Energy and Built Environment 1 (2020) 385–392

Contents lists available at ScienceDirect

Energy and Built Environment

journal homepage: www.elsevier.com/locate/enbenv

An Expandable, Contextualized and Data-Driven Indoor Thermal Comfort Model

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A R T I C L E I N F O

Keywords:
Fuzzy Logic
Thermal Comfort Model
Artificial Intelligence

A B S T R A C T

Continuous discrepancies in building performance predictions creates an ongoing inclination to link contextualized, real-time inputs and users' feedback for not only building control systems but also for simulation tools. It is now seeming necessary to develop a model that can record, find meaningful relationship and predict more holistic human interactions in buildings. Such model could create capacity for feedback and control with a level of intelligence. Fuzzy Logic Systems (FLSs) are known as robust tools in decision making and developing models in an efficient manner. Considering this capability, in this paper, FLSs is implemented to make a thermal comfort model in an educational building in the UK. Such implementation has an ability to respond to some identified desires of developers and performance assessors in addressing uncertainty in thermal comfort models. The results demonstrate the proposed method is practical to simulate the value of comfort level based on the input data.

1. Introduction

In the UK, non-domestic buildings are accountable for approximately 12% of carbon emissions and 17% of overall energy consumption. Even though considerable effort has been made on new low energy buildings, but the existing building stock dominant energy use in the country [1]. Numerous building regulations are introduced to facilitate low carbon design but they only focused on regulated energy loads, which created a challenge of building performance gap. As a result, researchers are now switching their attention to occupant behaviour and many efforts have been made in studying responsible energy usage in office buildings. However, there is still limited understanding of energy use during building operation.

Widely used simulation programs generally evaluate the heat flux, HVAC system loads and demands and lighting, on the basis of standards like ASHRAE55 for thermal comfort. Weather data, the geometry of buildings and materials as well as setpoints for temperatures are the inputs of such programs. Heating or cooling setpoints data are not always available, requiring researchers to use an estimate, which may not be always accurate and a true reflection of the occupants' comfort level. Therefore, there is a growing concern about a discrepancy between the predicted energy performance of buildings and actual measured performance, widely known as building performance gap (BPG). BPG is not only limited to energy efficiency but also likely to be on indoor air quality, acoustic performance and daylighting levels.

The importance of addressing the BPG issue lies on the fact that there is an increased pressure on the construction industry to reduce carbon emissions from heating and hot water substantially above 20% by 2030, with a further reduction to complete decarbonisation by 2050. This is due to legally-binding targets set by UK Parliament in the Climate Change Act [2]. Furthermore, under a system of the Fifth carbon budgets which run until 2032, if construction industry fails to achieve carbon reduction target then the UK will have to increase pressure on other sectors to achieve corresponding falls [3]. Therefore, a mismatch between designing and delivering could affect other sectors.

Bridging the performance gap can be achieve by designing a decision-making stage to deliver (i) higher quality homes with lower costs to meet the quantified targets, such as zero carbon Buildings, (ii) buildings that are robust towards arguably warmer conditions with considering growing concern of changing climate and health risk [4,5]. It is also a key requirement for building delivery and facility management, enabling the feasibility of concepts such as performance-driven buildings.

BPG can be controlled by an organised, multidisciplinary approach that incorporates improvement in data collection for simulations [6,7], data validation [8] and change of industry practice to minimise workmanship errors [9]. Therefore, the objective of this research is to address BPG challenge by make a contextualised thermal comfort model to address uncertainty in building energy management tools. Neural networks, clustering methods, data mining techniques, fuzzy logic systems

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https://doi.org/10.1016/j.enbenv.2020.04.005
Received 28 January 2020; Received in revised form 10 April 2020; Accepted 11 April 2020
Available online 11 May 2020

etc. are some of the engineering techniques that have been used for building performance prediction [10–13]. Each technique comes with different capabilities and shortcomings.

Generally, one of the most necessary and crucial activities in the real world is decision-making. Decision making is used to find an optimal or a nearly optimal solution based on input information. There are three models that are used for decision-making task; mathematical model, human experts' advice and an expert system. Each of these models has its own advantages and disadvantages. Inferring an accurate mathematical model to present the complex environment is a difficult and challenging task and even impossible in some cases; besides, the models cannot be applied to all environments. On the other side, querying an expert is usually a time consuming and expensive task. Recently, expert systems have drawn researchers' attention and are widely used in various domains. The key point about expert systems is that the knowledge base can grow and can be updated dynamically [14,15].

