOC (ppm)	0.01	41.28	32.29	87.68	3.36	87.68	38.29	3.00
CO_2 (ppm)	479.95	490.53	476.26	482.15	445.48	474.67	484.33	1,000.00

(a)



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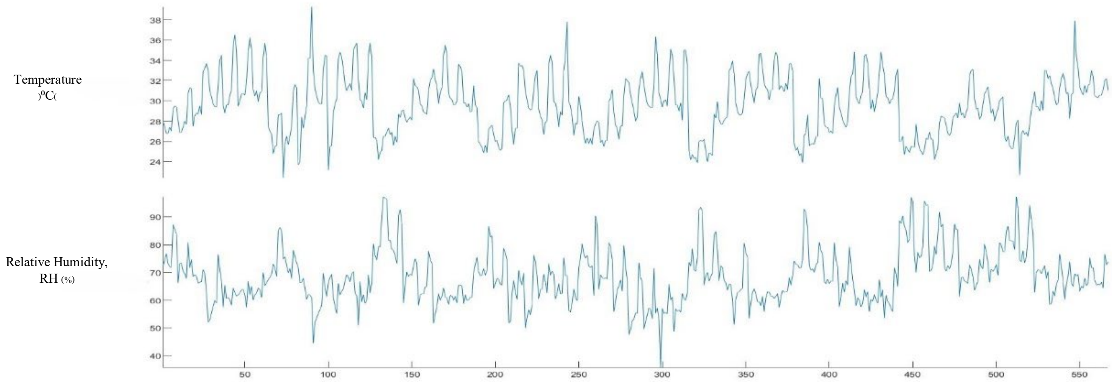

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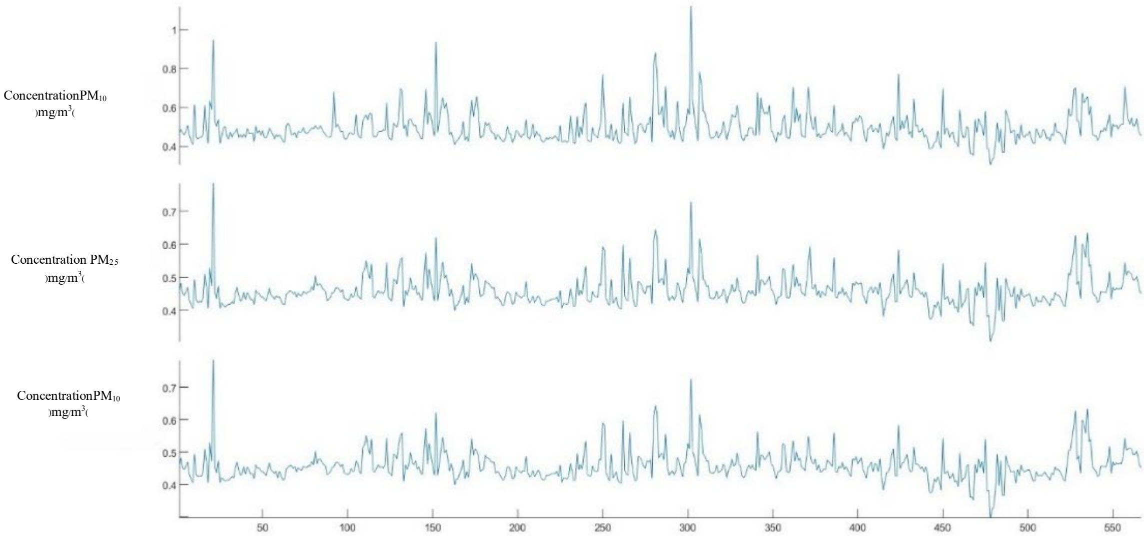
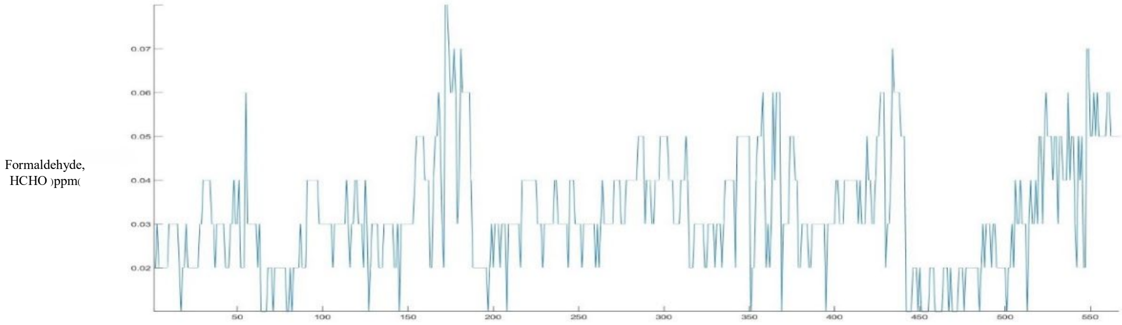


