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Research Article

Nonlinear Integrated Fuzzy Modeling to Predict Dynamic Occupant Environment Comfort for Optimized Sustainability

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In the ever-evolving vibrant landscape of our times, it is crucial that a peaceful environment is ensured taking into account all the likely ecological parameters along with humidity and temperature while conserving energy. Thus, besides mechanical and electric control systems, it has become vital to ensure that artificial intelligence (AI) is assimilated and deployed into the systems so as to raise the well-being of the environment. By disseminating intelligence across the building by utilizing the new internet of things (IoT) technology, along with control formats, local open standard data, AI algorithms, and cloud-based predictive analytics, the heating, ventilation, and air conditioning (HVAC) mechanism renders the capability to acclimatize to use patterns, alterations in use patterns, and equipment breakdown. By tracing human activity coupled with analysis of noise, energy, and temperature in the building, its occupants and facility managers can obtain vital insights for planning, optimum use of space, and behavioral changes, in turn ensuring more content and safer inhabitants and considerably more efficient structures. Moreover, fuzzy modeling shows its applicability factor with the execution of human rationale and reasoning with if-then rules as attained from the system's input-output info for model setup and training. Additionally, it presents advantages pertaining to predictive functions for tackling nonlinearity and uncertainty as well as studying the capability of the models recommended. Thus, the multi-dimensional model recommended in this study outlines a system architecture as an implementation methodology and how it harmonizes prevailing systems while offering comprehensive knowledge to HVAC systems for the accomplishment of lower energy consumption and inhabitant safety and well-being on the basis of the fuzzy modeling. With tolerance for CO_2 discharges moving towards zero, the recommended multi-dimensional model provides substantial advantages for the HVAC sector for meeting the essential objectives while taking into account enhanced sustainability in vibrant and nonlinear environments for enhancing the accuracy and fairness of the assessment outcomes.

1. Introduction

Assimilation of proficiency and uncertainty processing is vital for managing and regulating systems that are dependent on AI and data analytics. The input uncertainty is considered by means of fuzzy numbers as diverse fuzzy inputs and parametric architectures. Nonlinear functions, here, aid the assimilation of the concerned solutions along with tuning and adjustment for attaining viability and sustainability [1]. Most individuals spend around 80% to 90% of their time within indoor settings [2]. Control methodologies for HAVC systems in buildings have been recommended by several researchers for inhabitants' optimal comfort while reducing utilization of energy [3–6]. Nonetheless, recent research works have demonstrated that data-propelled control approaches through analytics and IoT can further enhance the security and comfort of the inhabitants [7–10].

HVAC today accounts for around 60% of the energy used up in buildings, and this includes domestic, major commercial, and industrial structures [11, 12]. Those responsible for management are presently encountering irregularity in energy pricing, jeopardizing financial planning for buildings and other structures. According to Saidur et al., the air conditioning in an office building accounts for the most energy utilization (57%), followed by illumination (19%), elevators (18%), pumps, and other tools (6%). In the past three decades, the significant economic progress in Malaysia has led to an intense rise in energy usage. Many research works have deduced a positive relationship between utilization of electricity and economic progress [13]. In other words, HVAC systems have to be more energy-effective and fitting [14]. In view of this, Raffaele et al. recommended an IoT-based design for executing the model predictive control (MPC) of HVAC mechanisms in smart buildings [15]. The mechanism recommended by the authors comprises a suite of smart actuators and sensors, a database server, a gateway, a control unit, and an easy interface or console, and these are all networked and linked to the Internet. The particular control algorithm augments online, within a closed-loop control mode, the indoor thermal comfort as well as the associated energy utilization for a single-zone setting. Hence, it allows the end users to regain information regarding comfort and ecological indices and to manage the temperature and the control functions of the system remotely. Notably, the system is focused more on thermal comfort and does not take into account other parameters such as air quality and visual comfort, which are vital in office settings. Furthermore, the majority of the researchers did not deploy IoT in the HVAC environment, which might lead to a dearth of enhancement and creativity in the development of the HVAC sector. In other words, HVAC systems have to be more energy-effective and fitting [14].

Controlling and monitoring carbon dioxide levels indoors are critical for everyone's health, safety, and building energy efficiency. Buildings also require fresh air to function properly. In a building, ventilation is the process of exchanging stale air with new air. Buildings without engineered ventilation become vulnerable to stagnant air, mildew, bacteria, and potentially dangerous gases such as radon, VOCs, and carbon dioxide. Long-term exposure to these elements can cause "sick building syndrome," in which inhabitants suffer from acute health and comfort problems [16]. Thus, it has turned into an urgent matter to bring the CO_2 emissions essentially to zero (or lower) for the related structures. CO_2 levels in the workplace should be between 350 and 900 ppm. Drowsiness and poor air quality are common when CO_2 levels exceed 1,000 ppm. With CO_2 levels over 2,000 ppm, headaches, poor focus, lack of attention, increased heart rate, and minor nausea may develop.

Recently, it has been increasingly claimed that changes in an occupant's mood, well-being, and overall happiness with the built environment can demonstrably influence their thermal comfort [17]. It has been claimed that if an occupant's assessment of thermal comfort is considered a cognitive process, then perceived thermal comfort may be influenced by the psychological effects of a variety of physical circumstances that occupants encounter in the built environment, not just thermal factors. Artificial intelligence has been used in research around the world to address ventilation strategies to minimize CO_2 and other pollutants (AI). Intelligent control modeling for improving occupant environment comfort employs fuzzy logic (FL), artificial intelligence (AI), and machine learning (ML) [18–20].

Fuzzy logic is used in various systems due to a few of its notable attributes such as not needing robust mathematics or an accurate dynamic model [21]. One of the crucial reasons why the usage of fuzzy logic has increased swiftly is that it offers the deployment of human thinking and rationale with if-then rules from the system input-output data, spawning the fundamental model structure (structural identification) and parametric identification or model training [22]. One more element of fuzzy logic when blended with fuzzy logic neural networks is dealing with uncertainty and studying the capability of the recommended model for forecasting reasons [23]. When pertaining studies in the literature are appraised, it is noted that Siham et al. emphasize the significance of a fuzzy expert mechanism for HVAC systems for ensuring a convenient environment with regard to ecological parameters coupled with humidity and temperature without omitting the objective of conserving energy [24]. Goswami et al. recommended the use of a learning algorithm for multivariable data analysis for advanced regulation in HVAC setups for buildings. The objective is to deal with the control issue by utilizing a fuzzy classification methodology that does not entail a mathematical model of the system or the plant [25].

As per Perumal et al., many works on indoor environmental supervision were conducted, such as Smart House, Gator Tech, and IDorm [18]. These accomplishments are a few of the innovative explorations with tailored execution, aimed at stowing and regaining data. There is a dearth of systems wherein data are acquired from the environment and treated to attain info that can aid in making decisions accordingly in a smart home environment. There are multiple modes to enhance the quality of the HVAC setup with human convenience. Notably, the HVAC setup in the market is depicting a dearth of the intelligence factor as of now. It is now essential that artificial intelligence is deployed into the system for raising the well-being of the environment. A suite of appropriate artificial intelligence attributes has to be recommended for prospective HVAC setups and for improving occupant environment comfort.