Fuzzy Logic Systems (FLSs), provides a robust, artificially intelligent solution that model human linguistics. FLSs attempt to represent knowledge in Fuzzy Sets by using sets of distributed membership functions and develop logic by generating rules. Also, the intermediate possibilities between the subject responses can be modelled in a manageable manner through the model rules. So far, many fields such as manufacturing, engineering, diagnosis, economics, and others have been benefited from FLSs as a control-engineering and decision-making system [16,17]. Also, some recent developments in BPG have been carried out. In [18] statistical analysis has been implemented on 30 subject responses and in [16], an interface is utilised to receive responses from subjects and again statistical tests are applied on the gathered survey responses. Although this approach is interesting, it fails to provide a comprehensive model which is able to capture all intermediate possible situations.

Numerous models demonstrate their potential to predict building users' thermal comfort, even though with a degree of inaccuracy. Advances in artificial intelligence methods and their rapid development across other disciplines can uncover the unknown relationship in a large amount of data, presenting a new opportunity to better understand diverse characteristics of thermal comfort in buildings. This study applied the FLS algorithm to a thermal comfort database in the UK context and developed a new and expandable model in thermal comfort. With variables of indoor air temperature, age, clothing insulation and working hours, the model can reduce the previous models' inaccuracy. Compared to the ASHRAE model, it can quantify the effects of each input variable on building users' thermal comfort. Furthermore, an open-access platform is developed to support machine learning algorithms applications in the interpretation of data associate with users' thermal comfort in buildings. This study can be an indication for further thermal comfort model development.

2. Fuzzy Sets

The Fuzzy set theory was firstly introduced by Lotfi Zadeh in 1960s [17] and it is designed to resemble the process of human decision making. Unlike classical computer-based Boolean logic (Crisp set) "True (1) or False (0)", fuzzy sets have no sharp boundaries and it involves intermediate possibilities between True or False in decision making [19]. Mathematically, crisp set A of universe X is defined by function μ_A *(x)* called the membership function (MF) and is described as follows:

$$\mu_A(x) = \begin{cases} 1 \; if \; x \in A \\ 0 \; if \; x \notin A \end{cases} \tag{1}$$

While, in the fuzzy theory, the MF is calculated as follows:

$$\mu_A(x) : \begin{cases} \mu_A(x) = 1 \; if \; x \; is \; totally \in A; \\ \mu_A(x) = 0 \; if \; x \; \notin A; \\ 0 < \mu_A(x) < 1 \; if \; x \; is \; partly \in A. \end{cases} \tag{2}$$

Based on the above description, we can have a continuum of possible choices. For any element x of universe X, μ_A *(x)* equals the degree to which x is an element of set A. This degree, a value between 0 and 1, represents the degree of membership, also called membership value of element x in set A. Fig. 1 (a) and (b) show the difference between crisp and fuzzy set theory. While the MF in Fig. 1 (a) has sharp edges, the MF in Fig. 1 (b) is formed in a continuous manner, which provides the intermediate possibilities. As it is shown in Fig. 1(a), someone at the age of 21 is considered as old. Because the value *x=21* is crossed the edge "20". However, the way of human thinking is completely different as the MF shows in Fig. 1 (b), the concept of being young gradually changes which include intermediate possibilities in the MF. Therefore, as it is circled in Fig. 1 (b), someone at the age of 21 has a membership degree around *0.3* of being old. It can be interpreted as this person can be considered old with degree of 0.3. Thus, the Fuzzy set theory can provide some degree of truth which is similar to human thinking.

2.1. Fuzzy Logic Systems

A fuzzy logic system generally consists of four stages [See Fig. 2 for the overall scheme of fuzzy logic system]:

- **Fuzzification:** it is the process of converting a crisp value into a fuzzy MFs and the most commonly used MFs can be seen in the literature as Gaussian, triangular and trapezoidal.
- **Rule base:** it contains fuzzy rules which are formulated by using Apriori algorithm. A rule consists of two main parts as Antecedent MFs and Consequent MFs. While the *IF* part combines antecedents, *THEN* part combines consequents or parameters which can be formulated as follows:

IF (a set of conditions are satisfied) *THEN* (a set of consequences can be inferred).

