An artificial neural network-based system to estimate the thermal comfort of buildings with energy efficiency

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Abstract. Heating Ventilation Air Condition (HVAC) systems consume the majority of energy in a building; it is essential to optimize this energy while improving the thermal comfort of the occupants. The Predict Mean Vote (PMV) model is considered as one of the most efficient models to define the thermal comfort of a structure. In this context this paper proposes a prediction of PMV index using ANN algorithm to classify the real-time thermal comfort states of occupants, which may provide future energy savings by adopting time-varying setpoints where real-time changes in thermal comfort may require less energy. The performance of studied algorithm was tested using several evaluation parameters such as mean square error (MSE) and correlation coefficient (R2). The algorithm studied in this article showed promising results in terms of correlation coefficient R2 and MSE.

Keywords— Energy, HVAC Systems, Thermal Comfort, Machine learning, Artificial Neural Network.

1 INTRODUCTION

The world's ability to reduce greenhouse gas emissions depends on the construction industry. Buildings account for more than a quarter of the region's total energy consumption and CO_2 emissions, according to the Association of Southeast Asian Nations (ASEAN) [1]. In addition, global building emissions increased by 2% in 2018, reaching 9.7 gigatons of carbon dioxide ($GtCO_2$) due to the large expansion of space and population leading to a 1% increase in energy consumption to about 125 exajoules (EJ), or 36% of global energy consumption [2]. By 2040, CO_2 emissions from buildings might be reduced by more than 60% [1] by increasing the use of renewable energy, enhancing energy access for low-income households in the area, and utilizing Artificial Intelligence (AI) techniques for energy optimization. Heating, ventilation, and air conditioning (HVAC) systems and their related activities account for most of the building consumption. Therefore, reducing the energy demand of HVAC systems is essential for total energy conservation and greenhouse gas reduction.

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Ventilation systems are crucial for HVAC systems. Commercial and industrial building lose up to 30% and 25% of their heat through ventilation, respectively [3]. Its potential to improve energy efficiency by increasing occupant comfort and decreasing energy consumption, the operation of HVAC systems has received a significant attention over the past decade [4]. Collective models, namely the Predicted Mean Vote (PMV) model, have traditionally been used in the design and management of HVAC systems to decide the layout of building systems based on the comfort of the occupants and to reflect their opinions. The American Society of Heat, Refrigeration, and Air-conditioning Engineers (ASHRAE) has standardized the PMV model, which combines two human-related parameters, clothing level and metabolic rate, to make indoor areas thermally bearable for most occupants [5]. For an appropriate building environment, ASHRAE 55 [5] recommends a PMV of 0.5. The PMV score can be calculated quantitatively using six comfort metrics (four interior environment variables such as Temperature (T), Humidity (H), Mean Radiant Temperature (MRT), and Air Velocity (Va), and two important components such as Metabolic Rate (Met) and Clothing Insulation (Clo)). In order to optimize energy usage globally and reduce greenhouse gas emissions while maintaining occupant thermal comfort, building energy optimization and thermal comfort modeling are among the most well-liked research subjects in recent years [6]. The use of machine learning techniques to predict occupants' thermal comfort has been shown to increase energy efficiency in buildings while also ensuring comfortable living conditions [7]. Abdulgader et al. [8] suggested an energy-efficient thermal comfort model for HVAC systems in intelligent buildings to improve thermal comfort while consuming less energy. They found that incorporating a large database could greatly improve the accuracy of the Support Vector Machine (SVM) model. Gao et al. [9] proposed the use of deep reinforcement learning (DeepComfort) to enhance thermal comfort control in buildings, using Deep Deterministic Policy Gradients (DDPG) and Deep Neural Networks (DNN). Their method resulted in a 4.31% reduction in energy consumption and a 13.6% increase in thermal comfort, with a potential 14.5% improvement in prediction accuracy. Zhang et al. [10] introduced an interpretable thermal comfort system that used Linear Regression (LR) and Decision Tree (DT) interpretable ML techniques. In this paper, an artificial neural network-based framework is presented to develop a thermal comfort model that can be integrated into HVAC systems to optimize energy usage while ensuring the thermal comfort of building occupants. The thermal comfort control system and the adopted ANN algorithm are described in Sections 2 and 3, respectively, while the results and performance evaluation of the algorithm are presented in Section 4.

