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Enhancing thermal comfort and indoor air quality through energy optimization with neural network

Sandip Mane[1] · D. Palaniswamy[2] · H. Shaheen[3] · J. S. Leena Jasmine[4]

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Abstract
Indoor thermal comfort and air quality are essential for occupant well-being, while simultaneously optimizing energy consumption in buildings. Achieving a balance between these factors presents a significant challenge, as indoor environments are dynamic and energy demands fluctuate. By modifying ventilation rates in response to real-time data, demand-controlled ventilation systems can reduce energy consumption and enhance indoor comfort and air quality. However, optimizing these systems with advanced predictive models remains a complex task. To address this challenge, this publication proposes a Dual-Stream Multi-Dependency Graph Neural Network (DMGNN)-based energy-efficient ventilation management technique that maximizes indoor air quality and thermal comfort. The suggested method seeks to enhance thermal comfort and air quality by maximizing heating, ventilation, and air conditioning (HVAC) operations while reducing energy consumption. Initially data are collected from an Indoor Air Quality Monitoring Dataset. The DMGNN is employed to capture the complex dependencies between environmental factors such as temperature, humidity, and CO_2 concentrations, considering both temporal and spatial relationships. Implementing the proposed system and evaluating it through simulations in various building environments demonstrates notable improvements in thermal comfort, indoor air quality, and energy economy. The suggested system's performance is contrasted with that of other current methods, showing superior energy efficiency and optimization of both indoor air quality and occupant comfort. This study presents an innovative, scalable framework for smart building management, promoting sustainable energy solutions.

Keywords Thermal comfort · Indoor air quality · Air conditioning · Ventilation · Temperature · Environment · Energy saving

Introduction

The successful functioning of HVAC systems is essential to preserving human comfort and optimizing energy use in interior areas [1, 2]. According to studies, Between 85 and 90 percent of people's time is spent indoors in the US and Europe, underscoring the importance of indoor environmental conditions in day-to-day living. Globally, buildings account for nearly 33% of total energy consumption, with HVAC systems alone contributing almost 50% of this demand [3, 4]. Beyond their impact on energy, HVAC systems directly affect thermal comfort, (IAQ),

✉ Sandip Mane
sandip.mane@djsce.ac.in

D. Palaniswamy
131ems@gmail.com

H. Shaheen
shaheen66@gmail.com

J. S. Leena Jasmine
leena@velammal.edu.in

[1] Mechanical Engineering Department, Dwarkadas J Sanghvi College of Engineering, Mumbai, Maharashtra 400056, India

[2] Associate Professor, Department of Mechanical Engineering, Adithya Institute of Technology, Coimbatore 641107, Tamil Nadu, India

[3] Sr Lecturer - Course Leader, Computer Science, Department of Computing and Engineering, University of West London - RAK Branch Campus,, Ras Al-Khaimah, UAE

[4] Department of Electronics and Communication Engineering, Velammal Engineering College, Chennai, Tamil Nadu 600066, India

and consequently well-being of humans, productivity, and well-being [5]. The global drive toward sustainability and carbon reduction has placed HVAC optimization at the center of both engineering research and policy agendas. Inefficient HVAC operations contribute significantly to greenhouse gas emissions, while advanced optimization approaches can help balance comfort, air quality, and energy efficiency. Moreover, rising energy costs create a strong economic incentive for building owners and facility managers to adopt smarter, data-driven control strategies. Thus, designing adaptive, energy-efficient HVAC management systems is not only a technical challenge but also an environmental and economic necessity.

Despite advancements, conventional HVAC systems are constrained by rigid operating schedules and static assumptions about occupancy levels. These systems often waste energy by conditioning unoccupied spaces or by failing to respond dynamically to changes in indoor environments. Single-point sensor measurements further reduce accuracy, while oversimplified comfort models neglect individual differences and changing conditions. To overcome these limitations, Demand-Controlled Ventilation (DCV) and intelligent optimization strategies have been introduced, yet their performance is heavily dependent on precise real-time monitoring and robust predictive models.

Recent years have witnessed HVAC management through the use of AI and ML approaches, ranging from reinforcement learning to neural network-based comfort modeling. While these approaches have demonstrated significant promise, challenges persist, including the need for large datasets, limited scalability across different climates, and insufficient adaptability to dynamic indoor conditions. Furthermore, existing frameworks often fail to integrate thermal comfort and IAQ in a holistic manner, leaving gaps in achieving true occupant-centric control.

Motivated by these gaps, this study introduces a DMGNN framework designed to maximize HVAC operations by modeling both temporal and spatial dependencies among environmental factors. Unlike traditional approaches, the DMGNN dynamically adapts to fluctuating indoor conditions, capturing complex interactions between temperature, humidity, CO_2 concentration, and occupancy. This innovation not only enhances predictive accuracy but also ensures energy-efficient HVAC control across diverse building types and climatic zones.

This research contributes a robust, scalable solution for sustainable building management by integrating advanced AI-driven predictive modeling with practical HVAC optimization. The proposed DMGNN framework advances the state of the art in indoor environmental control, offering improvements in thermal comfort, IAQ, and energy efficiency simultaneously.

Related work

Using a variety of methods, numerous research projects have attempted to maximize indoor thermal comfort and air quality; a few of these are covered below.