In the present work, we have emphasized the data analytic segment to augment the knowledge and competence in the HVAC sector as against manual comfort. It is devised to encapsulate how a building is utilized by the inhabitant in real-time and to offer analytical insights into systems, which primarily concentrated on the smart air-conditioning setups. Human comfort and safety benchmarks too would be encompassed in the system to optimize the level of comfort of the air-conditioning setup. The study will be carried out as per the lifecycle of the data analysis. The discovery stage emphasizes determining insightful data and knowledge from the IoT data collection. Then, we will elucidate how the acquired data and data preprocessing have been dealt with. During the model planning stage, the vision of the study, essential for the problem-solving, is introduced. The model building related to project planning is already implemented at this stage. The outcomes for ensuring precision and sustainability in ambiguous and nonlinear vigorous environments are presented in the final phase.

The work in the research article is divided into five sections: Section 2 provides the decision related to thermal comfort. Section 3 describes the materials and methods used in this research. The results and discussion part are presented in Section 4, and the conclusion of this study is presented in Section 5.

2. Thermal Comfort

According to the research done previously, thermal comfort is the next trend in developing HVAC systems. The factors that manipulate thermal comfort can be divided into three groups, which are concerned with the environment, humans, and psychology. Figure 1 illustrates the important parameter to be considered in categorizing thermal comfort factors.

To achieve thermal comfort, many researchers have considered temperature as the main factor. However, humidity should also be taken into consideration in the Malaysian climate and environment. The environmental factors include temperature, humidity, airflow, and heat radiation. In addition, human factors such as individuals' physical activities and metabolism level need to be taken into consideration regarding human comfort aspects. Another main factor of the overall human comfort could be visual comfort. Different situations and environments need different kinds of visual comfort. For example, a restroom should have a warmer light, but an office should have enough among of light. The environmental factors that determine visual comfort are illumination, optimal luminance, glare, contrast condition, colors, and intermitted light. The factors that determine visual comfort could be uniform illumination, optimal luminance, no glare, correct colors, adequate contrast, and the absence of intermittent light. According to Lu et al. [26], carbon dioxide (CO_2), total volatile organic compound (TVOCs), and volatile organic compound concentration (VOCs) will be the three factors of air quality comfort. The 800 ppm of concentration of carbon dioxide will be the desired level for most of the environment. If there is a huge increase the carbon dioxide level, it will bring about various health problems and even death.

There exists a lot of research on HVAC systems that specialized in human comfort. According to Fakhruddin et al., air-conditioning systems have already become an essential part of our daily lives [27]. They proposed the fuzzy system the consideration of various input parameters and applying the fuzzy logic system to the air conditioner. The fuzzy input in the proposed system is user temperature, temperature difference, time of day, dew point, and occupancy. Then, the output variable of the system is compressor speed, fan speed, mode of operation, and fin direction. Another research by Hang and Kim predicted mean vote (PMV) is used to control the indoor temperature of the environment by using the PMV index [28]. This research outlines an enhanced MPC system for measuring the human comfort index and maintaining indoor thermal comfort at the optimal level. An MLR-based PMV predictive model is proposed with a simplified PMV equation. The simulation results of the research show that the proposed control strategy can maximize indoor thermal comfort and also helps reduce energy consumption.

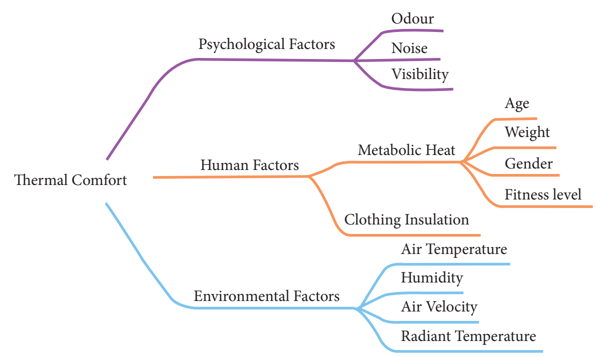

Figure 1: Categorization of thermal comfort factors.

Shah et al., in "A Review on Energy Consumption Optimization Techniques in IoT Based Smart Building Environment," stated that the area of the energy management system has already existed for many years [29]. Fuzzy controllers have become more important in the study of energy controlling and optimization methods. The technique is basically to improve the comfort index by using the references of user preferences. From the paper, we understand that the primary objective of the control system is trying to satisfy the user's thermal preferences, energy-saving, and monitoring. The rule base was designed well to solve the problem of energy overshooting. Therefore, automated controls and energy management systems could have a great potential to improve individual comfort and reduce energy consumption.

3. Materials and Methods

Fuzzy logic is an approach that will rather use a "degree of truth" than the usual "true or false" computing. For example, in fuzzy logic, we are more focusing on the uncertainty between 1 and 0, but the usual computing is more to 1 and 0 only. Fuzzy logic is a form of many-valued logic in which the truth values of the variable may be any real number between 0 and 1, as we considered it "fuzzy." Fuzzy logic has been further improved to handle the concept of uncertainty, where the truth-value may vary from the range between completely true and completely false.

In this case, fuzzy modeling is implemented accordingly for the prediction of human comfort level. Human comfort levels may vary between completely comfortable and completely the discomfort. Fuzzy modeling is capable of handling perceptual uncertainties such as the vagueness and ambiguity involved in a real system. The most crucial task in constructing a fuzzy model is to perform structure identification, which is concerned with determining the number of rules and parameter values that will provide an accurate system description. The results of transforming numeric data into fuzzy sets are used directly in making a rule-based system.

The structure identification is concerned with determining the number of rules and the parameter estimation. Various approaches have been proposed to construct the fuzzy model and its best parameter. One of the popular techniques for fuzzy modeling is the fuzzy c-means clustering algorithm. The fuzzy c-means produce a fuzzy partition of the input space by using cluster projections. The results of transforming numeric data into fuzzy sets are used directly in constructing a rule-based system.

We consider the problem of approximating a continuous multi-input and single-output (MISO) to clarify the basic ideas of the presented approach. The essence of fuzzy modeling is inherently associated with the inference schemes of approximate reasoning.

$$\begin{array}{r} x \text{ is } A \\ \text{if } x \text{ is } A_i \text{ then } y \text{ is } B_i, \quad i = 1, 2, \ldots, N \\ \hline y \text{ is } B, \end{array} \tag{1}$$

where B is a fuzzy set of conclusions to be determined. A and A_i are defined in a finite input space X, $\dim(X) = n$ while B_i and B are expressed in the output space Y with dimensionality, $\dim(Y) = m$. The set of indexes of the rules is denoted by N; in this case, it is simply a set of N natural numbers indexing the rules, $N = \{1, 2, \ldots, N\}$.