Figure 2. Trend of air movement (a) trend of temperature and relative humidity (b) trend of PM_{10}, $PM_{2.5}$ and PM_1 (c) trend of HCHO (d) trend of TVOC and CO_2 (e).

(d)



(e)

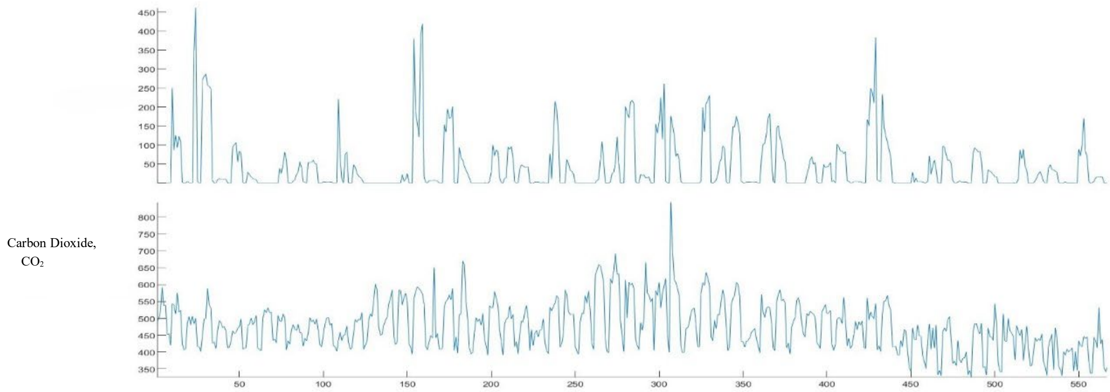


Figure 2. Continued.

The data presented in Table 3 shows the indoor-to-outdoor (I/O) ratios for particulate matter (PM) sizes PM_{10}, $PM_{2.5}$, and PM_1. Specifically, the ratios are PM_{10} = 1.22, $PM_{2.5}$ = 1.13, and PM_1 = 1.13. These ratios indicate that particulate matter, particularly PM_{10}, predominantly originates from indoor sources rather than external sources. The I/O ratio greater than 1 for PM_{10} suggests that there was minimal intrusion of external air into the research area, emphasizing that the majority of PM_{10} pollution was generated internally rather than coming from outside. The variability in pollutant concentrations, especially Total Volatile Organic Compounds (TVOC), over time further supports this finding. The I/O ratio for TVOC was 64.74, which highlights that TVOCs are primarily sourced from indoor activities and materials rather than external sources. This high I/O ratio indicates that TVOC levels are significantly influenced by indoor sources such as solvents, adhesives, and other chemicals used in the research area.