Yu et al. [6] have created a control strategy that uses Deep Q-Learning in the context of reinforced learning in order to maximize the energy usage of air conditioners and exhaust fans. Energy consumption, thermal comfort, and interior air quality (CO_2 levels) were all balanced in the agent's design. The algorithm was evaluated in a classroom with a maximum of 72 people after being trained in a simulated setting that was similar to the intended use. Over the course of a month-long summer test, the impacts of classroom activities and outdoor conditions on energy savings and interior air quality were thoroughly examined. The agent demonstrated its capability to optimize air-conditioning and exhaust fan operations, achieving balanced control of indoor air quality, energy consumption, and thermal comfort.

Lopez-Perez et al. [7] have demonstrated a thermal model based on artificial neural networks comfort modeling technique to predict the temperature that residents of tropical educational buildings would want (Tcomf). Field data were gathered from Tuxtla Gutiérrez, Mexico's 27 educational buildings, employing both NV and AC systems. These data facilitated the development of ANN-BM for Tcomf prediction. Predictor variables were mass, degree of exercise, relative humidity, air velocity, garment insulation, and the average temperature for outdoor jogging. When compared to local and conventional models, the ANN-BM framework significantly increased the accuracy of Tcomf predictions, highlighting its suitability for improving thermal comfort modeling in these kinds of environments.

The importance of thermal comfort modeling in developing HVAC control techniques has been examined by Somu et al. [8] aimed at enhancing living areas' energy efficiency and comfort of the occupants. Given the limitations of classic models like Fanger's PMV, the authors employed data-driven techniques to improve usability and accuracy. The study addressed the challenge of insufficient labeled thermal comfort data by implementing a transfer learning-based framework. A TL CNN-LSTM model was developed to effectively capture time-spatial relationships in thermal comfort measurements. The SMOTE was used to balance datasets with few thermal condition samples, and using the Chi-squared test, important parameters were found. Experiments utilizing target dataset (Medium US office) and source datasets (ASHRAE RP-884 and Scales Project) showed the model's efficacy in achieving robust performance under sparse data conditions, despite its reliance on intrusive parameters and adaptability challenges across varied climate zones.

Brik et al. [9] have emphasized the significance of keeping an eye on heat retention to ensure sustainable vitality use in residential buildings, particularly for disabled individuals whose thermal requirements may differ significantly from those without disabilities. Recognizing the challenges faced by disabled individuals in expressing their thermal comfort, the authors created a learning model based on deep neural networks to make real-time predictions about indoor thermal comfort. A novel IoT design was designed to generate the dataset, incorporating an efficient data collection scheme for targeted data acquisition and subsequent cloud-based analysis. This approach facilitated remote monitoring while guaranteeing the precision and dependability of the information gathered for the evaluation of thermal comfort.

Martínez-Comesaña et al. [10] have addressed given its effects on occupants' health, well-being, and productivity, indoor environmental quality (IEQ) monitoring in buildings is vital, particularly in light of the COVID-19 epidemic. To predict interior temperature, relative humidity, and CO_2 concentration at minute-level intervals, the researchers used an effective extreme gradient boosting technique to develop an interpolation model. This model eliminated the need for continuous monitoring in occupied zones. Optimization to minimize the required number of monitoring devices was achieved utilizing the NSGA-III multi-objective genetic algorithm. A research center in northwest Spain was the site of the methodology's application demonstrating its effectiveness in providing accurate environmental estimations with minimal monitoring equipment.

Morresi et al. [11] have conducted experimental study to investigate how well wristwatch sensors can forecast the thermal comfort of occupants in a range of environmental circumstances. The purpose of the study was to evaluate smartwatches' measurement accuracy when incorporated into HVAC (air conditioning, ventilation, and heating) control systems. Thirteen individuals were subjected to temporary situations, and ten participants received tests of discomfort generated by both warm and cold temperatures. A smartwatch and a network of sensors were used to collect data, which included heart rate variability (HRV) and ambient characteristics. Machine Learning (ML) classification systems used HRV features as inputs to assess pain levels. Furthermore, the thermal sensation vote (TSV) in transient situations was predicted using algorithms for machine learning and deep learning regression. The results showed that when environmental and physiological data were combined, the accuracy of TSV prediction was higher than when HRV features were used alone. The study highlighted the potential of physiological metrics to enhance TSV predictions when integrated with environmental factors.

Wang et al. [12] have explored Utilizing Building air quality, energy efficiency, and indoor thermal comfort can all be improved by OCHNVC. In order to generate real-time profiles of window operations and occupant behavior, deep vision algorithms and AI-powered cameras were employed. They developed predictive models based on shallow artificial neural networks to predict how buildings would react to different window-opening and occupant behaviors. The tailored OCHNVC strategy was implemented in a case study room, demonstrating its potential to reduce heating energy use and improve thermal comfort in comparison to traditional control techniques.

Energy efficiency, thermal comfort, and indoor air quality must all be balanced, recent research emphasizes the growing significance of energy optimization in buildings, especially for HVAC systems. However, significant challenges remain due to the lack of adaptability to varying climatic conditions, diverse occupant behaviors, and real-world scenarios. Existing methods, including CIBSE and ASHRAE standards, often misestimate comfort temperatures, while advanced techniques like Artificial Neural Networks (ANNs) require extensive field data, limiting scalability. Transfer learning approaches struggle with climatic variability and rely on intrusive parameters, while current IEQ monitoring systems fail to deliver accurate, real-time multi-zone assessments with minimal device deployment. Furthermore, occupant-centric control strategies and smartwatch sensors lack integration with environmental data, leading to inconsistent indoor air quality management. These limitations, coupled with the underexplored inclusion of differently abled individuals and subjective comfort metrics, motivated this research to develop a robust and adaptive solution. To address these gaps, energy efficiency, thermal comfort, and indoor air quality must all be balanced by capturing temporal and spatial dependencies among environmental factors, offering a scalable, inclusive framework for sustainable smart building management.