There is a wealth of realizations of the inference schemes with a large number of optimization mechanisms. In a nutshell, though, the inference scheme is realized by determining the activation levels of the individual rules (their condition parts) implied by some A. This is typically done by computing a possibility measure of A and A_i, poss (A, A_i). Denoting the possibility value by λ_i, the conclusion B is taken as a union of B_i weighted by the activation levels (possibility values), namely

$$B(y) = \max \quad i = 1, 2, \ldots N\left(\lambda_i(x) \Lambda Bi(y)\right), \tag{2}$$

where ∧ stands for the minimum operation. There are numerous variations of this inference scheme nevertheless the essence of the underlying reasoning process remains the same. Figure 2 shows how the fuzzy inferences system works.

To get the research done, the choice of machine learning or data analysis tools is very important. There are eight suggested applications for big data analytics that are well described and examined with the performance available, namely Apache Hadoop, Apache Spark, Apache Storm, Apache Cassandra, MongoDB, R programming Environment, Neo4J, and Apache SAMOA. In this research, we use R programming because this research involves machine learning and a fuzzy inference process. A wide range of libraries in R programming enables the project to be done smoothly. Besides R programming, according to http://www.mathworks.com, MATLAB also provides a fuzzy inference system function for users to create a fuzzy modeling system. Fuzzy Logic Toolbox software provides command-line functions and an app for creating Mamdani and Sugeno fuzzy systems. The website is detailed with many kinds of functions that are related to fuzzy inference systems, for example, creating fuzzy systems, specifying membership functions, specifying fuzzy rules, evaluating and visualizing fuzzy systems, importing and exporting, creating the fuzzy membership function, and constructing custom fuzzy systems, as the main functions required to be considered to develop a fuzzy inference system.

4. Experimental Results and Discussion

4.1. Data Set Description. The current study has employed 39,636 instances in the data set. Due to there being different sensors will be placed in different locations of the office, the sensor will be denoted to different UnitID in the data set. Based on the data set provided, 45 sensors are functioning in the HVAC data collection. Next, data are collected in a time series. Based on the rough understanding of the data, the data_time feature is formatted as DD/MM/YYYY HH:MM. The data is recorded every second, but not as a fixed or uniform timeline. Table 1 shows the data that will be used in this research. All the data will be denoted as noise (dB), light (lux), temperature (°C), CO_2 (ppm), and humidity (%).

In this phase, we need to understand the data obtained for this research. Every feature/variable included in the data set should have a high understanding so that we know which features in the data set are suitable for this research development. The histogram function has been used to see the distribution of the data. The histogram is a chart representing a frequency distribution. Then, correlation analysis has also been carried out in this research at the same time. Correlation analysis is a statistical method that allows us to compare the strength of the relationship between the attributes in the data set. The higher the correlation between two attributes is, the higher the relationship between the two attributes is. A weak correlation value indicates that the variables are not related to each other.

To observe and examine the correlation, linearity, and histogram of the data, we used ppclust, factoextra, dplyr, cluster, fclust, and psych library in the RStudio library. Then, by calling the pairs.panels (x, method = "Pearson") function, we can get a multi-info chart that includes histogram, correlation value, and linearity diagram. Figure 3 presents the result of the functions for three months.

Figures 3–5 show that the data distribution of the three months data are almost the same. First, the noise value histogram shows that the data are right-skewed, which means the surroundings always have a low noise value. The light value data are also skewed to the right; we can see that most of the light values are near 0; and we assume that maybe the light sensor is not sensitive enough to collect the

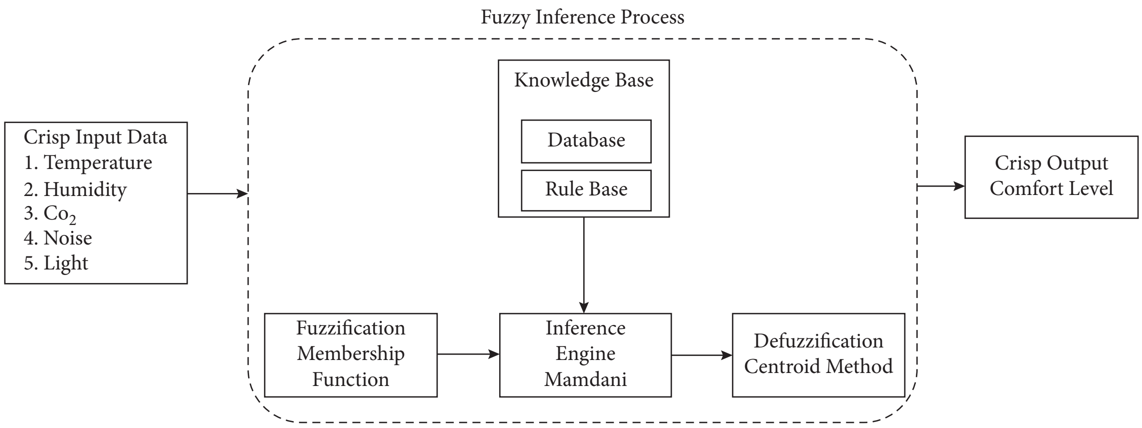

Figure 2: Fuzzy modeling inference system concept.

Table 1: The data set information for the study.

Parameters	Min	Max	Denomination
Temperature	15	35	°C
Humidity	0	100	%
CO_2	200	2,000	ppm
Noise	40	80	dB
Light	0	400	Lux
Comfort level	0	10	Level

accurate data. This conclusion can be drawn because an office should not have such low light intensity for productivity. Next, temperature and humidity values both have the normal distribution depicted in the figures provided. Based on the histogram, the workers are feeling comfortable at a temperature of 25°C in the office area due to its highest count in the data. Besides that, the temperature in the office will always maintain from the lowest 20°C to the highest 30°C, from which it can be inferred that an area with 30°C; the meeting room not often used by the workers or the data is recorded during night time, which is after the office hours. Lastly, the carbon dioxide and volatile organic compounds in the office area are considered to be at a slightly higher level. According to some studies, the acceptable carbon dioxide level and volatile organic compounds in air quality should be maintained below 500 ppm and 1,000 ppm, respectively. The data recorded for this both attributes are higher than the expected value of about 500 ppm; company should have a solution to solve this problem after this analysis has been done.

From these points, it can be noted that noise and light have the most positive correlation in Figures 3–5, followed by noise and carbon dioxide. We may have an assumption that the noise level is increasing with light and carbon dioxide value because there is an occupant for the covered area. These three attitudes are correlated with each other because the carbon dioxide and noise level will increase if a worker is using that area and whether or not he or she will be using the area with the lights.

In this section, we shall discuss the result of clustering. To provide an unsupervised learning–clustering, Visual Studio Code has been used to provide a better processing speed to achieve the task. The data are clustered into three clusters with six attributes (temperature, humidity, CO_2, VOC, noise, and light). The algorithm used to perform clustering is the k-means algorithm. The algorithm nicely clustered the data into three parts. We need to decide whether the data clusters belong to categories of good, normal, and bad since it is unsupervised learning.