The prevalence of Respirable Suspended Particulate (RSP) indoors is influenced by several factors, including the quantity of outside pollution, the amount of pollution brought inside, and the presence of indoor sources. The I/O ratio for RSP, as shown in Table 3, suggests that natural ventilation, which could have reduced indoor pollutant levels, was not a preferred method in this setting. At this sampling point, the workshop is an open space where natural ventilation plays a role in managing indoor air quality. The natural airflow, typically provided through windows, doors, and other openings, can facilitate the exchange of indoor and outdoor air, potentially helping to dilute and remove pollutants. However, as indicated by the I/O ratio for RSP in Table 3, it appears that natural ventilation, although potentially beneficial in reducing indoor pollutant levels, was not fully optimized in this setting. One possible reason for this could be that the workshop's design or environmental factors, such as external wind patterns or the arrangement of the openings, may not have been conducive to promoting sufficient air movement to effectively manage pollutant concentrations. Additionally, the potential advantages of natural ventilation in enhancing the deposition velocity of pollutants such as promoting the settling of particulate matter were not effectively utilized, which likely contributed to the lower I/O ratios for RSP. This suggests that pollutants, including particulate matter, may have remained suspended in the air longer than desired, leading to higher indoor concentrations. Given these factors, it is possible that the use of air conditioning, which can provide more controlled and consistent air movement and filtration, might be more effective in this scenario. Air conditioning could help maintain a more stable indoor environment by regulating both temperature and humidity, while also improving the efficiency of air circulation and pollutant removal. Thus, in this particular setting, air conditioning might offer a more reliable method for managing air quality compared to relying solely on natural ventilation. The impact of natural ventilation on the deposition velocity of pollutants was not effectively utilized, leading to lower I/O ratios for RSP. The lower I/O ratio values for RSP indicate that the buildings were relatively well-protected from external contaminants. This suggests that the indoor air quality issues were primarily a result of internal sources rather than external pollution. The data underscores the need for better management of indoor sources of pollutants and highlights that improving natural ventilation could potentially enhance indoor air quality by reducing the concentration of pollutants.

Table 3. I/O ratio for assessing the influence of external factors on indoor air quality.

	AT	AM	RH	PM_{10}	$PM_{2.5}$	PM_1	HCHO	TVOC	CO_2
I/O RATIO	0.925	0.822	0.872	1.222	1.133	1.132	1.198	64.739	1.213

Interrelationship of indoor air quality parameters

To analyze the relationships between pairs of parameters, Spearman's correlation coefficient was utilized due to the non-parametric nature of the data and its violation of the normality test. Spearman's correlation is suitable for assessing the strength and direction of monotonic relationships between variables when the data does not follow a normal distribution. These correlations provide a comprehensive overview of the interrelationships between various air quality parameters and environmental factors, highlighting the complexity of indoor air quality dynamics and the influence of different factors on pollutant levels. According to the results summarized in Table 4, a very strong positive correlation was found ($r = 0.919$, $P < 0.01$), indicating that as PM_{10} levels increase, $PM_{2.5}$ levels also increase proportionally. Another strong positive correlation was noted ($r = 0.916$, $P < 0.01$), suggesting that PM10 and PM1 levels are closely related. PM2.5 and PM_1 showed an exceptionally strong positive correlation ($r = 0.994$, $P < 0.01$), reflecting a nearly perfect relationship between these particulate matter sizes. A strong positive correlation was identified ($r = 0.553$, $P < 0.01$), indicating a significant association between CO_2 levels and TVOC concentrations. A strong negative correlation was observed ($r = -0.516$, $P < 0.01$), suggesting that as TVOC levels increase, RH tends to decrease, or vice versa. A moderate positive correlation ($r = 0.325$, $P < 0.01$) was found, indicating a noticeable association between formaldehyde levels and temperature. Moderate positive correlation ($r = 0.312$, $P < 0.01$), showing a moderate relationship between HCHO and PM10 levels. A moderate positive correlation ($r = 0.361$, $P < 0.01$) was identified, indicating some degree of association between HCHO and $PM_{2.5}$. Similar moderate positive correlation ($r = 0.371$, $P < 0.01$) was found, reflecting a moderate link between HCHO and PM_1. A moderate positive correlation ($r = 0.453$, $P < 0.01$) was observed, indicating a notable relationship between TVOC and PM_{10}. A moderate positive correlation ($r = 0.383$, $P < 0.01$) was detected, showing a significant association between TVOC and $PM_{2.5}$. Moderate positive correlation ($r = 0.375$, $P < 0.01$) was noted, indicating a moderate link between TVOC and PM_1. A moderate positive correlation ($r = 0.379$, $P < 0.01$) was found, showing a moderate association between TVOC and formaldehyde.

A moderate positive correlation (r = 0.474, P < 0.01) was observed, reflecting a significant relationship between CO_2 and PM_{10} levels. Another moderate positive correlation (r = 0.412, P < 0.01) was detected, indicating a moderate association between CO2 and PM2.5. A moderate positive correlation (r = 0.409, P < 0.01) was found, showing a notable link between CO_2 and PM_1. A moderate negative correlation (r = -0.414, P < 0.01) was observed, suggesting that as RH increases, AM tends to decrease. Moderate negative correlation (r = -0.425, P < 0.01) indicates that HCHO levels and RH are inversely related. A moderate negative correlation (r = -0.423, P < 0.01) was found, showing that CO_2 levels and temperature have an inverse relationship.