This study's innovation the DMGNN, optimizes HVAC systems to improve indoor air quality, thermal comfort, and energy efficiency. Unlike traditional models, the DMGNN captures dynamic temporal and spatial dependencies between environmental factors, offering real-time adaptability to fluctuating conditions. This approach overcomes limitations of fixed settings, inaccurate real-time monitoring, and poor scalability, providing a comprehensive solution for sustainable and efficient smart building management.

The contributions of this research are as follows:

- Introduces a DMGNN for optimizing HVAC systems.
- Enhances energy savings by optimizing ventilation and HVAC operations while maintaining comfort and air quality.
- Captures dynamic environmental dependencies for real-time adjustments to temperature, humidity, and CO_2.
- Provides a scalable framework adaptable to various building types and climates.

- Using simulations, shows enhanced performance in thermal comfort, indoor air quality, and energy efficiency.

The rest of the manuscript is structured like this: Sect. "Related work" examines associated work and highlights the limitations of existing approaches. Sect. "Proposed methodology" presents the proposed methodology, including data collection, the DMGNN architecture, and the overall system flow. Sect. "Results and discussion" reports the experimental results, with detailed discussion of the findings, implications, and limitations. Finally, Sect. "Conclusions" concludes the paper and outlines future research directions.

Proposed methodology

The suggested methodology's framework is depicted in Fig. 1. The suggested methodology optimizes HVAC systems utilizing a DMGNN for indoor air quality and energy-efficient thermal comfort. Gathering environmental data, like CO_2 levels, temperature, humidity, and occupancy trends, is the initial stage. The DMGNN model captures complex dependencies among these factors and predicts necessary adjustments in HVAC operations, dynamically controlling ventilation rates, temperature, and CO_2 levels.

Data collection

The dataset was collected using a custom-built air quality monitoring system deployed indoors for 24 h(https://www.kaggle.com/datasets/hemanthkarnati/indoor-air-quality-dataset). It consists of real-time data from various sensors measuring seven environmental factors: Carbon Monoxide (CO) levels (MQ7 sensor) in ppm, general air quality (MQ135 sensor) as a composite air quality index, ambient temperature in °C, relative humidity as a percentage, estimated CO_2 levels (eCO_2) in ppm (CCS811 sensor), Total Volatile Organic Compounds (TVOC) in ppb (CCS811 sensor), and particulate matter density, specifically dust particles, in μg m^{-3} (GP2Y1010 sensor). These fields provide comprehensive insights into the indoor air quality and environmental conditions.

Prediction based on DMGNN

In this part, the DMGNN is introduced, designed to optimize HVAC operations in smart buildings [13]. In an effort to lower energy usage and improve air quality and

