

# Optimization of indoor quality and thermal comfort for university classrooms using data-based machine learning

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**Abstract.** Improving indoor environment quality on university classrooms is a hot research topic. The on-site experiment was conducted on indoor environmental quality regarding temperature, humidity, air pollutants, light and acoustics during different seasonal conditions. The result shows that nearly 25% of indoor particulate matters exceeded the GB18883 standard when the outdoor environmental pollution was severe under natural ventilation conditions in autumn. More than 20% of students experienced symptoms of drowsiness, dizziness, chest tightness, poor breathing, as well as depression and irritability. From the analysis of occupant demand, indoor air pollution and thermal comfort are the most anticipated areas for students to improve their learning environment. This paper proposes an optimal IEQ prediction model integrated with students' satisfaction and indoor environmental features using machine-learning classification algorithms. The back-propagation neural network shows the high prediction accuracy among different algorithms. The traditional PMV-PPD model shows an accuracy rate of only 28% for thermal sensation prediction, while the highest prediction accuracy obtained through machine learning algorithms is about 75%. Moreover, the influence of individual's thermal adaptation ability, including gender, long-term thermal experience, and psychological factors, and environmental factors was analyzed in this study.

## 1 Introduction

With the pandemic of corona-virus disease and severe world wildfires, there is an increasing focus on indoor environment quality (IEQ). Poor IEQ in university classrooms can significantly reduce students' learning efficiency and affect their health [1-2]. Thermal comfort and perceived air quality (PAQ) are two main subjective effects to the indoor environment. Fanger [3] proposed a PMV and PPD model to evaluate the thermal comfort with air conditioning, which has been adopted in ASHRAE 55 and ISO 7730 standards. PAQ defines as the perception of indoor air by occupants in CEN-CR1752 report [4]. Most literatures focus solely on thermal comfort or air quality, while few studies evaluate the university classroom environment from four aspects covering thermal, air quality, light and acoustics [5-7].

It has been widely believed that improving indoor environmental quality comes at the cost of increasing building energy consumption for a long time [8]. However, there is no trade-off between the comfort of indoor environments and building energy efficiency. The key to solving the contradiction between the two lies in whether people can fully utilize their ability to regulate the environment, accurately judge the environmental needs of building users and match energy consumption with environmental needs. Then it can improve energy utilization efficiency and achieve the dual goals of comfort and energy conservation.

As university classrooms are quite unique semi-public spaces, students are freedom to make their decision on course attendance and to express their opinions on education quality [9]. Recent studies indicate that various perceptions of learning environment were received from students due to individual characteristics, such as thermal adaptation, gender, culture background, and psychological factors [10-13]. It is necessary to combine personal characteristics into traditional indoor environmental analysis in order to estimate the needs of user and environment.

The purpose of this study is to evaluate the indoor environment quality of university classrooms, including thermal, air quality, light and acoustics, through experimental and subjective measurements under different building ventilation and air-conditioning operation modes. Considering external environment factors and personal characteristics, an optimal IEQ prediction model integrated with students' satisfaction and indoor environmental features is developed using back-propagation neural network machine-learning classification algorithms.

## 2 Methods

### 2.1 Site description

The experiments were conducted on the building group of a university campus in Xi'an (108°9'E, 34°3'N), of

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which the climate zone was 4B based on ASHRAE 169 standard. Three classroom sizes (90, 150 and 250 seats) were chosen for a detailed description in our previous research [14]. In this study, four experimental stages have been summarized throughout the year, including natural ventilation (NV) stage with moderate outdoor temperature in spring, cooling air conditioning in summer, NV stage with lower outdoor temperature in autumn, and central heating regulation in winter.

## 2.2 Data collection

The measurement instruments were deployed in the classroom with plum blossom method. The temperature-humidity self-recorder (Hygroclip 2-S), black globe thermometer (SWEMA05), omni-directional hot-wire anemometer (SWEMA03), illuminometer (TES1330A), sound meter (TES 1350A), CO<sub>2</sub> meter (TES1370) and particle matter counter (QD-W1) were selected to record experimental data. To investigate the characteristics of classroom users (students) and their demands for indoor environment, the subjective questionnaires were designed [15]. The first part was about the thermal sensation referred to ASHRAE 55 standard, and the second part was regarding air quality referred to EN15251 standard. A total of 3552 valid questionnaires were collected. The selected students stayed in the classroom for at least 50 minutes, believing that they had fully adapted to the indoor environment and avoiding short-term heat experiences on their subjective feelings.