A weak positive correlation (r = 0.204, P < 0.01) was observed, indicating a slight association between AM and temperature. A weak positive correlation (r = 0.206, P < 0.01) was found, suggesting a minor relationship between CO_2 and formaldehyde. Weak positive correlation (r = 0.279, P < 0.01) was noted, showing a slight association between NOP and PM_{10} levels. A weak positive correlation (r = 0.197, P < 0.01) was observed, reflecting a minor relationship between NOP and $PM_{2.5}$. Another weak positive correlation (r = 0.194, P < 0.01) was found, indicating a slight link between NOP and PM_1. A weak positive correlation (r = 0.256, P < 0.01) was detected, suggesting a minor association between NOP and TVOC. A weak positive correlation (r = 0.233, P < 0.01) was observed, indicating a slight relationship between NOP and CO_2. A weak negative correlation (r = -0.085, P < 0.01) was found, showing a minimal inverse relationship between PM_{10} and temperature. A weak negative correlation (r = -0.117, P < 0.01) was detected, suggesting a slight inverse relationship between PM_{10} and AM. A weak negative correlation (r = -0.232, P < 0.01) was observed, reflecting a minor inverse relationship between PM_{10} and RH. A weak negative correlation (r = -0.096, P < 0.01) was found, indicating a slight inverse relationship between PM2.5 and AM. A weak negative correlation (r = -0.232, P < 0.01) was observed, reflecting a minor inverse relationship between $PM_{2.5}$ and RH. A weak negative correlation (r = -0.087, P < 0.01) was detected, suggesting a slight inverse relationship between PM_1 and AM. A weak negative correlation (r = -0.233, P < 0.01) was found, indicating a minor inverse relationship between PM_1 and RH. A weak positive correlation (r = 0.086, P < 0.01) was observed, reflecting a minor association between TVOC and temperature. A weak negative correlation (r = -0.183, P < 0.01) was detected, suggesting a slight inverse relationship between TVOC and AM. A weak negative correlation (r = -0.203, P < 0.01) was found, indicating a minor inverse relationship between CO_2 and AM. A weak negative correlation (r = -0.172, P < 0.01) was observed, reflecting a slight inverse relationship between NOP and temperature.

Table 4. Spearman correlation coefficients among indoor air quality parameters.

	AT	AM	RH	PM_{10}	PM_{25}	PM_1	HCHO	TVOC	CO_2	NOP
AT	1.000	0.204**	-0.414**	-0.085*	-0.005	0.008	0.325**	-0.086*	-0.423**	-0.172**
AM		1.000	0.036	-0.117**	-0.096*	-0.087*	0.031	-.0183**	-0.203**	-0.027
RH			1.000	-0.232**	-0.225**	-0.233**	-0.425**	-0.516**	-0.364**	-0.028
PM_{10}				1.000	0.919**	0.916**	0.312**	0.453**	0.474**	0.279**
$PM_{2.5}$					1.000	0.994**	0.361**	0.383**	0.412**	0.197**
PM_1						1.000	0.371**	0.375**	0.409**	0.194**
HCHO							1.000	0.379**	0.206**	-0.056
TVOC								1.000	0.553**	0.256**
CO_2									1.000	0.233**
AOP										1.000

Note: **. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
NOP = Number of People