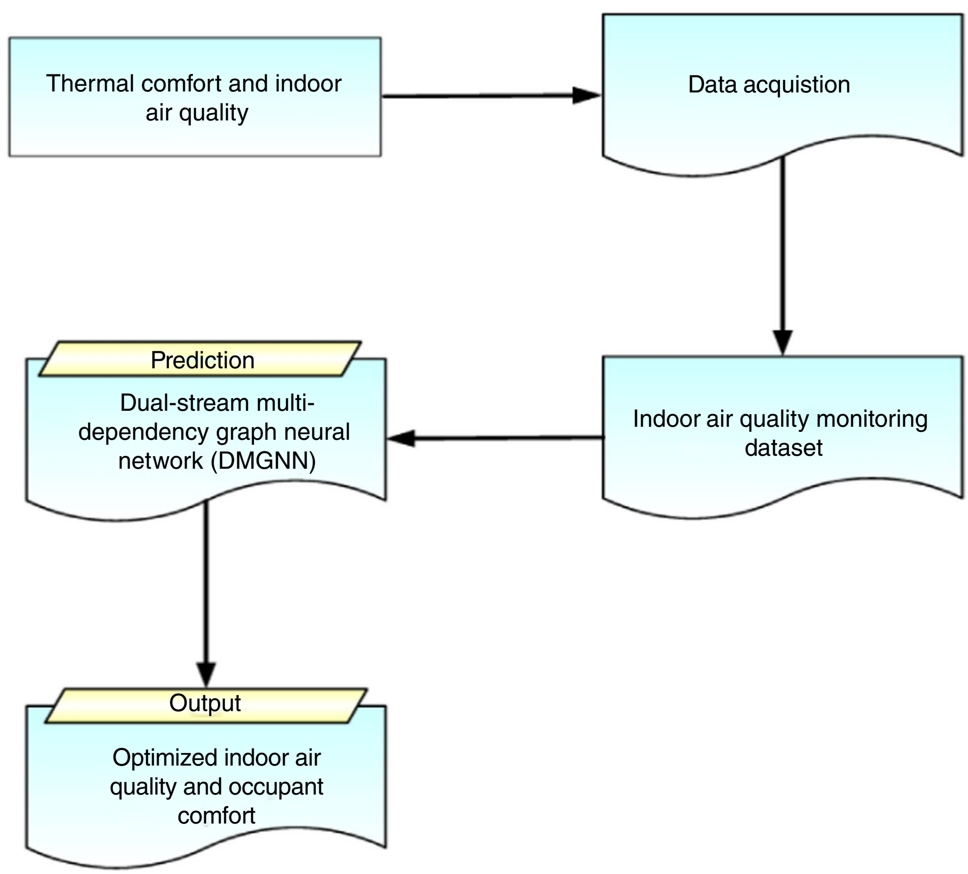

Fig. 1 Structure of the proposed methodology

thermal comfort, DMGNN forecasts and modifies interior environmental parameters like temperature, humidity, and CO_2 levels. DMGNN uses its dual-stream mechanism to capture temporal (time-based) and spatial (location-based) dependencies, allowing it to model complex relationships between environmental variables and HVAC systems. By processing high-dimensional data from real-time monitoring systems, it provides adaptive HVAC scheduling, resulting in increased occupant comfort and effective energy use.

The predictive capabilities of DMGNN enable precise control over ventilation and energy use, achieving significant improvements in IAQ, energy savings, and occupant well-being. Its adaptability to dynamic indoor environments and diverse building scenarios makes it a robust and scalable solution for smart building management, promoting both energy efficiency and sustainability. It forecasts energy demand is given in (1).

$$\mathrm{GCN}(X, A) = \delta(\overline{D}^{-\frac{1}{2}}\overline{AD}^{-\frac{1}{2}}\mathrm{XW}) \tag{1}$$

where $\overline{D}_{\mathrm{ij}} = \sum_{\mathrm{j}} A_{\mathrm{ij}}$ and W is the feature transformation mass matrix that can be trained. It allows for the dynamic adjustment of features to better represent the underlying structure and dependencies in temperature, humidity, and CO_2 concentration flow, and HVAC system behavior. It integrates these transformed features to estimate power distribution and balance across the HVAC system. Power flow is calculated in Eq. (2).

$$\mathrm{AW}_{\mathrm{s}} = (\mathrm{sigm}(W_1 F + b_1) \cdot \tanh(W_2 F + b_2))W_3 + b_3 \tag{2}$$

where W and b stand for the bias and the learnable transformation matrix, respectively, while sigm indicates the sigmoid function. In light of the present climatic conditions, it incorporates these changes and activations to estimate the energy requirements of HVAC systems, including the needs for heating, ventilation, and AC. The system's HVAC operational cycles to balance the load and optimize energy usage are described in Eq. (3).

$$\mathrm{MAM} = \alpha + (1 - \alpha) \cdot \mathrm{sigm}(\mathrm{AW}_{\mathrm{s}}) \times \mathrm{sigm}(\mathrm{AW}_{\mathrm{s}})^{\mathrm{T}} \tag{3}$$

where α is a predetermined hyper-parameter that will drop as training goes forward. This equation models the adaptive control of HVAC operations, adjusting for heat, humidity, and CO_2 concentrations to optimize energy use while maintaining thermal comfort and indoor air quality in real time. The DMGNN predicts the demand for HVAC control in Eq. (3), where, MAM is a momentum attention matrix, W_{s} is employed to predict the cycles of HVAC to maximize the usage of energy and thermal comfort. This is shown in Eq. (4).

$$F = \mathrm{soft\ max}\,(\beta \frac{\mathrm{AFM} \times \mathrm{AW}_{\mathrm{s}}}{\sqrt{d_{\mathrm{k}}}} + (1 - \beta)\mathrm{AW}_{\mathrm{s}}) \times [F_1, F_2] \tag{4}$$

where β is the pre-defined hyperparameter, $F_1 = \mathrm{FUB}(F)$ and $F_1 = \mathrm{GAB}(F)$ indicate the characteristics of the two sections, and [,] symbolizes the process of fusion. This model predicts and optimizes the HVAC cycles to mitigate overloading and ensure efficient thermal comfort and air quality control by dynamically adjusting according to data that is current. After the concatenation operation, the combined feature vector undergoes further transformation through a learnable mass matrix and bias, allowing complicated relationships to be captured by the model. This enables the model to capture complex relationships, helping refine the prediction of optimal HVAC operational schedules for efficient energy management. The system model is represented as follows:

$$f_{\mathrm{surv}}(y_{\mathrm{j}}, F_{\mathrm{j}}) = \prod_{i=0}^{y_{\mathrm{j}}} (1 - f_{\mathrm{hazard}}(i, F_{\mathrm{j}})) \tag{5}$$

where the system's state and performance are correlated with the variables F and y_{j}, respectively, while f_{hazara} symbolizes the method used to calculate threat rates. By accurately forecasting HVAC operations, the DMGNN helps strike a balance between energ use, air quality, and thermal comfort, mitigating overloading and inefficiencies within the building's systems.

The general layout of the suggested DMGNN-based ventilation control system is shown in Fig. 2. The process begins with the Indoor Air Quality Monitoring Dataset, from which environmental parameters such as temperature, humidity, and CO_2 concentrations are collected. These parameters serve as inputs to the DMGNN model, which captures their temporal and spatial dependencies. The model then informs energy-efficient ventilation management by dynamically adjusting HVAC operations in response to real-time environmental changes. The outputs of this process include improvements in thermal comfort and indoor air quality, which in turn lead to multiple benefits such as energy savings, CO_2 emission reduction, optimization of IAQ, enhanced operational efficiency, and reduced costs. Collectively, the framework demonstrates how advanced neural network modeling can provide a scalable solution for sustainable building management while maintaining occupant comfort.