Table 2 shows the results of the k-means clustering of the data set. The results are transformed into a table form, in which the values are recorded, in mean value. From the table, we can see that the surrounding temperature of the office range from 24.5°C to 26°C. The clustered temperature for these 3 clusters is not much different that only has a mean of 25°C to 26°C. Based on the research, the best temperature for a working environment, especially, the office, should be kept at 21°C to 22°C. Therefore, the working environment is warmer compared to the ideal temperature. Next, the optimum humidity level of an office as per research is between 40% and 60%. Based on the results obtained, the humidity level for the data set remains between 55% and 60% that is considered to be under the good category. Furthermore, the humidity value of cluster 2 was 55.9%, which is very good for a human working environment. Next, for the CO_2 level, cluster 2 contains the highest mean value of CO_2 level that is abnormally high, 1,075 ppm. The carbon dioxide level in the office is maintained at approximately 600 ppm for clusters 1 and 3. Meanwhile, the CO_2 level for cluster 2 achieves a less healthy level that is 1,000 ppm due to the crowd in location and being a small area. Although the researcher stated that 2,000 ppm of carbon dioxide will cause harm to human health, 1,000 ppm of carbon dioxide did not bring about many benefits to the worker because it will cause sleepiness. The VOC level also has a big range of average value based on the clustered result, cluster 3 has a 2,298 ppm of the highest amount of VOC, which is bad for health. The light and noise value does not have much difference in terms of the three clusters obtained. The noise data is also an important attribute of this data set since it has a high correlation with other attributes. The noise level in the office is maintained at the level between 47 dB and 52 dB in this data set. The environment of the office is comfortable if the reading is at 47 to 52 dB because it is considered to be a quiet environment for a worker. Workers can stay focused all the time

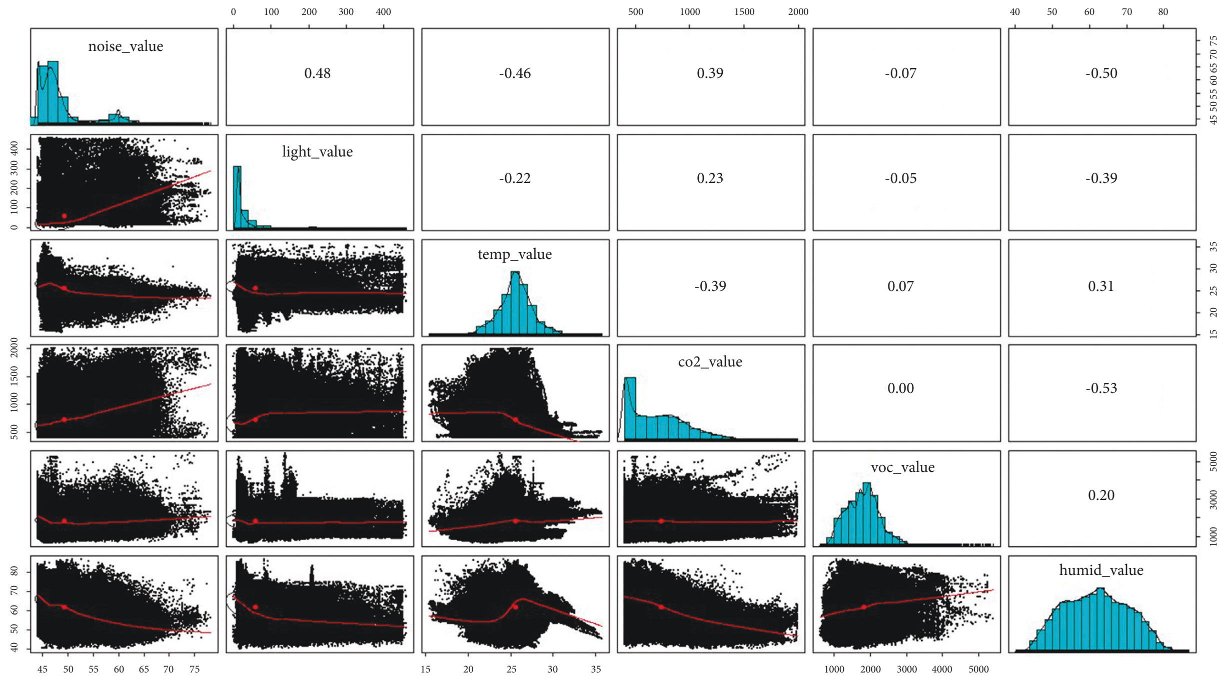

Figure 3: Correlation of input data for the first month.

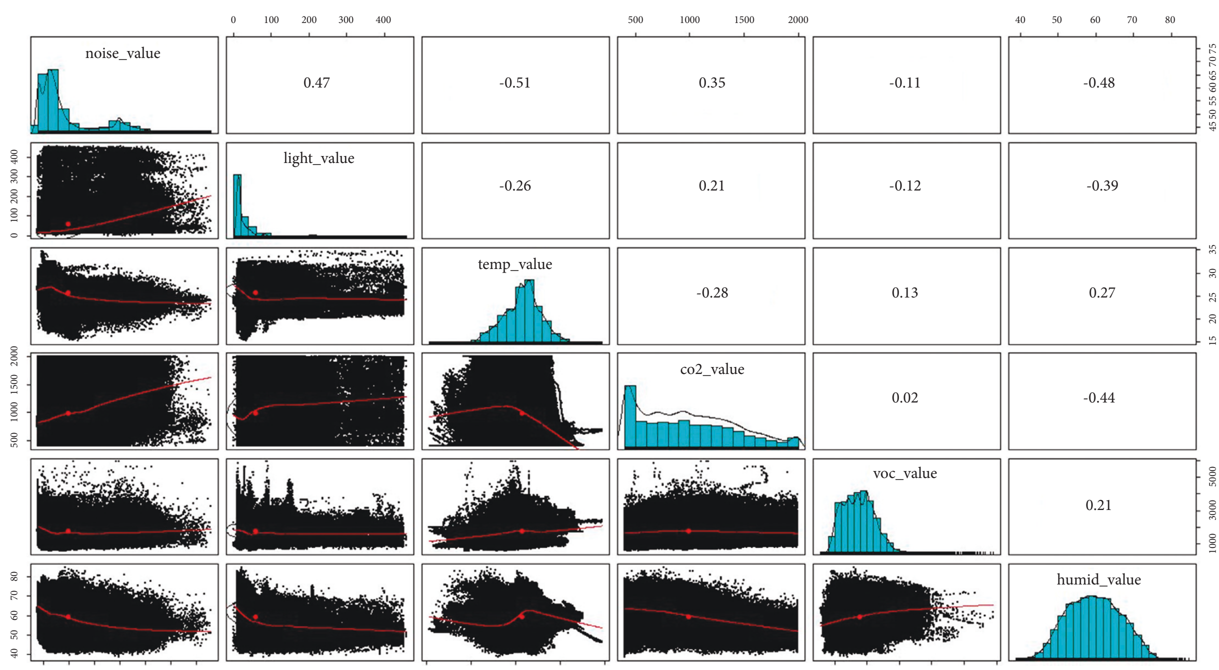

Figure 4: Correlation of input data for the second month.

in this range of noise. Furthermore, workplace lighting may also affect the efficiency of a worker. A recommended light level is more common in the range of 500 and 1,000 lux, depending on the activity. The highest mean value of the light data is only 76 lux. This indicates that the light power for this company is not enough for the activity. Besides that, there is also a probability that the sensor is placed at a coordinate that may not be a strategy to collect light data, which has affected the results. Last but not least, the volatile organic compound in the office is also recorded in this data set. As the table depicts, the volatile organic compound has a 1,000 ppm difference between the maximum and minimum levels. This part has not been included in this discussion part because VOC is the least correlated data attribute in this data set.