Predictive model for CO_2 concentrations in boat manufacturing facility

In this study, Multilayer Perceptron Neural Network (MLP-NN) models were developed to predict the ventilation performance indicator of carbon dioxide (CO_2) within a boat manufacturing facility. The models were constructed using the Levenberg-Marquardt (LM) training algorithm, a widely recognized and effective method for training neural networks due to its efficiency in handling non-linear relationships and providing faster convergence. The performance of the MLP-NN models was rigorously evaluated during both training and validation phases. The correlation coefficient (R), which measures the strength and direction of the linear relationship between the observed and predicted CO_2 levels, was used as a key performance metric and the results are tabulated in Table 5. During the training process, the R-values achieved by the models ranged from 0.7556 to 0.8725. These values indicate a strong positive correlation, suggesting that the models were able to accurately learn the underlying patterns in the training data and predict CO_2 concentrations with reasonable accuracy. In the validation phase, where the models were tested on unseen data, the R-values ranged from 0.6798 to 0.8163. While slightly lower than the training phase, these values still represent a good level of predictive accuracy, demonstrating that the models generalize well to new data. The Mean Squared Error (MSE) was utilized to quantify the prediction error of the MLP-NN models. MSE provides a measure of the average squared difference between the observed and predicted values, with lower values indicating better model performance. During training, the MSE values ranged between 0.0048 and 0.0087. These low error margins indicate that the models were able to closely approximate the actual CO_2 levels during the learning process. During validation, the MSE values varied between 0.0010 and 0.0108. Although there was a slight increase in error compared to the training phase, the results remained within an acceptable range, reflecting the models' robustness and reliability in predicting CO_2 levels even on new data. To determine the most effective neural network structure, various configurations were tested by adjusting the number of neurons in the hidden layer. After extensive experimentation, the optimal architecture was found to consist of 8 input neurons, 15 hidden neurons, and 1 output neuron, denoted as an 8:15:1 structure. This configuration provided the best balance between complexity and performance, enabling the model to predict CO_2 concentrations with an accuracy of 87.25% during training, accompanied by a minimal prediction error of 0.0048 ppm. When applied to validation data, the model maintained a high accuracy of 81.63%, with the error reduced to as low as 0.0064 ppm. These results confirm that the selected architecture is well-suited for predicting CO_2 levels in the context of the boat manufacturing facility. Based on the trained model, a prediction algorithm was established to facilitate the estimation of CO_2 levels in similar industrial environments. The derived formula is expressed as: $CO_2=0.75\times$ (ObservedCO_2) +0.074. This algorithm is straightforward and can be easily applied to predict CO_2 concentrations, thereby aiding in the optimization of indoor ventilation systems. It is particularly useful for enhancing air quality management within the studied facility and in other environments with comparable characteristics, especially in the boat manufacturing industry. Figure 3 illustrates the alignment between the observed and predicted CO_2 concentrations within the boat manufacturing facility. The observed values were measured directly from the facility, capturing the actual CO_2 levels during various indoor activities. The close correspondence between the two sets of values indicates the model's accuracy and reliability in forecasting CO_2 concentrations as in Figure 3, highlighting its potential as a valuable tool for real-time monitoring and ventilation management in similar industrial settings. In this figure, we present a side-by-side comparison of the observed CO_2 concentrations and the predicted values generated by the model. The data demonstrates a near-identical pattern between the two sets, with minimal deviations observed at different points in the measurement period. This alignment between the observed and predicted values reflects the model's ability to closely replicate actual conditions, thereby supporting the conclusion that the model is both accurate and reliable in forecasting CO_2 levels. The strong correspondence also suggests that the model captures the key dynamics influencing CO_2 concentrations in the studied environment, further validating its effectiveness as a predictive tool. The development of these MLP-NN models represents a significant advancement in the predictive monitoring of indoor air quality within industrial settings. By accurately forecasting CO_2 levels, the models provide valuable insights that can be used to optimize ventilation strategies, ensuring a healthier and more productive working environment in boat manufacturing facilities and beyond.

Table 5. Modelling and execution for CO_2 prediction in the boat manufacturing facility.

Neuron Number	Training			Validation		
	R	MSE	Output	R	MSE	Output
1	0.7556	0.0087	Y=0.56X+0.130	0.7641	0.0076	Y=0.62X+0.110
2	0.8069	0.0074	Y=0.63X+0.100	0.7568	0.0072	Y=0.65X+0.100
3	0.8281	0.0060	Y=0.68X+0.094	0.7215	0.0010	Y=0.51X+0.140
4	0.8036	0.0075	Y=0.58X+0.130	0.6996	0.0091	Y=0.56X+0.130
5	0.8119	0.0067	Y=0.65X+0.100	0.8015	0.0073	Y=0.68X+0.110
6	0.8371	0.0060	Y=0.69X+0.088	0.7467	0.0084	Y=0.6X+0.110
7	0.8094	0.0062	Y=0.65X+0.100	0.8007	0.0085	Y=0.62X+0.110
8	0.8349	0.0054	Y=0.69X+0.089	0.7425	0.0108	Y=0.52X+0.140
9	0.8220	0.0065	Y=0.67X+0.093	0.8006	0.0068	Y=0.67X+0.095
10	0.8193	0.0065	Y=0.67X+0.097	0.7910	0.0075	Y=0.68X+0.078
11	0.8561	0.0051	Y=0.73X+0.007	0.7640	0.0089	Y=0.64X+0.100
12	0.8401	0.0058	Y=0.68X+0.093	0.6798	0.0011	Y=0.55X+0.130
13	0.8579	0.0053	Y=0.73X+0.076	0.8054	0.0066	Y=0.70X+0.086
14	0.8352	0.0059	Y=0.71X+0.078	0.7532	0.0015	Y=0.69X+0.079
15	0.8725	0.0048	Y=0.75X+0.074	0.8163	0.0064	Y=0.67X+0.087
16	0.8200	0.0066	Y=0.68X+0.078	0.7383	0.0095	Y=0.66X+0.090