Results and discussion

The following portion illustrates how well the suggested approach is based on the simulation's findings. The main objective of the recommended approach is to efficiently

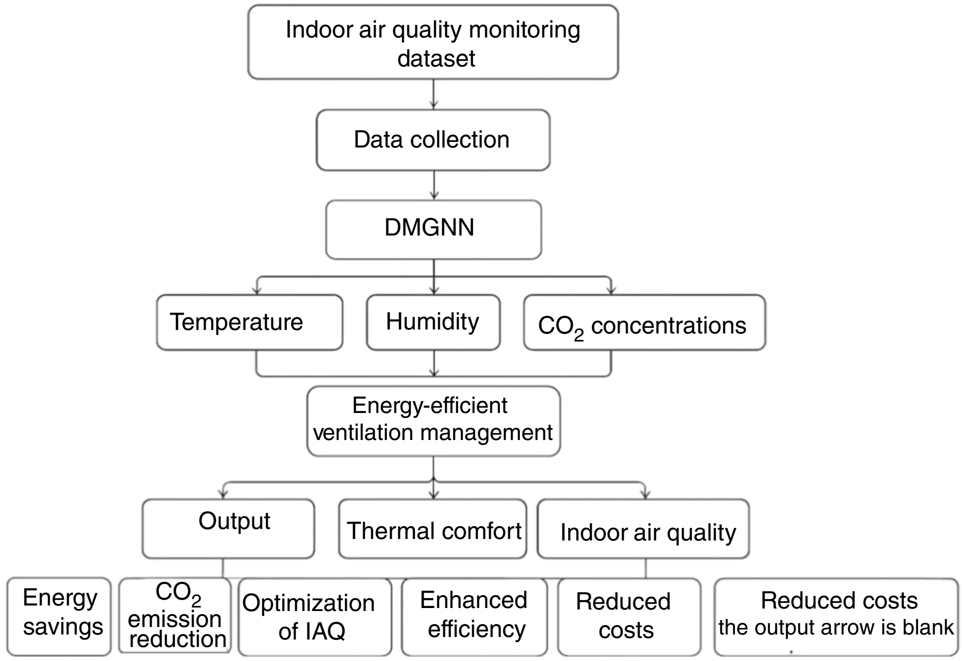

Fig. 2 The suggested methodology's flow chart

optimize HVAC system performance while preserving interior air quality and thermal comfort. The approach was implemented using Python, and its performance was evaluated through simulations across various indoor building scenarios. The results demonstrate significant improvements in both energy efficiency and occupant comfort compared to existing approaches.

Figure 3 shows the correlation between measured and predicted CO_2 concentrations, demonstrating the effectiveness of the DMGNN model. A high R^2 value of 0.95 indicates that 95% of the variance in measured CO_2 levels is explained by the predictions, highlighting the model's strong accuracy. Additionally, the RMSE of 16 confirms minimal deviation between measured and predicted values, showcasing the model's reliability in estimating CO_2 concentrations for enhancing indoor air quality and using less energy. The correlation between the DMGNN model's projected temperature and the actual temperature is displayed in Fig. 4. The data points closely align and show a strong linear relationship, suggesting that the model is capable of accurately capturing temperature trends. The high R^2 value of 0.98 highlights that 98% of the variance in measured temperature is explained by the predictions. Additionally, the RMSE of 0.23 demonstrates that the model maintains an average prediction accuracy within 0.23 °C of actual values. These results confirm the DMGNN model's reliability in forecasting temperature in indoor environments.

The relationship between the power predicted by the DMGNN model and the measured power usage is depicted in Fig. 5. The data demonstrate a strong linear correlation, with 99% of the variance in measured power accurately

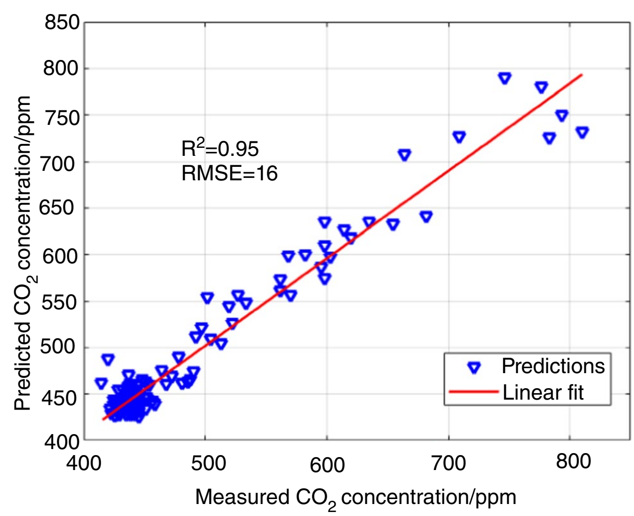

Fig. 3 Measured vs. predicted CO_2 concentrations with DMGNN

explained by the predictions, demonstrated by a 0.99 R^2 value. The precision of the model is highlighted by an RMSE of 0.22 kW, showing minimal deviations between measured and predicted values. These results confirm the model's exceptional capability for reliable and accurate power consumption prediction.