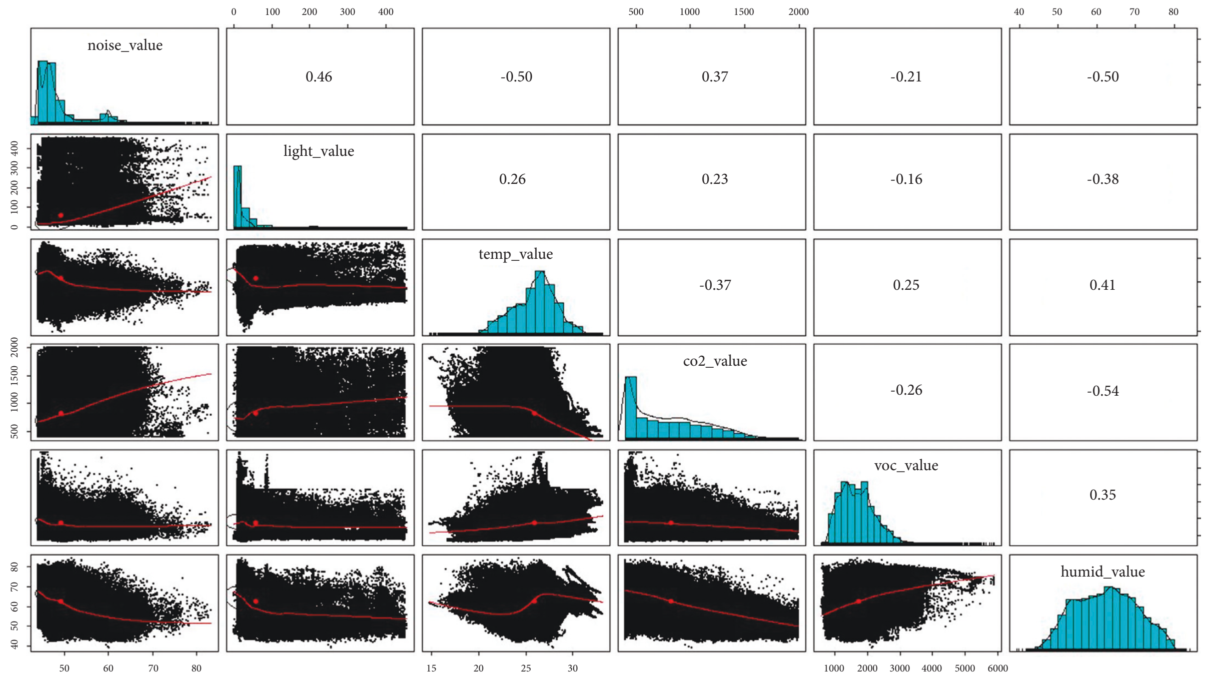

Figure 5: Correlation of input data for the third month.

Table 2: Average values for six attributes categorized into three clusters.

No. of cluster	Temp	Humidity	CO_2	VOC	Noise	Light
1	25.65765	62.24335	613.9729	1,388.163	48.79849	57.72873
2	24.5565	55.98562	1,075.342	1,768.494	51.69869	76.28403
3	26.05804	65.39577	637.2665	2,298.839	47.89209	47.63216

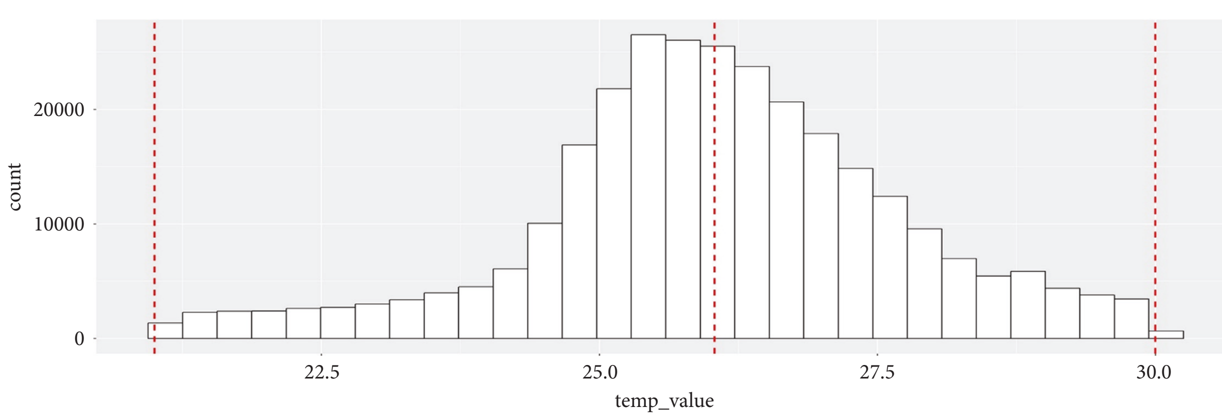

Figure 6: Histogram of temperature.

4.2. Frequency Analysis. A histogram is a plot that allows us to discover and show the underlying frequency distribution (shape) of a set of continuous data. The shape of the histogram will be a factor in designing the fuzzy inference system. The subsequent part explains the findings from the histogram.

Figure 6 depicts that the shape of the temperature histogram is normally distributed. The histogram has an approximate minimum value ranging from 20°C to an approximate maximum value of 30°C. Based on the peak and the mean of the histogram, the office is usually comfortable at a temperature range of 25°C–26°C.

Figure 7 presents the histogram concerning the humidity parameter. The shape of the histogram is normally distributed. Based on the histogram, the environment of the office is usually located between 60% and 70%.