Y=Predicted CO_2 (ppm); X=Observed CO_2 (ppm)

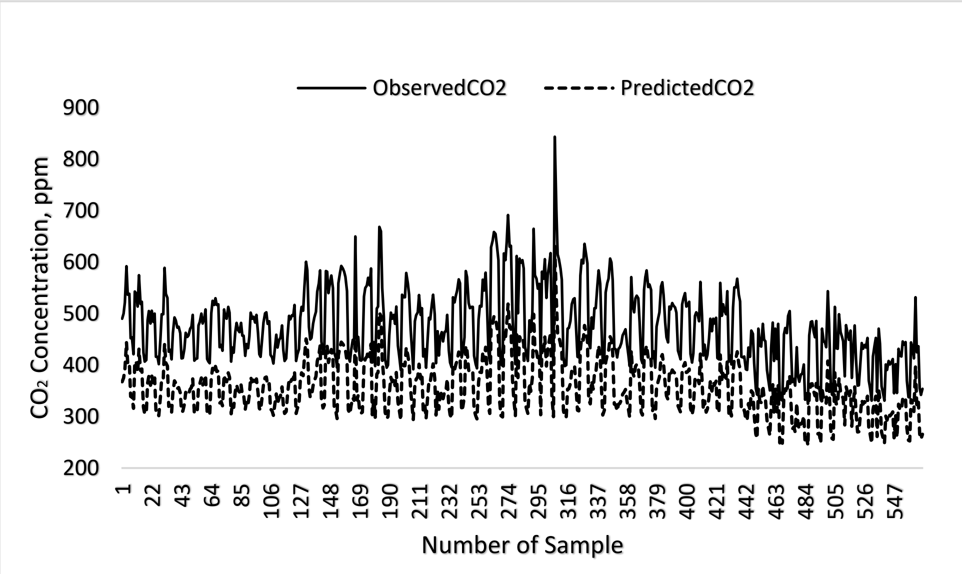


Figure 3. Comparison of observed and predicted CO_2 concentration values.

DISCUSSION

Indoor pollution sources can significantly impact workers' comfort levels. Factors influencing this include the amount of pollution entering the indoor environment, the presence of indoor activities, and the levels of various chemical parameters (Kalimeri et al., 2019). Research shows that buildings with an indoor/outdoor (I/O) ratio greater than 1.2 typically have notable indoor pollution sources (Deng et al., 2017). This implies that using static I/O ratios can simplify understanding different environmental modes within buildings, such as how mechanical ventilation is used, the extent to which windows can be opened, the layout of internal partitions, and ongoing indoor activities. Measuring I/O ratios over time helps assess their variability under different conditions and the significance of internal sources. Exposure to indoor Total Volatile Organic Compounds (TVOCs), including toluene, poses health risks. The boat manufacturing industry emits TVOCs, a group of chemicals that can evaporate into indoor air at room temperature (Mu et al., 2025). Toluene is found at higher levels indoors than outdoors, leading to most exposure occurring within enclosed spaces (Wang et al., 2024). Various industrial products, such as paints, adhesives, automotive products, and personal care items, often release toluene, which is commonly used as a solvent (Pelletti et al., 2018). The impact of humidity and temperature on formaldehyde and TVOC emissions remains unclear due to the complex and not well-understood emission mechanisms. A comprehensive study was conducted to investigate how temperature and humidity affect the release of volatile organic compounds (VOCs) from fiberglass. The findings revealed that variations in temperature and relative humidity do not significantly influence the emission trends of formaldehyde and VOCs from fiberglass and wood panels used in boat construction (Zhou et al., 2019).