As a clear example:

IF (Food Service is **good**) *THEN* (the waiter tip is **high**)

- **Fuzzy inference:** In this step, each rule is evaluated throughout some fuzzy operators and a decision is made as a result. Generally, this part is capable to simulate human decisions by performing approximate reasoning.
- **Defuzzification:** The gathered output set, from the Inference step, is converted to a crisp value by utilising defuzzification process. The most commonly used process can be listed as a centre of gravity (COG), a centre of area (CEA) or first of maximum (FOM) [20].

As one of the most commonly used models, in the presented work, Mamdani [21] model is utilised to construct the Fuzzy Logic System.

3. An overview on Thermal Comfort

Thermal comfort is a complex subject and is dependent on the way humans perceive their environment and how they control their conditions. Therefore, general quantification is a challenge for designers in order to create a built environment that is sustainable in terms of minimizing energy consumption. The clarification of user's comfort level is crucial to the success of a building, not only because of the air quality but also because it will decide the overall energy consumption. There are two well-known approaches for thermal comfort definition, the rational or heat-balance approach and the adaptive approach. The most well-known method, in the heat balance approach is "Predicted Mean Vote" (PMV) and "Predicted Percentage of Dissatisfied" (PPD) model proposed by Fanger that has been accepted widely among scholars. However, Fanger's model has failed in the results for naturally ventilated buildings and cumulative dissatisfaction with this approach shifted focus in variable indoor temperature standards [22]. Besides, ASHRAE 55 developed a standard in 2010, which also included metabolic rate into the consideration [See Fig. 3].

However, several studies have questioned the thoroughness of the standard for simulation programs and highlighted discrepancies between users' actual thermal comfort and ASHRAE's prediction model

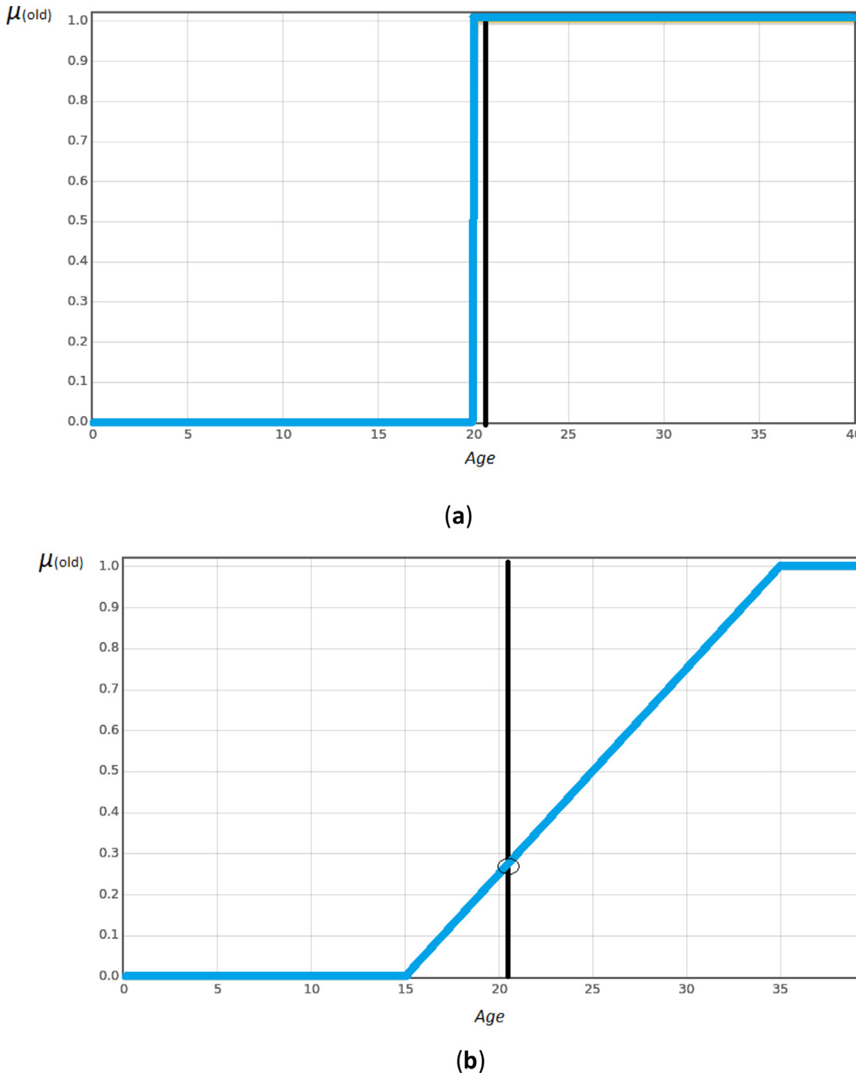

Fig. 1. (**a**) Crisp set, (**b**) Fuzzy set.