Figure 6 shows the outdoor airflow (OA) rates across three scenarios: baseline, minimum, and optimized, over a specific period. The baseline scenario maintains a steady OA rate around 1000 L s^{-1}, reflecting a consistent supply of fresh air without optimization. In contrast, the minimum scenario significantly reduces the OA rate, fluctuating between

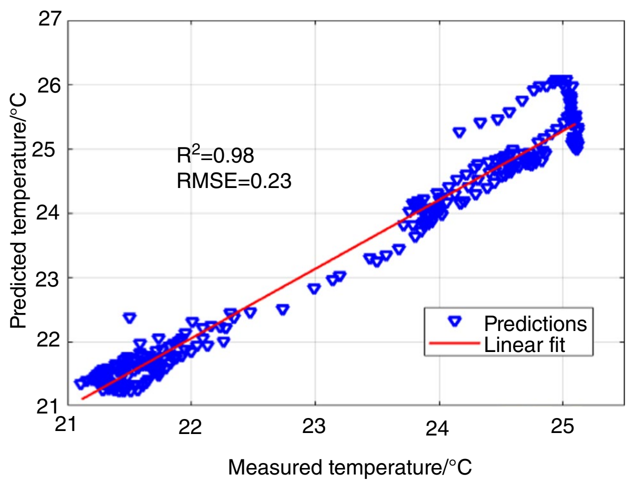

Fig. 4 Measured and predicted correlation temperatures using DMGNN

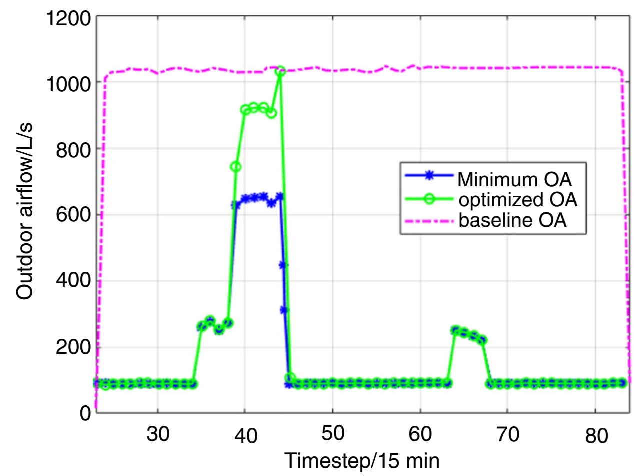

Fig. 6 Ventilation rate comparison for baseline, minimum, and optimized scenarios

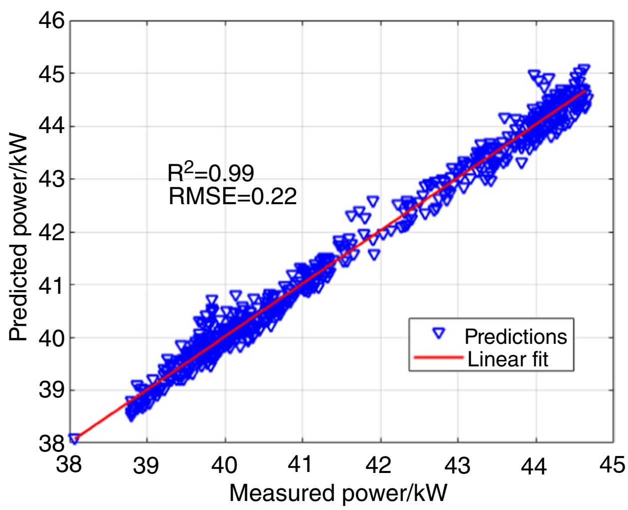

Fig. 5 Measured and predicted correlation power using DMGNN

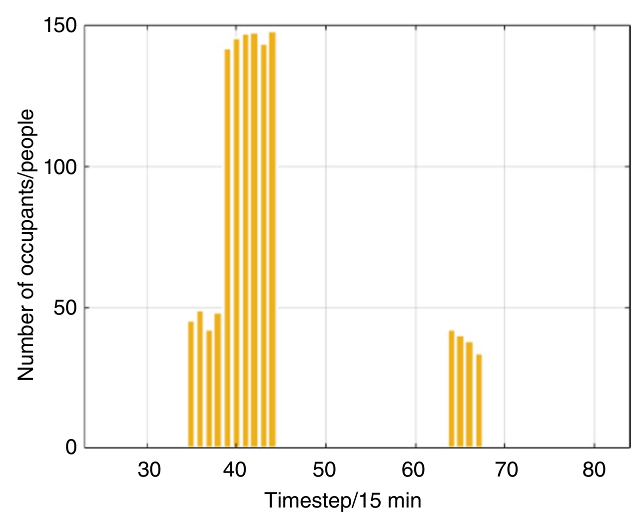

Fig. 7 Occupancy trends over time

approximately 200 L s^{-1} and 400 L s^{-1}, occasionally peaking near 600 L s^{-1}, indicating an energy-saving approach with limited ventilation. The optimized scenario, controlled by the DMGNN model, demonstrates a dynamic adjustment of OA rates based on predicted requirements. It ranges from 200 to 1000 L s^{-1}, balancing energy efficiency and indoor air quality. These findings demonstrate how well the framework can adjust ventilation rates, striking a balance between conserving energy and preserving the supply of fresh air.