## 2.3 Data pre-processing

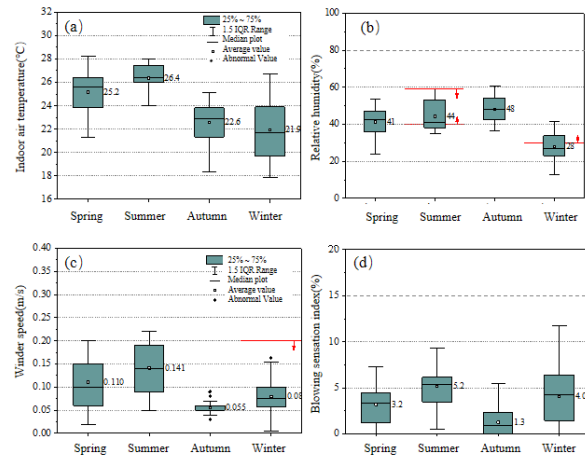
Machine learning models including Decision Tree (DT), K-Nearest Neighbour (KNN), Random Forest (RF), Naive Bayes (NB) and Back Propagation (BP) were utilised and compared. After missing and low-quality data was taken, there are 2500 total instances with 11 characteristics. The eleven characteristic parameters contained air temperature, radiation temperature, wind speed, relative humidity, clothing thermal resistance, metabolic rate, seasons, long-term thermal experience, cognitive level of environmental importance, environmental attention and emotion state. To effectively carry out machine learning, the last five kinds of non-numerical variables were converted into numerical variables. The performance evaluation on accuracy was established by splitting training and testing datasets into 8:2 ratio.

## 3 Results and discussion

### 3.1 Indoor environment quality statistical analytics

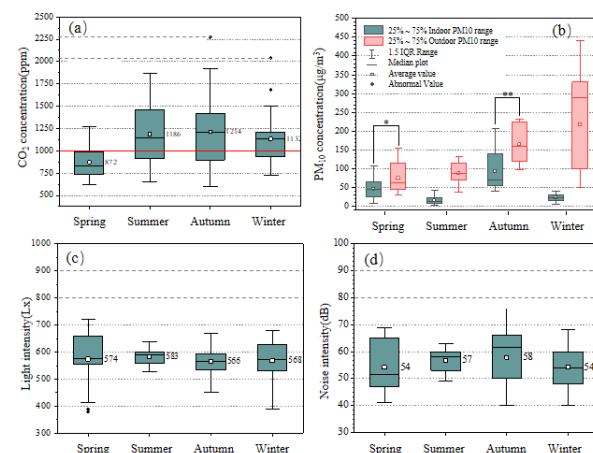
The measurement results of university classrooms during the whole year are shown in Fig.1-2, including main three aspects of indoor thermal, air quality, light and acoustics environment. The average indoor air temperature ranged from 21.5 to 26.4 with a maximum standard deviation of 2.6. Fig.1(b) shows

low relative humidity in winter due to central heating in Northwest China. The indoor air velocity was relatively small in autumn and winter, but met the requirements of less than 0.2 m/s. The draught rates were calculated less than 20%, which met with ISO 7730 standard, indicating that overall indoor wind speed will not cause occupant dissatisfaction and complaints.



**Fig. 1.** Indoor environment quality measurement results a) Indoor air quality, b) Relative humidity, c) Wind speed, d) Blowing sensation index.

The classroom experienced mean indoor CO<sub>2</sub> concentration exceeding the GB18883 standard limit ( 0.1%, ~1000ppm) throughout the year except the spring in Fig.2(a). The maximum CO<sub>2</sub> concentration reached 2274 ppm during the experimental conditions, exceeding the standard limit by 127.4% and occurring in a naturally ventilated environment in autumn because of poor ventilation control method. Nearly 25% of indoor PM10 concentration exceeded the GB18883 standard ( 100 µg/m<sup>3</sup>) when the outdoor environmental pollution was severe in autumn NV conditions (Fig.2b). The PM10 concentration in winter was well controlled because people tended to close windows during the heating periods, thereby reducing the direct impact of outdoor pollution on indoor environments.



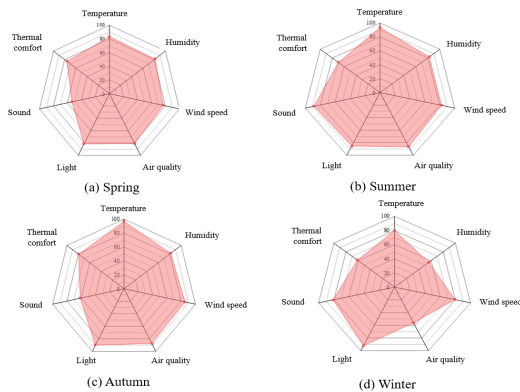
**Fig. 2.** Environment quality measurement results a) Indoor CO<sub>2</sub>, 2) Outdoor and indoor particular matter, c) Light intensity, d) Noise intensity.

The light intensity was ranged from 378 to 721 lx in Fig.2(c), with an average value of 574 lx during the

whole year. The minimum light intensity was met with the requirement of 300 lx from GB50034 architecture light design standard. The noise intensity was ranged from 41 to 76 dBA, which was higher than the standard value of 45 dBA for normal classroom without amplification equipment (GB50118 standard). This study conducted a further questionnaire survey on the clarity of indoor sound environment. Only less than 5% students regarded that the sound was very clear in the classroom during four seasons, suggesting the improvements on indoor audio quality.