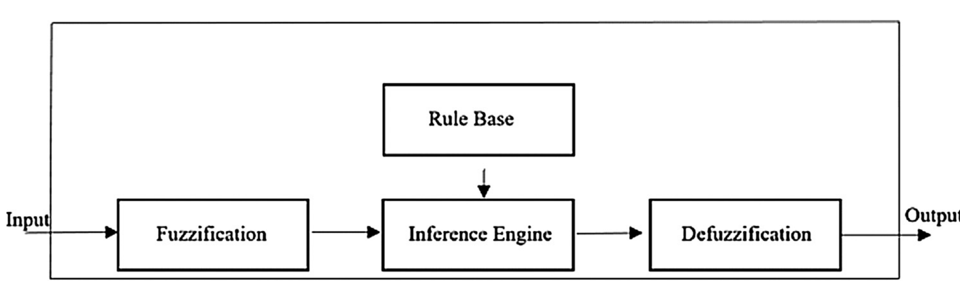

Fig. 2. the overall scheme of the fuzzy logic system.

[24–26]. The organization updated the standard in 2017 and suggested three comfort level calculation approaches for simple situations, more general cases and a method that uses elevated air speed for comfort [27]. The ASHRAE recent updates highlight the complexity and contextual dependency of thermal comfort.

Furthermore, CIBSE [28] recommended comfort temperature based on common environmental and physiological factors for non-domestic buildings implying that a minimum temperature range of 18°C (in most non-domestic building types) and maximum of 25°C for offices (indoor comfort temperature for non-air conditioned buildings) will satisfy most users.

Even though aforementioned standards have been developed regularly and their recent updates improved their potential, the difference between actual users' comfort level and their prediction models still exist. This has shifted researchers focus toward more local assessment of thermal comfort in which users communicate their comfort level through interviews and data gathering devices [24,29–34], all proved significant advantages of such approach and demonstrate the capacity of their models for further use in a similar context and users' size.

Murakam et al. [35] used an interactive control systems in an office space to use users' requests in controlling air conditioning systems and showed a reduction in energy consumption without compromising users' satisfaction. Lee et al. [36] developed a methodology to infer occupants comfort level by using a Bayesian approach and a subset of the ASHRAE RP-884 and showed better prediction performances compared to methods using constant values for un-observed variables. Kim et al.

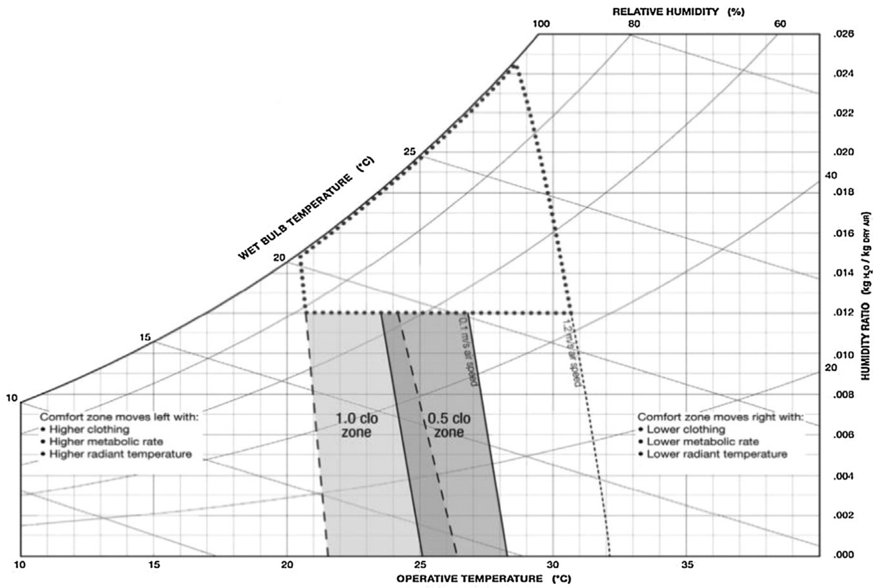

Fig. 3. ASHRAE 55 Standard, source: [23].