Figure 7 shows the variation in the number of occupants within a space over a specified duration, highlighting two distinct periods of high occupancy. The first peak, around timestep 30–45, shows a rapid increase in occupancy reaching approximately 150 people, followed by a gradual decline. The second peak, between timestep 60 and 75, shows a smaller maximum occupancy of about 50 people. During the intervals between these peaks, occupancy remains significantly lower, indicating reduced space utilization. These patterns suggest opportunities for dynamic ventilation adjustments. For periods of high occupancy, increased ventilation is essential for maintaining air quality, while lower occupancy allows reduced ventilation to enhance energy efficiency. This figure underscores the utility of such data for optimizing ventilation strategies and HVAC operations, demonstrating the DMGNN model's potential for effective energy management based on occupancy trends.

Performance measures

This is an important step in deciding which optimization algorithm to explore. A performance metric to assess performance, such as precision and accuracy.

Accuracy

According to the equation, the accuracy value is calculated as the ratio of the number of samples correctly classified by the scheme to the total number of samples (6).

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \quad (6)$$

Here, TP signifies true positive, TN denotes true negative, FN means false negative and FP denotes false positive.

Precision

Precision in the classification of cervical spine disease is essential for minimizing false positives, ensuring that only patients who truly have the condition are identified.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (7)$$

Performance analysis

Figures 8, 9 displays the simulation results for the suggested DMGNN approach. The suggested DMGNN approach is then compared to existing methods for Deep Q Learning (DQL), Artificial Neural Network (ANN), and Transfer Learning.

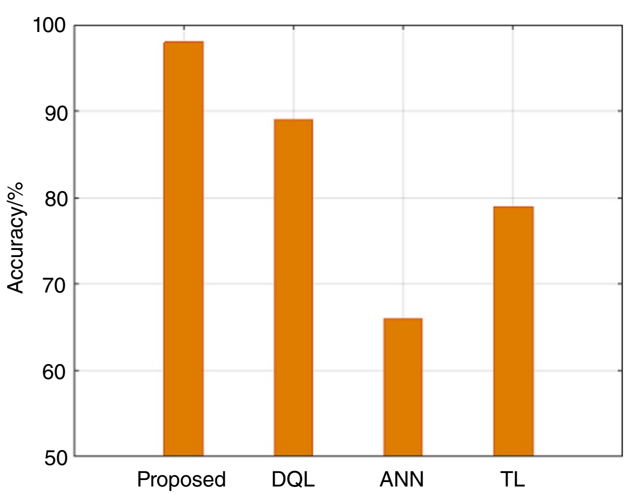

Fig. 8 Comparison of accuracy with proposed and exisiting methods

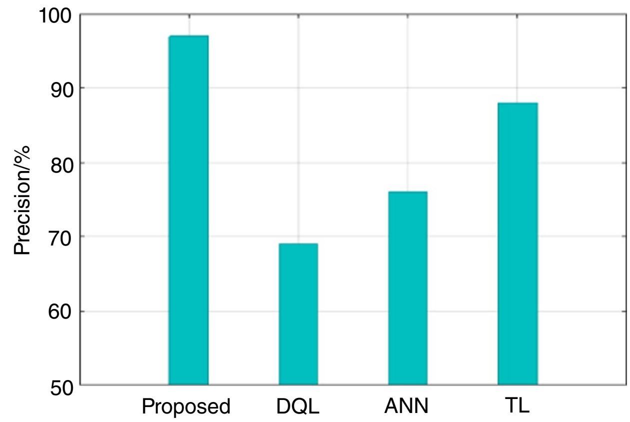

Fig. 9 Comparison of precision with proposed and existing methods

The accuracy comparison of the suggested and current methods is shown in Fig. 8. For the DQL method the accuracy is 89%, for the ANN method the accuracy is 66%. The accuracy for TL is 79%. With an accuracy of 98%, the suggested approach outperforms current techniques. Figure 9 displays a comparison of precision between suggested and existing approaches. The precision for the DQL method is 69%, ANN method is 76% and TL is 88%. The suggested solution outperforms the current methods with a 98% precision rate.

The findings show that the DMGNN model outperforms existing techniques for optimizing HVAC operations in terms of accuracy and precision. The model demonstrated high accuracy in predicting CO_2 concentrations ($R^2 = 0.95$, RMSE = 16), temperature ($R^2 = 0.98$, RMSE = 0.23 °C), and power consumption ($R^2 = 0.99$, RMSE = 0.22 kW). Dynamic adjustments in ventilation rates, as shown in Fig. 6, balance energy efficiency and air quality by adapting airflow between 200 and 1000 L s^{-1} based on occupancy. Occupancy trends reveal opportunities for energy-saving ventilation during low-occupancy periods. With an accuracy and precision of 98%, DMGNN significantly outperforms DQL, ANN, and TL methods, showcasing its capability to optimize HVAC systems while preserving interior air quality and thermal comfort.