Air movement can significantly aid in dispersing contaminants such as particulate matter (PM). It helps to spread pollutants that are concentrated in specific areas, thereby reducing the intensity of pollutants in any single location (Deng and Gong, 2021). However, factors like furniture placement can obstruct air circulation, leading to higher concentrations of particulate matter in certain areas (Maung et al., 2022). While long-term measurements of temperature and CO_2 levels are crucial for understanding the Earth's carbon cycle, they have limited impact on indoor air quality. This is because indoor air quality is more directly affected by CO_2 emissions from occupants and temperature management through building ventilation (Hou et al., 2021). CO_2 and TVOC concentrations varied significantly in each room based on occupancy and activities, with a strong correlation observed, particularly in areas contaminated with chemical substances. Human activities and material use are major factors influencing TVOC levels, as certain VOCs are more likely to be emitted during active periods when workers are present (Tzoutzas et al., 2021). Frequent use of cleaning products, disinfectants, and industrial processes in these environments contributes significantly to indoor VOC levels and has a strong relationship with CO_2 concentrations (Baudet et al., 2021). To improve indoor air quality and reduce pollutant levels, it is recommended to enhance ventilation through methods such as opening windows or installing mechanical ventilation systems (Fromme et al., 2019; Saleem et al., 2022).

Exposure to indoor pollutants is significantly higher compared to outdoor environments, largely due to the accumulation and internal sources of these contaminants (Stratigou et al., 2022). Fine particulate matter (PM) such as PM_1, $PM_{2.5}$, and PM_{10}, which can be inhaled, poses varying risks based on particle size (Radarit et al., 2024). PM_{10} particles, being larger, are more likely to deposit on the surfaces of the upper airways in the respiratory tract. Conversely, $PM_{2.5}$ particles, due to their smaller size, can penetrate deeper into the lungs, reaching the lower regions and depositing on the surfaces of these deeper airways (Madureira et al., 2020). The deposition of these particles in the lung can lead to a range of health issues. Particles that settle on the lung surfaces have the potential to cause inflammation and damage to lung tissues, contributing to respiratory problems and other health concerns (Olesiejuk et al., 2023).

The developed MLP-NN model uses total volatile organic compounds (TVOC), respirable suspended particulate (RSP), formaldehyde (HCHO), temperature, air movement, and relative humidity (RH) as inputs to predict carbon dioxide (CO_2) levels. This input-output relationship allows the model to assess environmental factors that influence CO_2 concentration, providing insights for better indoor air quality management in the facility. A study conducted by Kim et al. (2020) highlighted the high performance of CO_2 prediction models developed using ANNs. In this study, the model demonstrated an exceptional ability to accurately predict indoor CO_2 levels, achieving a relative error of less than 5%. This level of accuracy underscores the potential of ANNs in maintaining precise control over indoor air quality, ensuring that CO_2 concentrations remain within safe limits, and reducing the risk of poor ventilation-related health issues. Further supporting the utility of ANNs, Taheri and Razban (2021) explored the application of the Multilayer Perceptron (MLP) model in predicting volatile CO_2 behavior. Their findings revealed that MLP is particularly effective in scenarios where demand-controlled ventilation (DCV) is implemented. In buildings with variable occupancy rates, where CO_2 levels can fluctuate significantly, the ability of MLP to accurately predict CO_2 concentrations allows ventilation systems to adjust in real-time. This not only ensures optimal air quality but also contributes to significant energy savings by avoiding unnecessary ventilation when occupancy is low. The findings of Taheri and Razban (2021) are further corroborated by Kallio et al. (2021), who identified machine learning methods, particularly the MLP, as powerful tools for forecasting indoor CO_2 concentrations. Their research demonstrated that by accurately predicting CO_2 levels, MLP models could enhance the energy efficiency of buildings. By optimizing ventilation based on predicted CO_2 levels, energy consumption is reduced, leading to lower operational costs. Moreover, maintaining appropriate CO_2 concentrations contributes to the overall well-being of occupants, as proper ventilation is closely tied to indoor comfort and health.