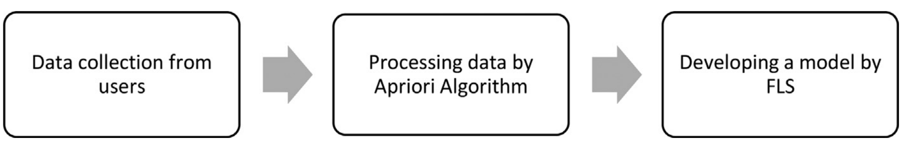

Fig. 4. Proposed method.

[37] used machine learning process to improve consistent data collection from occupants and proved in a study with 64 survey inputs that comfort models based on Personal Comfort System (PCS) produce the best prediction accuracy. Dai et al. [38] have also used machine learning to predict thermal demands. Daum et al. [39] also conducted a study to measure thermal comfort by using data from a field study and showed an advantage of personalized measures in comparison with standard non-adaptive methods.

On another note and in relation to uncertainties associated with thermal comfort studies, a study by Wang et al. [40] claims higher uncertainty of subjective measurements if the environment of the comfort study is significantly different from the outdoor ambient temperature and that more samples are required if the warm indoor environment is surveyed during winter period and if the cool indoor environment is surveyed during the summer period. Further investigation has also been carried out by Hopf and Hense [41] in relation to uncertainty analysis and in particular for building performance simulations and their study highlighted the influence of what-if-analysis in decision making support systems. This study acknowledges the superiority of using contextual and personalized comfort measures in comparison with standard models and integrate a robust and artificially intelligent method to gather and process data from occupants.

4. Methods

In this paper, we aim to use an AI approach, the fuzzy logic systems to make a predictive model in thermal comfort. Fig. 4 shows the objectives in each step to achieve the study's aim. Thermal comfort is a decisive factor in HVAC systems' operational settings and also how simulation tools quantify heating and cooling loads required to keep the operative temperature within the comfort zone. This investigation is built on a vision that some user-specific factors vitally affect the comfort level. Initially a field experiment was conducted to observe occupants feeling about certain temperature by noting their gender, age, clothing level and the time they spend in the office spaces in an educational building. These are considered as driving factors in their comfort level very similar to the ASHRAE model. We then try to find some relationships between these factors by implementing conditional statements using Apriori Algorithm. These conditional statements, in this case, if-then rules are features of a computer language in which Fuzzy logic system is a widely-accepted method for that [42,43].

4.1. Data set

The research collected a dataset from 100 occupants with no pre-set criteria for selection, the occupants of an educational building in the UK were chosen to collect the data with a very simple questionnaire (whether they feel comfortable or need warmer or cooler environment) and observation of their working area, clothing level and recorded temperatures. Fig. 5 shows the layout where occupants were surveyed over a period and location of the recordings until we reached 100 figure. A Thermo-hygrometer as shown in Fig. 6 is used to measure indoor air temperature in their working environment.

The considered dataset has 100 samples and four features as below:

Age: The survey respondent's age in years. The values of this feature vary between 18 and 65.

The Activity Time (AT): This feature indicates that the survey respondent's working hours on average in a day. This feature is between 2 to 8 hours.

The Clothing Level (I_{cl}): A column with a value in the range of [0.25 to 1] that indicates the level of clothing in a day, with 0.25 being a typical summer clothing, 0.5 being clothing for mild temperature, whole body covering (long sleeves), 0.75 being a typical winter clothing with coat/jacket and 1 being very cold winter clothing (jumpers or similar clothing + coats and jackets).

The Comfort Zone (CZ): This feature is only presented in the training data. This feature can take a lower bound and an upper bound value ranged [18-25°C operative temperature]. The lower bound values are

Fig. 5. Case study layout with location of users

Fig. 6. Thermo-hygrometer for indoor air temperature recordings

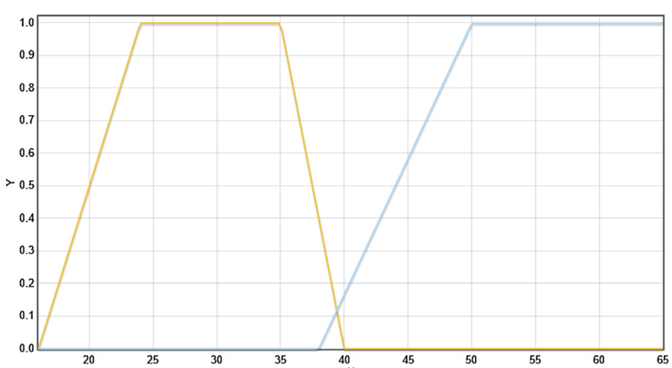

Fig. 7. the MFs for Age.