Discussion

The results of this study show how well the Dual-Stream Multi-DMGNN optimizes HVAC operations for decreased energy consumption, increased thermal comfort, and better indoor air quality. The excellent accuracy of the predictions achieved across CO_2 concentration ($R^2 = 0.95$), temperature ($R^2 = 0.98$), and power consumption ($R^2 = 0.99$) confirms the robustness of the proposed model in capturing both temporal and spatial dependencies among environmental variables. Compared to existing approaches such as Deep Q-Learning

Table 1 Comparative summary of related studies on HVAC optimization, IAQ, and thermal comfort

Author & year	Method/model	Key focus	Dataset/environment	Strengths	Limitations
Yu et al. [6]	Deep Q-learning (DQL)	Optimize energy use, IAQ, thermal comfort in classrooms	Simulated & classroom with up to 72 occupants	Balanced control of AC & exhaust fan operations	Dependent on training environment; limited scalability
Lopez-Perez et al. [7]	Artificial neural network (ANN-BM)	Comfort temperature prediction in tropical educational buildings	27 buildings, Mexico (AC + NV)	Improved accuracy over conventional models	Location-specific; requires large field data
Somu et al. [8]	TL CNN-LSTM + SMOTE	Comfort in terms of heat prediction with transfer learning	ASHRAE RP-884, US office, Scales Project	Robust under sparse data; spatiotemporal modeling	Intrusive parameters; adaptability issues across climates
Brik et al. [9]	IoT + Deep neural network	Thermal comfort prediction for disabled individuals	Custom IoT dataset	Inclusive focus; real-time comfort monitoring	Limited to specific population; high complexity
Martínez-Comesaña et al. [10]	XGBoost + NSGA-III	IEQ monitoring & optimization	Research center, Spain	Accurate predictions with fewer devices	Does not capture multi-zone dynamics
Morresi et al. [11]	ML/deep learning with HRV sensors	Thermal comfort via physiological sensing	13 participants + smartwatch sensors	Combines physiology + environment data	Small sample; wearable dependence
Wang et al. [12]	Occupant-centric HVAC control (OCHNVC)	Real-time adaptation to window & occupant behavior	Case study room	Improved comfort + energy savings	Requires vision-based monitoring; privacy concerns
Proposed (This study)	DMGNN	HVAC optimization for IAQ, comfort, and energy efficiency	Indoor Air Quality Monitoring Dataset + simulations	Captures temporal & spatial dependencies; scalable; real-time adaptability	Validation needed in real-world multi-zone settings

(DQL), Artificial Neural Networks (ANN), and Transfer Learning (TL), the DMGNN framework consistently outperforms in terms of accuracy and precision, underscoring its superiority in real-time adaptability and scalability. A key advantage of the DMGNN lies in its ability to dynamically adjust ventilation and HVAC cycles in response to occupancy trends and fluctuating indoor conditions. The optimized ventilation rates shown in this study reveal the model's capacity to reduce energy consumption without compromising indoor environmental quality. This adaptability is particularly relevant in modern smart buildings where energy demand patterns are highly variable and traditional fixed control systems fail to respond effectively. From a practical perspective, the proposed framework contributes to the ongoing global efforts toward sustainable energy use in buildings. By enhancing both energy efficiency and occupant well-being, the DMGNN aligns with international sustainability goals and green building standards. Additionally, the model provides economic benefits by lowering operational costs associated with HVAC systems, thereby offering strong incentives for its adoption in both residential and commercial buildings. Despite these promising outcomes, it is important to recognize a number of restrictions. First, the present study relies on simulation-based validation, which may not fully capture the complexities of real-world building operations, particularly under extreme weather conditions or irregular occupancy patterns. Second, while the dataset employed includes multiple environmental parameters, additional variables such as outdoor climatic conditions, pollutant levels, and personalized comfort preferences could further enrich the model. Third, computational complexity may pose challenges in large-scale deployments where real-time processing speed is critical. Therefore, future studies should concentrate on testing for reliability in diverse building environments to confirm scalability and robustness under practical operating conditions. Integrating wearable physiological sensors or smart IoT devices could also improve personalized comfort modeling, while hybrid frameworks combining DMGNN with reinforcement learning may further enhance control efficiency. Moreover, expanding the model's application to multi-zone HVAC systems and integrating renewable energy sources would strengthen its role in sustainable smart building management. The DMGNN provides a comprehensive, adaptive, and scalable approach to HVAC optimization. Its demonstrated ability help lower energy use, preserve indoor air quality, and improve thermal comfort positions it as a promising solution for next-generation intelligent building systems (Table 1).

Conclusions

To summarize, the DMGNN model demonstrated excellent performance in optimizing HVAC operations while preserving interior air quality and thermal comfort. Through comprehensive simulations, the model achieved superior predictive accuracy for CO_2 concentrations, temperature, and power consumption, with R^2 values reaching up to 0.99 and low RMSE values. Its adaptive control of ventilation rates dynamically adjusted airflow based on current environmental and occupancy data, effectively balancing energy efficiency and air quality. Comparative analysis highlighted the DMGNN's significant performance improvements over existing methods such as DQL, ANN, and TL, achieving an accuracy and precision of 98%. These findings establish the DMGNN model as a robust, scalable, and practical solution for power control in smart buildings, offering a transformative method for sustainable HVAC systems and improved indoor environmental quality. Future studies may include expanding on this research by including advanced optimization techniques to boost the effectiveness of the DMGNN model and adaptability to various building settings and dynamic circumstances.

Author contribution Each author has examined all findings, taken ownership of the manuscript's substance, and approved the final draft.

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Data availability This article does not qualify for data sharing because no datasets were created or examined for this investigation.

Declarations

Conflict of interest The writers affirm that there is no possible conflict of interest between them.

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