Figure 8 shows the histogram of carbon dioxide, and the shape is skewed to the left. This left-skewed

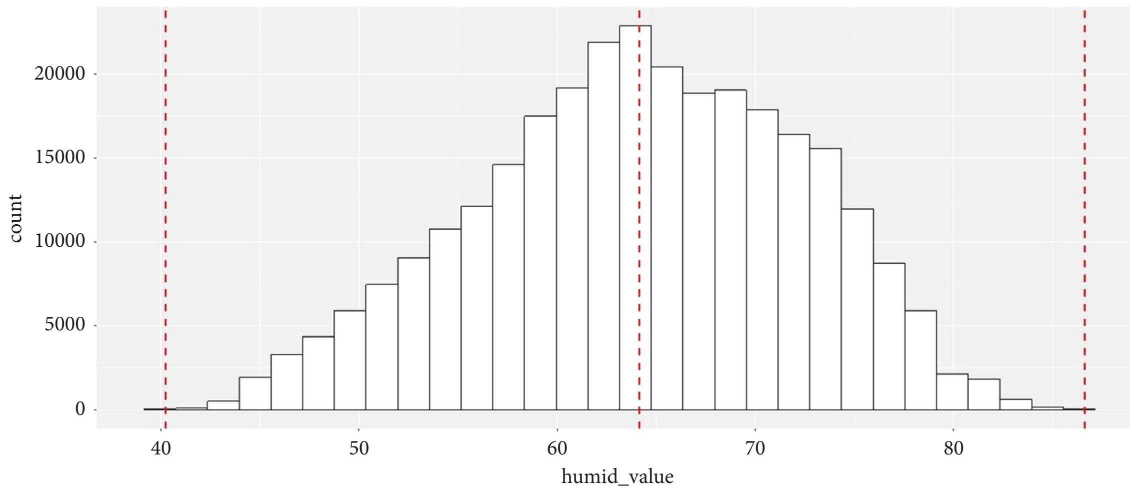

Figure 7: Histogram of humidity.

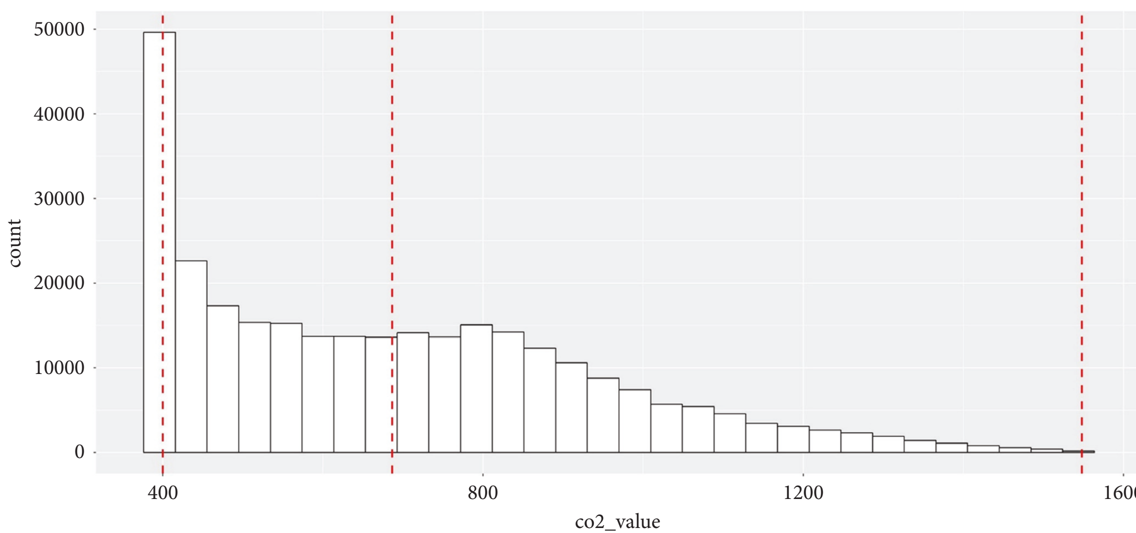

Figure 8: Histogram of carbon dioxide.

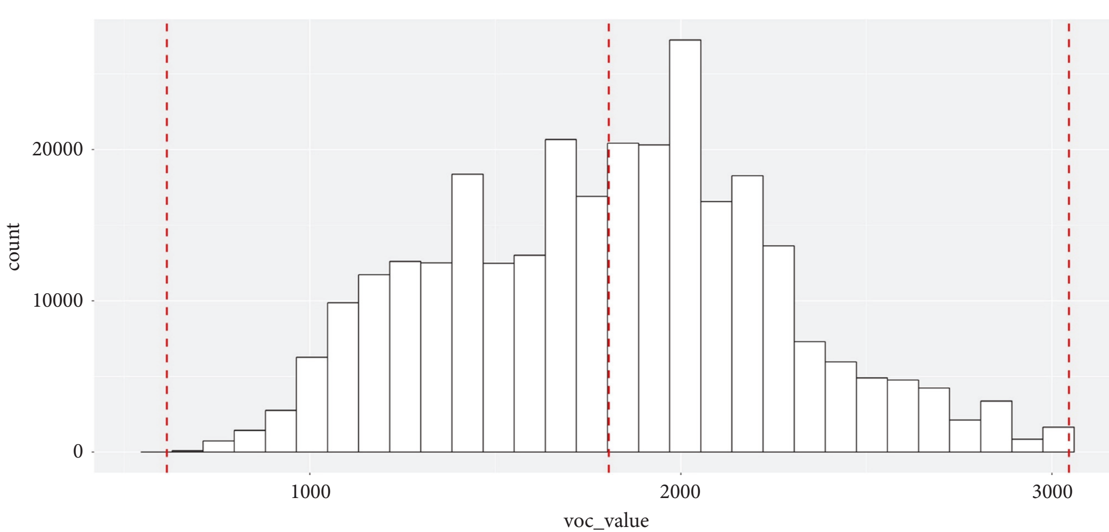

Figure 9: Histogram of VOC.

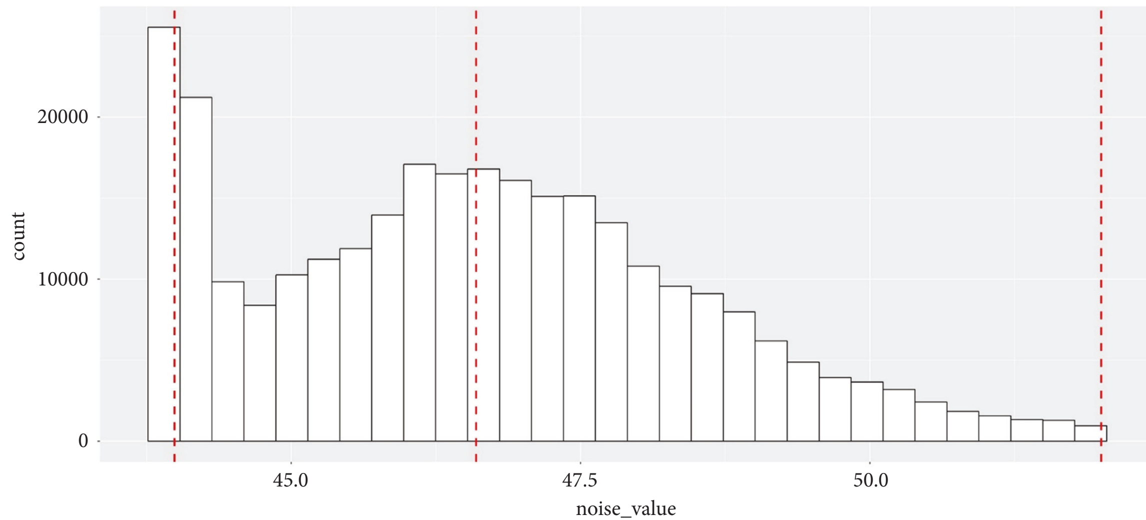

Figure 10: Histogram of noise.