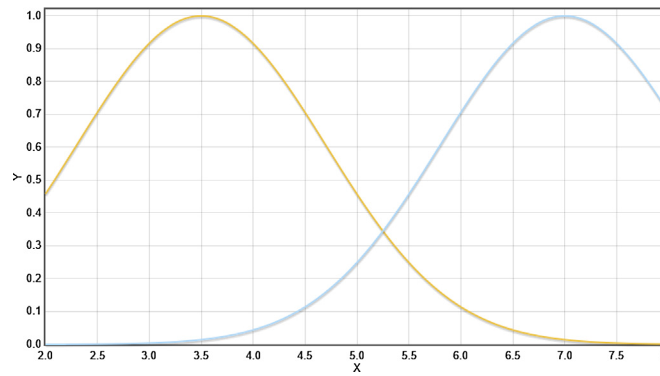

Fig. 8. the MFs for Activity Time.

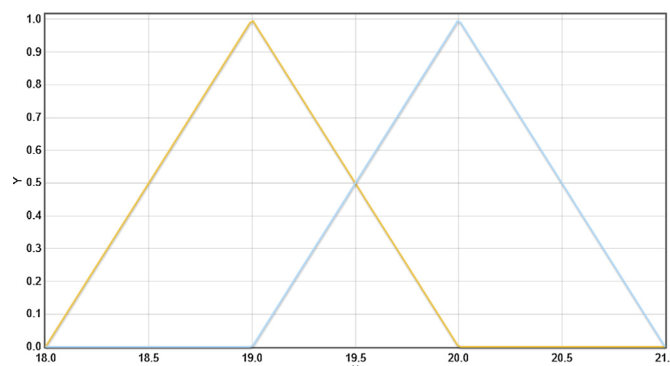

Fig. 9. the MFs for comfort zone lower.

chosen from 18 to 22 and the upper bound values are selected from 23 to 25.

In the experiments, three inputs and two outputs are defined to construct FLSs rules. As the system inputs, Age is defined in two MFs (*Young* and *Old), both ATs* and CLs are defined as Low and *High* MFs. Two outputs are determined, lower and upper bound of CZ, LB and UB respectively. Two MFs are also assigned to LB and UB. After constructing system inputs and outputs as Fuzzy MFs, the fuzzy rules are defined by the Apriori Algorithm and Mamdani Fuzzy model [21] is implemented with the *min-max* operator. At the defuzzification step of FLS, the centroid method is utilised and the crisp output of the FLSs is gathered. After constructing the Fuzzy model, in order to evaluate our approach, Root Mean Square Error (RMSE) measure is used between the predicted outputs of the FLSs and actual output.

5. Results and Discussion

FLS has more prominence due to its imitation ability of humans' decision making. Such decision making allows for intermediate possibilities by giving a degree of membership to a set [44]. This level of possibilities would create a more realistic and functional platform for comfort related studies which are mostly fraught with uncertainty. The FLS can be implemented in the systems with various sizes and help to deal with uncertainty.

With the help of membership function and If-Then rules, the method can handle continuous states. It is also a flexible system and allows modifications in the rules. As described before the FLS has four parts, fuzzi-