### 3.2 Indoor environment quality evaluation

Figure 3 show the satisfaction rate voting results for different aspects of overall indoor environment. The highest level of comfort occurred during the natural ventilation stage in autumn, with 79.4% of students considering the environment comfortable. The worst IEQ voting was winter, with only 61.2% satisfaction rate. The comfort level of NV mode was significantly higher than that of artificial cold and heat source environments. The results indicated that overall indoor comfort was related to both original environmental aspects and the adjustment to the indoor environment.



**Fig. 3.** Overall indoor environmental satisfaction evaluation.

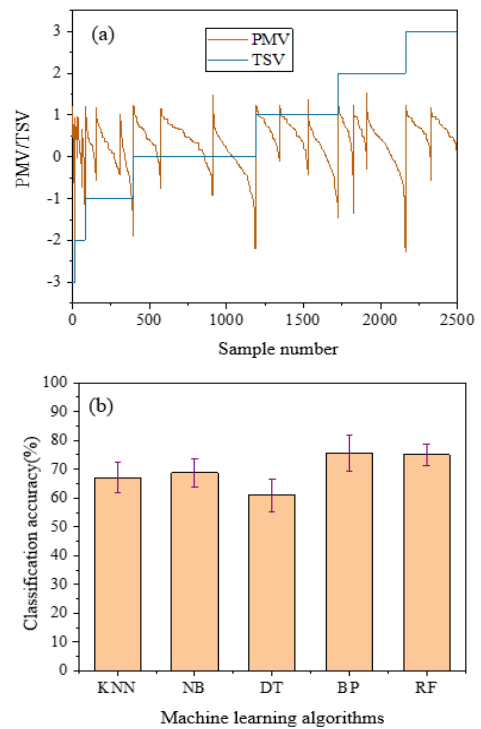
Through questionnaire survey analysis, only 7.6% students did not report any adverse symptoms. The rest results of adverse symptom distribution are shown in Fig.4. Drowsiness was the symptom with the highest reported proportion during four seasons. Besides drowsiness, the proportion of reported symptoms such as dizziness, chest tightness, dry throat, suppression, and irritation was also relatively high that exceeded 20%. Moreover, people often experienced symptoms of dry eye and dry throat in the autumn and winter seasons. This may be related to the lower moisture content of indoor air even with higher relative humidity. Hence, it is necessary to pay attention to replenishing moisture.

	Spring	Summer	Autumn	Winter
Drowsiness	60.5%	60.0%	71.4%	82.2%
Nausea	11.2%	14.0%	9.4%	6.3%
Dizziness	22.6%	23.1%	22.9%	24.0%
Headache	9.9%	9.3%	9.9%	10.5%
Chest tightness	33.6%	26.8%	28.5%	40.2%
Asthma	8.5%	9.5%	8.3%	10.9%
Dry eye	15.4%	15.8%	44.4%	24.7%
Shed tears	4.9%	4.7%	9.5%	6.3%
Difficulty breathing	25.8%	18.8%	23.1%	29.2%
Itchiness	6.3%	5.5%	8.0%	6.1%
Dry throat	29.3%	21.6%	44.4%	56.2%
Stuffy nose	15.6%	10.7%	25.7%	18.5%
Suppression	31.6%	27.4%	38.6%	23.6%
Worry	6.6%	6.5%	12.9%	7.2%
Irritation	38.5%	37.6%	33.6%	35.5%

**Fig. 4.** Symptom report during university classroom.

### 3.3 Back-propagation neural network machine learning analytics

The comparison results between the thermal sensation obtained based on the traditional PMV-PPD equation and the actual human thermal sensation votes (TSV) are shown in Fig. 5a. There was a significant error between the predicted results of the model and the actual results, with an accuracy rate of only 28%. Figure 5b shows the classification accuracy of different machine learning models. Among these algorithms, BP model achieved the highest accuracy about 75%, indicating the applicability and effectiveness of machine learning methods for predicting human thermal sensation.



**Fig. 5.** Prediction accuracy of traditional and different ML models a) Comparison of PMV and TSV model, b) Different classification ML algorithms.

Although the overall accuracy of the classification algorithms currently used was limited, the main reason was that indoor environment sensation was related to many human characteristic attributes. The questionnaire survey in this study cannot include all factors, but it provides a new approach to individual sensation prediction considering psychological factors. More individual adaptabilities and application of these classification algorithms could be further investigation and exploration.

## 4 Conclusion

Indoor environment quality (IEQ) of university classrooms was evaluated during different seasonal conditions. The measurement results showed that the serious classroom environment quality issues were caused by dry winter, severe outdoor particulate matter pollution, indoor CO<sub>2</sub> accumulation and unclear sound. Moreover, the questionnaire survey also revealed the

relationship between the adverse IEQ and health symptoms, with the most obvious symptoms being drowsiness (68.5%), dry throat (37.9%), irritation (36.3%) and chest tightness (32.3%). As the traditional PMV-PPD model was not appropriate to university classrooms, this paper proposed a students' satisfaction prediction model of indoor environment based on the back-propagation neural network machine learning with an accuracy rate of 75%, providing guidance for creating a positive learning environment. Furthermore, future studies will adopt a comparative analysis for varied regions and countries.

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