Table 3: Features and fuzzy linguistic operations.

Parameters	Type	Linguistic expression
Temperature	Input	Low, medium, high
Humidity	Input	Low, medium, high
CO_2	Input	Low, medium, high
Noise	Input	Low, medium, high
Light	Input	Low, medium, high
Comfort level	Type	Linguistic expression

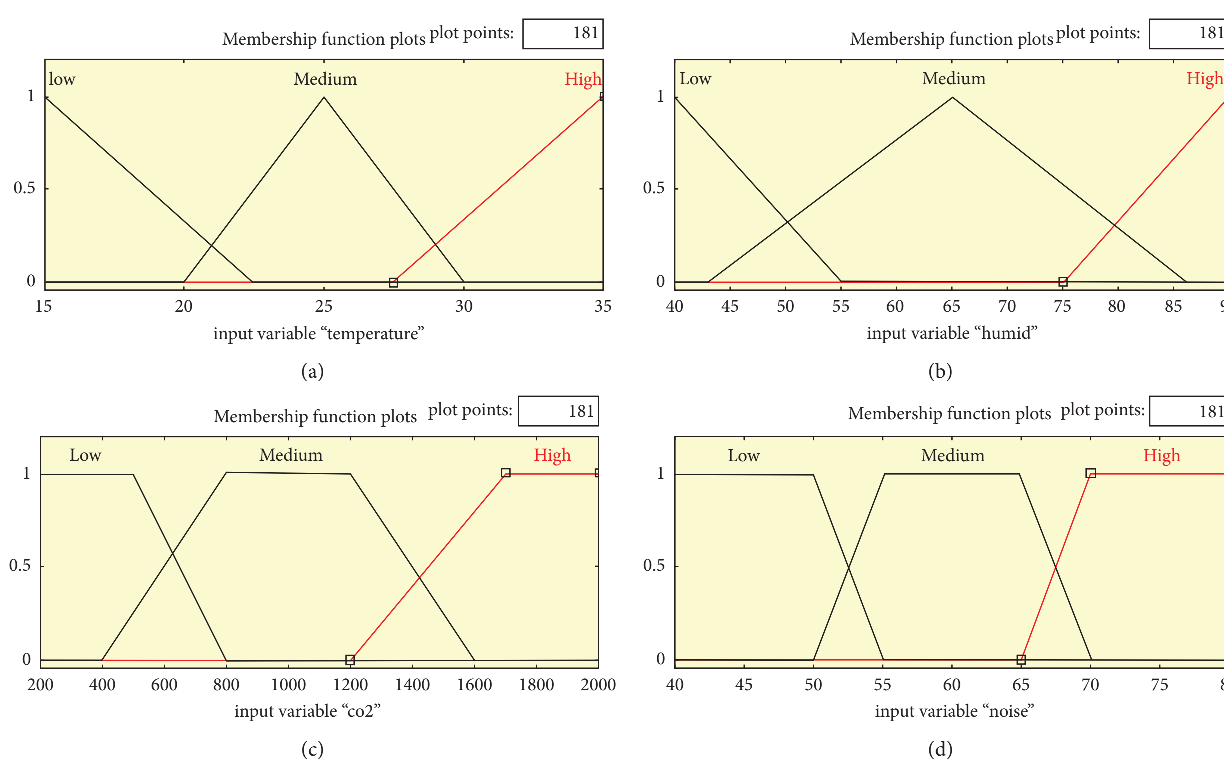

Figure 11: Continued.

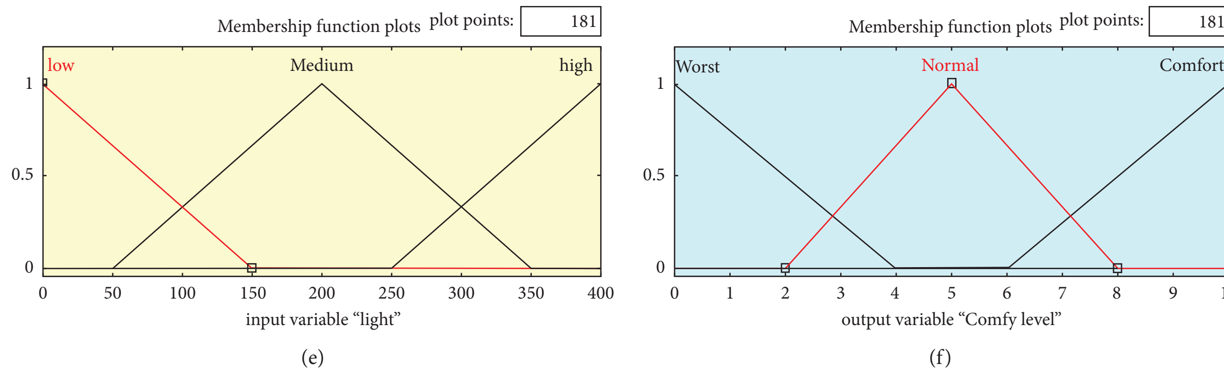

Figure 11: Membership function: (a) input 1: temperature, (b) input 2: humidity, (c) input 3: CO_2, (d) input 4: noise, (e) input 5: light, and (f) output: comfort level.

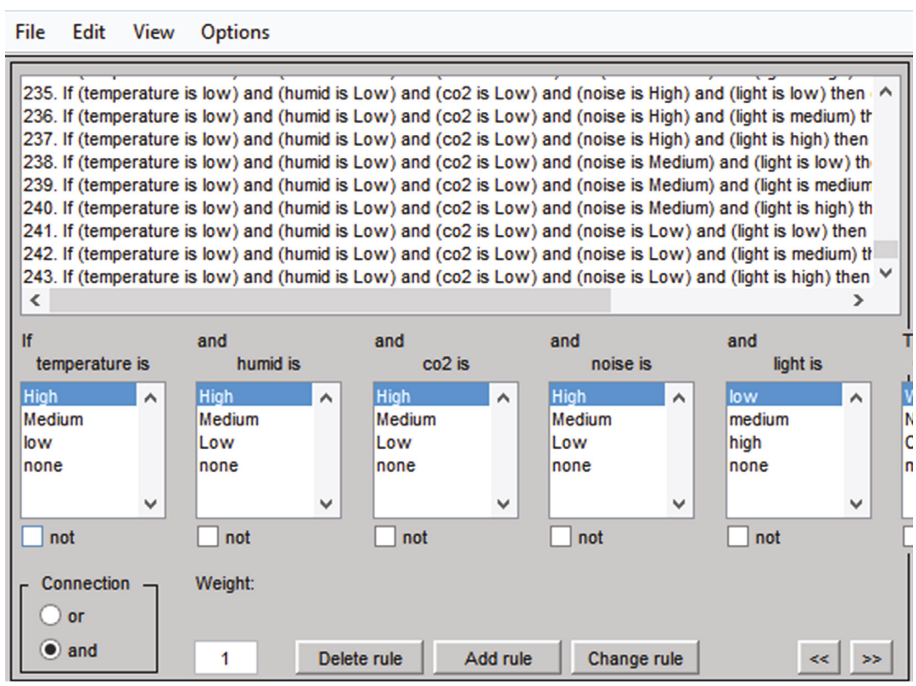

Figure 12: Rule information.

histogram shows that the data of carbon dioxide in the office are less than 400 ppm of carbon dioxide that is the comfortable range in terms of health.