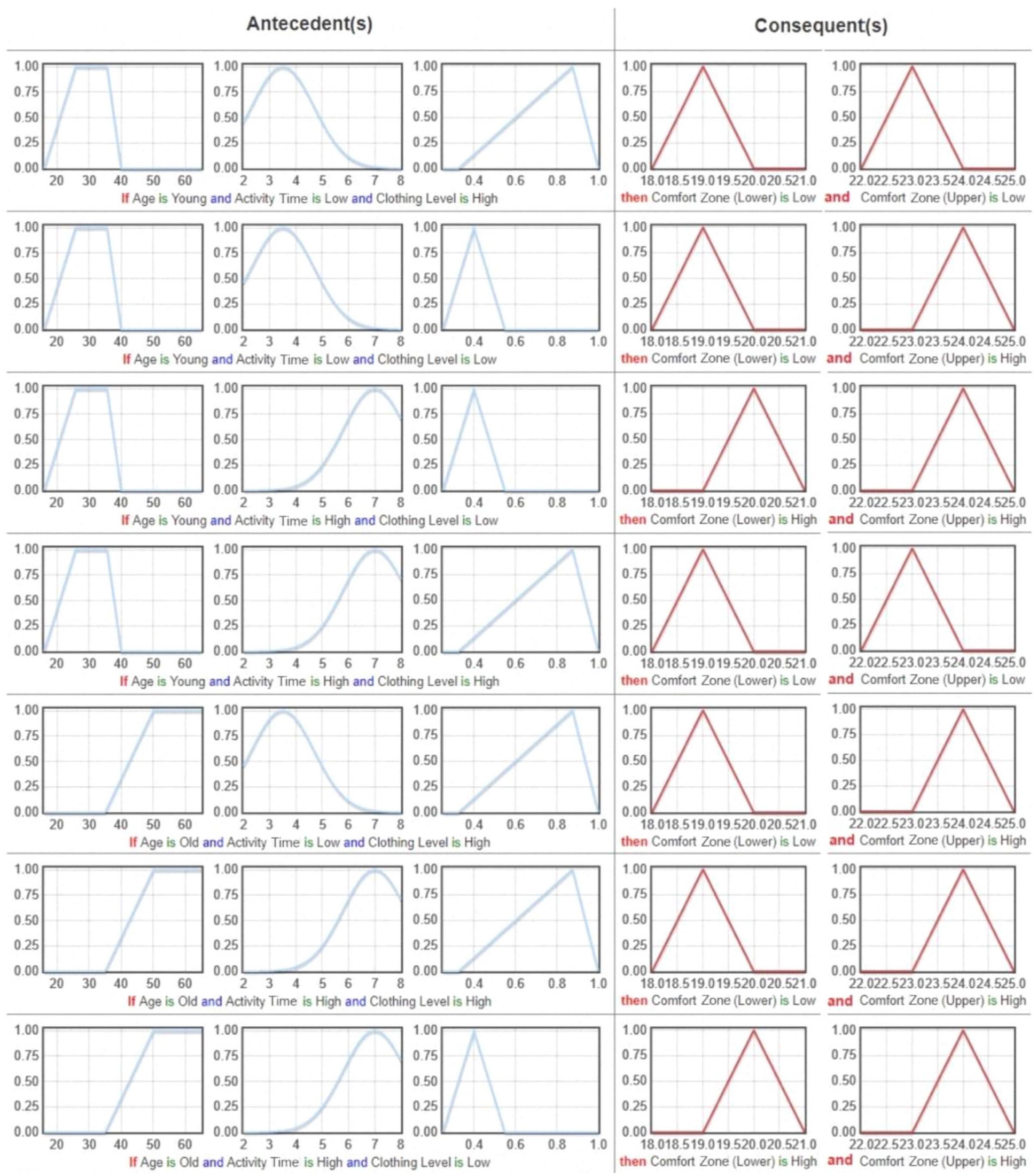

Fig. 10. Antecedents and consequences of the rules

fier, rules, inference and defuzzfier [45]. A crisp set of data, in this case, influential factors on building users comfort level is collected and converted to a fuzzy set using fuzzy membership functions (fuzzifications) and then an inference is made on a set of rules and the output is mapped to a value in a defuzzification part. Such output could reduce the uncertainty, improve data collection and influence decision making process.

The proposed framework is implemented in MATLAB and figures are drawn by using the open source library JuzzyONLINE [46]. The whole analysis is done using a 2.50 GHz Intel Core i5 processor with 4GB RAM. The key point in this work is the factors that are related and effective on the level of comfort are considered as the inputs. In the first step, the MFs for input, output and state variables are defined. As mentioned before, a building with one hundred agents has been considered for this study, each agent with different age, gender, clothing level and activity time. The label in the data includes two values, the lower bound and the upper bound; therefore, to predict both values, two output are considered, one of them is used to predict the lower bound and the other one reveals the upper bound of the level of comfort. Therefore, based on our data, there are three inputs- age, Activity time (AT), Clothing Level (CL), and there are two outputs- the Lower Bound of comfort level (LB) and the Upper Bound of comfort level (UB). The domain intervals of age, AT, CL, LB and UB are defined as [16, 65], [2, 8], [0.25, 1], [19, 22] and [23, 26], respectively, where domain interval of a variable means that most probably this variable will sit in this interval. Each domain interval is

Table 1
Fuzzy rules.