2 THERMAL COMFORT CONTROL SYSTEM

2.1 Systeme architecture

The occupants tend to spend most of their time in buildings. Hence, thermal comfort takes a major role in the design process of buildings. In smart buildings, the thermal comfort of occupants is influenced by several personal and environmental factors. Thermal comfort control strategies in buildings can be divided into two groups: model-based strategies and learning-based strategies, according to Gao et al. [9]. The first group bases its control policy determination on simulating the dynamics of the environment, whereas the second category bases its control policy determination on learning through interactions with the environment [9]. This section presents an ANN algorithm approach that uses an open access database [11] containing occupants' thermal comfort features of buildings. The aim is to design efficient thermal control methods for intelligent buildings that optimize HVAC energy consumption while ensuring acceptable occupant comfort levels. The objective of this study is to develop a thermal comfort system that can maintain occupant thermal comfort with optimal energy usage. Figure 1 illustrates the overall architecture of the proposed thermal comfort system.

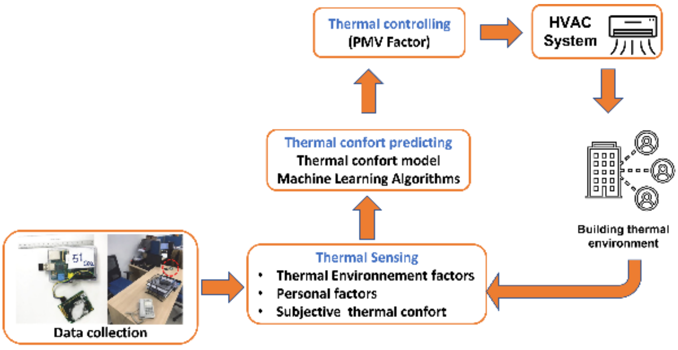

Fig. 1. Proposed architecture of the thermal comfort control system

2.2 Data set

The dataset used in this work was originally collected by Elnaklah [11] from the University of Bath in Amman, Jordan, from summer 2017 to winter 2019. According to the collector, a portion of the dataset, subjective data, were generated by interviewing employees in the offices. The rest of the dataset is a subjective data, that were generated by measuring environmental parameters inside the workplaces using an embedded system based on a raspberry pi linked to several sensors, the study involves 13 office buildings in total. The dataset contains data on occupant satisfaction with the quality of the indoor environment and data on four interior environment indicators (air temperature, mean radiant temperature, relative humidity, air velocity). In addition to thermal comfort indicators, the dataset contains absenteeism and presenteeism.

3 METHODOLOGY AND EXPIRMENTS

3.1 ANN Algorithm

3.1.1 The perceptron model

Perceptron models are a basic form of neural network that take an input, weight each input, sum the weighted input, and then apply an activation function. They are a relatively simple type of neural network.

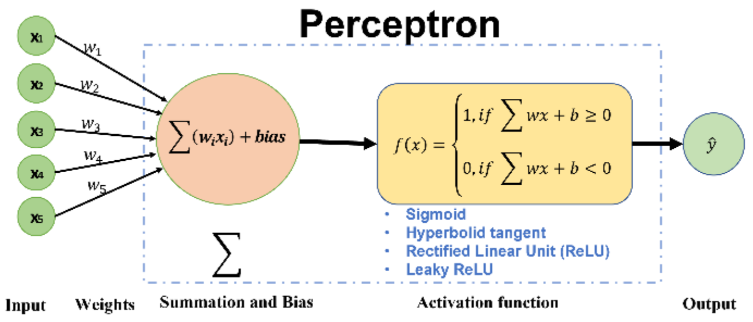

Fig. 2. Architecture of the perceptron model

3.1.2 Multilayer perceptron

. A multi-layered perceptron is a neural network consisting of multiple layers of artificial neurons. Various activation functions such as Sigmoid, TanH, and ReLU can be used in these networks.

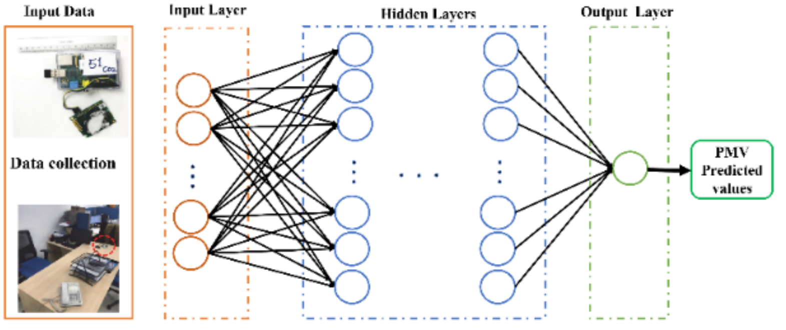

Fig.3. Propose architecture of ANN algorithm

3.1.3 Evaluation metrics

The performance evaluation of a model is a very important aspect to have the accuracy of the thermal comfort model according to [12,13]. In this section, we present the used metrics to evaluate our proposed ML models. Three metrics were used, RMSE, MAE, and the R2 coefficient. These evaluation matrices are a helpful tool to estimate the difference between two vectors. In our case, the first vector contains PMV predicted values using RF and ANN models, and the second contain PMV measured values, hence, this metrics give an idea of how much difference (error) the ML model typically makes when predicting PMV values. They can be calculated as follows:

$$RMSE(y_{act}, y_{pred}) = \sqrt{\frac{\sum(y_{act} - y_{pred})^2}{n_{samples}}} \quad (1)$$

$$MSE(y_{act}, y_{pred}) = \frac{\sum(y_{act} - y_{pred})^2}{n_{samples}} \quad (2)$$

$$MAE(y_{act}, y_{pred}) = \frac{\sum|y_{act} - y_{pred}|}{n_{samples}} \quad (3)$$

$$R^2 = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 (y_i - \bar{y})^2}} \quad (4)$$

Where:

y_{act}, y_{pred} refers to actual and predicted values.

$n_{samples}$: refers to number of instances in the database.

x_i, $\bar{x}$: refer to the values and mean value of the x-variable (features input) in a data base

y_i, $\bar{y}$: are the values and mean value of the y-variable (actual PMV) in a database.

4 RESUTLS AND DISCUTION

The optimization of energy usage in buildings depends on the ability to predict PMV values. Better HVAC system control is possible as a result of this forecast. The best possible regulation of HVAC systems has numerous financial and environmental advantages. There are a number of factors that affect the PMV value, including (temperature, relative mean temperature, relative humidity, air velocity, metabolic rate, clothing insulation....). The relationship between PMV and the other factors in our data was examined for this reason. The correlation matrix created using Pearson's approach is shown in Fig. 3. The values of the Pearson coefficients are shown in Table 1 together with the correlation matrix, which demonstrates a high connection between the values of PMV and (PPD, Tr, Ta, Rh, Met, Clo, Av).

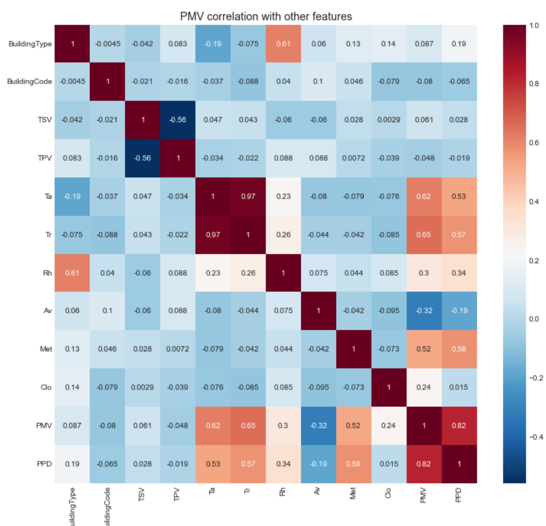

Fig.3. Correlation Matrix

Table 1. PMV correlation coefficient by the Pearson method

	PPD	*Tr*	*Ta*	*Met*	*Rh*	*Clo*	*Av*
Pearson coefficient	0.82	0.65	0.62	0.52	0.30	0.24	-0.32

Based on the collected data, the model was implemented and tested using ANN algorithm. Table 2 and Fig.4 shows the evaluation results in the training and testing phases for the anticipated PMV model. Using four evaluation metrics - MSE, RMSE, MAE, and R2 Score - the actual PMV in the database was compared to the predicted PMV values.

Table 2. Metrics results for both model during training and testing phases.

	Phase	R2	MAE	MSE	RMSE
ANN	Train	0.76	0.114	0.037	0.191
	Test	0.801	0.102	0.029	0.171

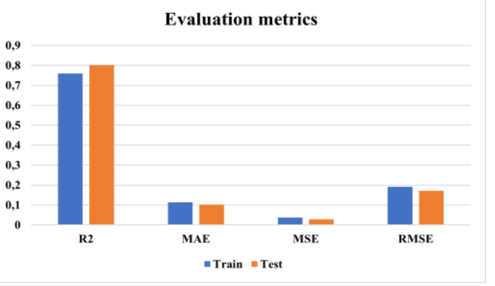

Fig.4. Metrics results for both model during training and testing phases.