Figure 9 shows the histogram of VOC. The shape of the histogram is in the form of multimodal distribution. It is observed that the highest amount of the volatile organic compound is approximately 2,000 ppm from the data collected. However, the volatile organic compound is normally around ranging from 1,000 ppm to 2,000 ppm.

Figure 10 shows the histogram of noise, and the noise in the office is not very loud. The noise in the office is less than 55 dB, which means that it is a very comfortable place to work. Yet, the results of this data may be different from the real experience because the location of the sensor is a critical matter to be taken into consideration.

4.3. Nonlinear Fuzzy Inference System for Human Comfort. Based on the literature review and the analytic results from the previous chapter, a data-driven fuzzy inference system based on human comfort has been carried out. The objective of this fuzzy inference system is to predict or analyze the human comfort level in an environment. The organic volatile compound (VOC) will be excluded from the fuzzy inference system input because the correlation analysis shows that the VOC does not have an impact on human comfort. Therefore, the input of the fuzzy inference system will consist of five factors, which are temperature value, humidity value, carbon dioxide value, noise value, and light values. These five inputs will be created based on the analysis results, and they have their membership function to have an accurate human comfort level results in the output.

Fuzzy control input and output values are defined in three linguistic expressions as four different parameters:

(a)

(b)

Figure 13: Rule viewer: (a) comfortable environments and (b) less comfortable environments.

temperature, humidity, CO_2 level, light level, and noise level. Two parameters are chosen as output-comfort level. The features and fuzzy linguistic operations of the input and output system are provided in Table 3, respectively.

The membership degree quantifies the grade of membership of the element to the fuzzy set. The value 0 means that is not a member of the fuzzy set; the value 1 means that is fully a member of the fuzzy set. The values between 0 and 1 characterize fuzzy members, which belong to the fuzzy set only partially. After the results of the histogram are observed and interpreted, three membership functions have been obtained regarding the temperature that is high, medium, and low. The range of high temperatures will vary from 27.5 to 36. Then, the temperature for the medium is from 20 to 30. Lastly, 15 to 22.5 will be the membership range for low temperatures, After the results of the histogram are observed and interpreted, three membership functions are obtained for humidity that is high, medium, and low. The range of high humidity will vary from 75% to 90%. Then, the humidity for the medium is from 43% to 86%. Lastly, 40% to 55% will be the membership range for low humidity. Figure 11(b) shows the membership function of humidity. The results of the histogram show that three membership functions have been obtained for CO_2 that is high, medium, and low. The range of high CO_2 will vary from 1,200 ppm to 2,000 ppm. Then, CO_2 for the medium is from 400 ppm to 1,600 ppm. Lastly, 200 ppm to 800 ppm will be the membership range for low CO_2. Figure 11(c) describes the membership function of CO_2. The results of the histogram show that three membership functions have been obtained for noise that is high, and medium, low. The range of high noise will vary from 65 dB to 80 dB. The noise for the medium is from 50 dB to 70 dB. Lastly, 40 dB to 55 dB will be the membership range for low noise. Figure 11(d) shows the membership function of noise. Three membership functions have been obtained for the light that is high, medium, and low. The range of high levels of light will vary from 250 lux to 400 lux. Then, the light for the medium is from 50 lux to 350 lux. Lastly, 0 lux to 150 lux will be the membership range for low noise. Figure 11(e) shows the membership function of light. In order to make the understanding easy, we have decided to use a simple scale that is 1 to 10 as the parameter of human comfort level. One represents the worst situation, and 10 refers to the most comfortable and optimal situations. Figure 11(f) shows the membership function of comfort level.

In a standard fuzzy partition, every fuzzy set will correspond to a linguistic concept, for instance, low, medium, and high that are being used in this comfort level fuzzy inference system. Fuzzy rules are always written as If situation-Then conclusion. In this research, 243 rules have been used to get the best performance of the fuzzy inference system. Figure 12 shows the rule editor for this system.

In Figure 13, input of 25°C, 65% humidity, 625 ppm of CO2, 60 dB of noise, and 200 lux of light was used. The comfy level generated by the fuzzy model by using the histogram analysis method is 8.7 out of 10.

5. Conclusions and Future Directions

The ever-changing dynamic landscape of our time requires that a comfortable environment is ensured considering all the possible environmental parameters, temperature, and humidity while saving energy. Thus, in addition to the electric and mechanical control system, it has become critical and required that artificial intelligence (AI) be integrated and implemented into the systems in order to increase the comfortability of the environment. Moreover, the applicability of the fuzzy model is evident since it includes the implementation of human thinking and reasoning with if-then rules as obtained from the input-output data of the system for model structure and training. The fuzzy model is also advantageous pertaining to purposes of prediction to deal with uncertainty and nonlinearity and to investigate the ability of the models proposed. The strength of the current research is that we can obtain a lot of information from the data set by using a statistical analytic method. It is possible to encounter some missing important data if we just read the real-time data from the dashboard. By using statistical analytic means, we can combine all the data into one graph or chart to see the pattern of the data. For instance, it can be ensured to know that the light of the office is low for a workplace or maybe the sensor needs some improvement in collecting light data. There is a lot of information that we can actually extract from a set of data. In the present study, human comfort data have been used as the main part of the research. By interpreting the data provided, we can clearly know about the comfort level of the working environment that affects the health and productivity of a worker indirectly. The office management may take action based on the result obtained in the future to improve their workers' efficiency. The fuzzy model could also be regarded as another strength and motivational aspect of this research. The fuzzy model can predict human comfort based on the six attributes provided in the data set. In the future, researchers may improve the fuzzy model and implement it into a smart building system in order to get an intelligent controller for occupants' comfort. Thus, it may be concluded that it will be more humanized if there is a larger data set available for us to deal with. This research can still be improved by using another data set, and the results will be more interesting. The more attributes and duration are involved in a big data set, the more closely it may be possible to achieve the intended objectives while considering optimized sustainability in dynamic and nonlinear environments towards improving the accuracy and objectivity of the evaluation results. This proposed prediction model is only valid for similar input data having similar statistical properties. The proposed study can help the researchers and professionals to predict the comfort level inside the office building and its effect on individual health. In future work, efficient machine learning models with large data sets can be used to predict the comfort level of various parameters like visual comfort and acoustic comfort.

Data Availability

The data sets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

Authors' Contributions

All authors contributed equally to the preparation of this manuscript.

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