In a boat manufacturing facility, CO_2 levels can be influenced by a combination of environmental factors such as TVOC, RSP, HCHO, temperature, air movement, and relative humidity. These factors do not impact CO_2 in a straightforward, linear manner. Instead, they interact in complex ways that are difficult to model using traditional linear methods. The MLP-NN, with its multiple layers and non-linear activation functions, is well-suited to capture these complex interactions (Taheri and Razban, 2021). It can learn how changes in the input. For example, an increase in temperature or humidity affects CO_2 levels, even when these effects are subtle or involve multiple factors simultaneously. The MLP-NN is trained using historical data where the inputs (TVOC, RSP, HCHO, temperature, air movement, and RH) and corresponding CO_2 levels are known. During training, the network modifies internal parameters to reduce the discrepancy between predicted and actual CO_2 readings. During training, the MLP-NN recognizes patterns and correlations between inputs and CO_2 levels. Once trained, it may apply the learned knowledge to make accurate predictions on new data (Buratti and Palladino, 2020). The MLP-NN's hidden layers enable the model to translate the input data into more abstract representations, allowing it to capture the complicated connections between the inputs and the output. Each layer examines inputs to emphasize the most essential aspects for estimating CO_2. The network's capacity to include a hidden layer allows for greater flexibility when modeling complicated occurrences. This adaptability is critical when working with environmental data, where the connection between variables might be extremely nonlinear and impacted by a variety of interacting factors. Once trained, the MLP-NN can generate predictions based on new input data, even if the data differs somewhat from the training set. This capacity to generalize is critical in real-world applications because facility conditions might alter over time. The MLP-NN can adapt to varied situations and conditions within the facility, making it a valuable tool for forecasting CO_2 levels under diverse operating conditions (Martínez-Comesaña et al., 2021). The MLP-NN accurately predicts CO_2 based on inputs by modeling non-linear and complicated interactions between many environmental parameters. Learning from previous data creates a strong interaction that influences CO_2 levels, resulting in accurate and trustworthy forecasts for the research area.

CONCLUSION

This study explored the physio-chemical assessment of indoor air quality parameters and the forecasting of CO_2 ventilation performance using artificial neural networks (ANN) in a boat manufacturing facility. The findings highlight the critical role that indoor activities and inadequate ventilation play in influencing air quality within the facility. Specifically, elevated levels of total volatile organic compounds (TVOC), particulate matter (PM_{10}, $PM_{2.5}$, PM_1), and formaldehyde (HCHO) were observed, exceeding acceptable limits due to processes such as sanding, cutting, painting, and adhesive application. The ANN model developed in this study, with a multilayer perceptron architecture optimized using the Levenberg-Marquardt algorithm, demonstrated high accuracy in predicting CO_2 concentrations based on input parameters like temperature, relative humidity, air movement, and chemical pollutants. The model's correlation coefficients and mean squared error (MSE) values during training and validation phases underscored its robustness and reliability in forecasting ventilation performance. The study's findings suggest that the ANN model can serve as an effective tool for monitoring and improving indoor air quality in similar industrial settings. By enabling real-time predictions of CO_2 levels, this model can guide adjustments in ventilation strategies, helping to maintain a healthier indoor environment and enhancing worker comfort and safety. In conclusion, this research provides valuable insights into the dynamics of indoor air quality in a boat manufacturing facility and offers a practical solution for mitigating the impacts of indoor pollutants through advanced predictive modeling. The adoption of such models could be crucial in other industrial contexts where air quality management is vital for occupational health and operational efficiency.

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AUTHOR CONTRIBUTIONS

Muhammad Salahuddin Mohd Azman designed the study, managed data analysis, and wrote and revised the manuscript. Amalina Abu Mansor collected and analyzed data, interpreted results, and revised the manuscript. Aimi Nursyahirah Ahmad assisted with data analysis and manuscript drafting and reviewed the manuscript for accuracy. Marzuki Ismail contributed to the prediction model design, methodology, and manuscript revisions. Mohammad Nor Khasbi Jarkoni supported data collection and experimental design and helped draft and revise the manuscript. Samsuri Abdullah provided feedback on research design and analysis and contributed to manuscript revisions.

CONFLICT OF INTEREST

The authors declare that they hold no competing interests.

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