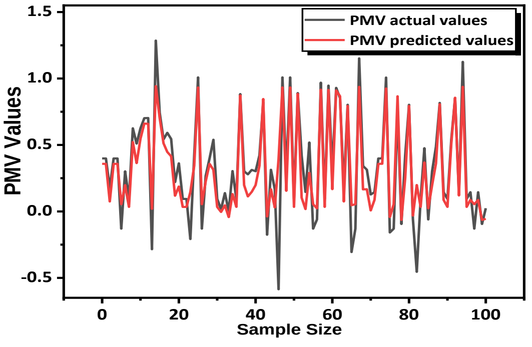

Fig. 5. Difference between the value of the PMV index predicted by ANN and its real value.

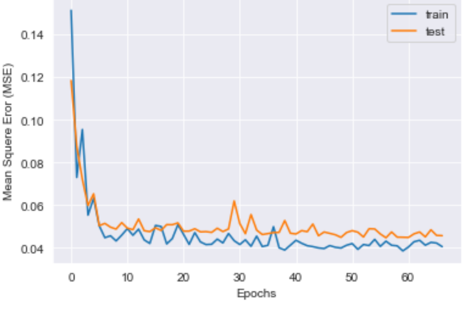

Fig.6. Mean Square Error variation.

Fig. 6 showing a convergence to the value 0 and fully built algorithm performance, allowing for the optimization of the prediction model and afterwards an acceptable thermal comfort.

5. CONCLUSION

This paper proposes an AI-based framework for developing a model that ensures both thermal comfort and energy efficiency in buildings. The main objective is to examine the use of ANN algorithms to predict the PMV index, which can be integrated into HVAC systems to optimize energy consumption while maintaining thermal comfort in accordance with ASHRAE standards. We began by discussing the impact of thermal comfort control systems on building energy efficiency. Then, we utilized ANN algorithms to train the dataset and predict the PMV values. The performance of the model was assessed using various evaluation metrics, such as MAE, RMSE, and R2 coefficient. The results showed that the ANN algorithm performed better, achieving an R2 coefficient of 80.1% and RMSE of 0.171 in the test phase and an R2 coefficient of 76% and RMSE of 0.191 in the training phase.

References

1. Roadmap for Energy-Efficient Buildings and Construction in the Association of Southeast Asian Nations, https://www.iea.org/reports/roadmap-for-energy-efficient-buildings-and-construction-in-the-association-of-southeast-asian-nations, last accessed 2022/06/15.
2. 2019 Global Status Report for Buildings and Construction, https://www.worldgbc.org/news-media/2019-global-status-report-*buildings-and-construction
3. P. W. Tien, S. Wei, T. Liu, J. Calautit, J. Darkwa, C. Wood, A deep learning approach towards the detection and recognition of opening of windows for effective management of building ventilation heat losses and reducing space heating demand, Renewable Energy 177, 603-625 (2021).
4. W. Jung, F. Jazizadeh, T. E. Diller, Heat flux sensing for machine-learning-based personal thermal comfort modeling. *Sensors*, *19*(17), 3691(2019).
5. ASHRAE: *Thermal Environmental Conditions for Human Occupancy*; ASHRAE: Atlanta, GA, USA, (2017).
6. X. Zhou, L. Xu, J. Zhang, B. Niu, M. Luo, G. Zhou, X. Zhang, Data-driven thermal comfort model via support vector machine algorithms: Insights from ASHRAE RP-884 database. *Energy and Buildings 211*, 109795, (2020).
7. W. Valladares, M. Galindo, J. Gutierrez, W. C. Wu, K. K. Liao, J. C. Liao, C. C. Wang, Energy optimization associated with thermal comfort and indoor air control via a deep reinforcement learning algorithm. *Building and Environment155*, 105-117, (2019).
8. M. Abdulgader, F. Lashhab, Energy-efficient thermal comfort control in smart buildings. In *2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC)*, pp. 0022-0026. IEEE (*2021*).
9. G. Gao, J. Li, & Y. Wen, Energy-efficient thermal comfort control in smart buildings via deep reinforcement learning. *arXiv preprint arXiv:1901.04693*, (2019).
10. W. Zhang, Y. Wen, K. J. Tseng, G. Jin, Demystifying thermal comfort in smart buildings: An interpretable machine learning approach. IEEE Internet of Things Journal, 8(10), 8021-8031, (2020).
11. R. Elnaklah, Dataset for "Indoor environment quality and work performance in 'green' office buildings in the Middle East". Bath: University of Bath Research Data Archive. 2020
12. Z. Deng, Q. Chen, Reinforcement learning of occupant behavior model for cross-building transfer learning to various HVAC control systems. *Energy and Buildings238*,110860,(2021).
13. X. Zhou, L. Xu, J. Zhang, B. Niu, M. Luo, G. Zhou, & X. Zhang, Data-driven thermal comfort model via support vector machine algorithms Insights from ASHRAE RP-884 database. *Energy and Buildings 211*, 109795, (2020).