Number	Rules
Rule 1	If Age is young and Activity Time is Low, Clothing Level is High then Lower Comfort Level is Low and Upper Comfort Level is Low
Rule 2	If Age is young and Activity Time is Low, Clothing Level is Low then Lower Comfort Level is Low and Upper Comfort Level is High
Rule 3	If Age is young and Activity Time is High, Clothing Level is Low then Lower Comfort Level is High and Upper Comfort Level is High
Rule 4	If Age is young and Activity Time is High, Clothing Level is High then Lower Comfort Level is Low and Upper Comfort Level is Low
Rule 5	If Age is old and Activity Time is Low, Clothing Level is High then Lower Comfort Level is Low and Upper Comfort Level is High
Rule 6	If Age is old and Activity Time is Low, Clothing Level is Low then Lower Comfort Level is High and Upper Comfort Level is High
Rule 7	If Age is old and Activity Time is High, Clothing Level is High then Lower Comfort Level is Low and Upper Comfort Level is High
Rule 8	If Age is old and Activity Time is High, Clothing Level is Low then Lower Comfort Level is High and Upper Comfort Level is High

divided into some regions to define MFs of FLSs. As mentioned before each input domain is covered by using two MFs. The *Age* is characterised as *Young* (16 – 35), *Old* (36 - 65), the *AT* is divided into *Low* (2 - 4) and *High* (5 - 8). Also, the output comfort level is constructed as; the LB for *Low* (19 - 20) and *High* (21 - 22), *UB* is *Low* (23 - 24) and *High* (25 – 26). In order to represent each interval, the fuzzy MFs are generated as shown in Figs. 7, 8 and 9.

In the experiment the FLSs rules are generated based on Association rule mining. Association rule mining finds rules that predict the occurrence of a feature based on the occurrences of other features by satisfying some measures of interestingness [47,48]. The rules are shown in Table 1. The experience of the human controller is usually expressed as some linguistic “IF-THEN” rules that state in what situation(s) which action(s) should be taken. The generated if-then rules in Table 1 are integrated with the JuzzyOnline FLSs as shown in Fig. 10.

As mentioned before, in this paper, inputs and the outputs are combined by using the AND *(min) operator*. Lastly, the defuzzification is completed by utilizing the centroid of gravity *(COG)* calculation. The experiment continued by processing all the input values, from the collected dataset, into the constructed FLS. After each operation, the error is measured between the output and the actual value by using RMSE. The accuracy of the proposed method is calculated, as follows, where *actual* is the ground truth value and *predicted* is the predicted value:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} predicted_i - actual_i^{\,2}}{N}} \tag{3}$$

The lower value of RMSE refers to the more accurate model. Based on Eq. 3, the RMSE values for lower bound of comfort level and upper bound of comfort level are 1.2291 and 0.8153 respectively. Thus, it can be said the predicted values are similar to the real values. There is no fixed threshold limit for RMSE, the common practice is to keep it as low as possible.

In this experiment, a model is created that can provide a comprehensive analysis not only the given subject answers but the combination between those answers. Therefore, as the further experiment, rather than using the actual individual data points from the dataset, we investigate/explore the functional relationship between Comfort zone and AT-Age by plotting a fuzzy control surface. In this experiment, all the possible input values for AT (between 2 to 8) and all the possible inputs for Age are investigated in the created Fuzzy Logic Systems. Firstly, the system input AT is set 2 and different Ages (between 16 to 65) are given to the Fuzzy Logic System. In each experiment the result is stored. Then the AT level is increased to 3 and all the Ages (between 16 to 65) are procced again. These procedures are repeated for all the possible AT (between 2 to 8) and Ages (between 16 to 65). Each combination results are stored and visualized in Fig. 11. As Fig. 11 reveals the relationship in the system parameters, it can be argued that this surface could be a suitable initial step to provide a guideline for comfort level determination.

Linking user feedback and simulations to deliver better prediction creates opportunities to provide improved operations and maintenance, correct predictions and eventually more sustainable buildings. The interface developed in this study creates a new type of assessment to assist in building simulation and building control systems. Currently, conceptual design developments are largely based on experimental knowledge of simulation users and the current simulation tools have not played a significant role to influence that. If the issue of BPG is to be affected then there is a necessity to develop more of various recording systems for occupants’ behaviour with ability to improve over time. Computers tools are expected to be less dependent on widely used standards and user’s expert knowledge and more on actual recording data and decisions that are derived from it. Artificial Intelligence based approaches such as the fuzzy logic systems used in this study have attempted this approach and are expected to have a lasting impact.

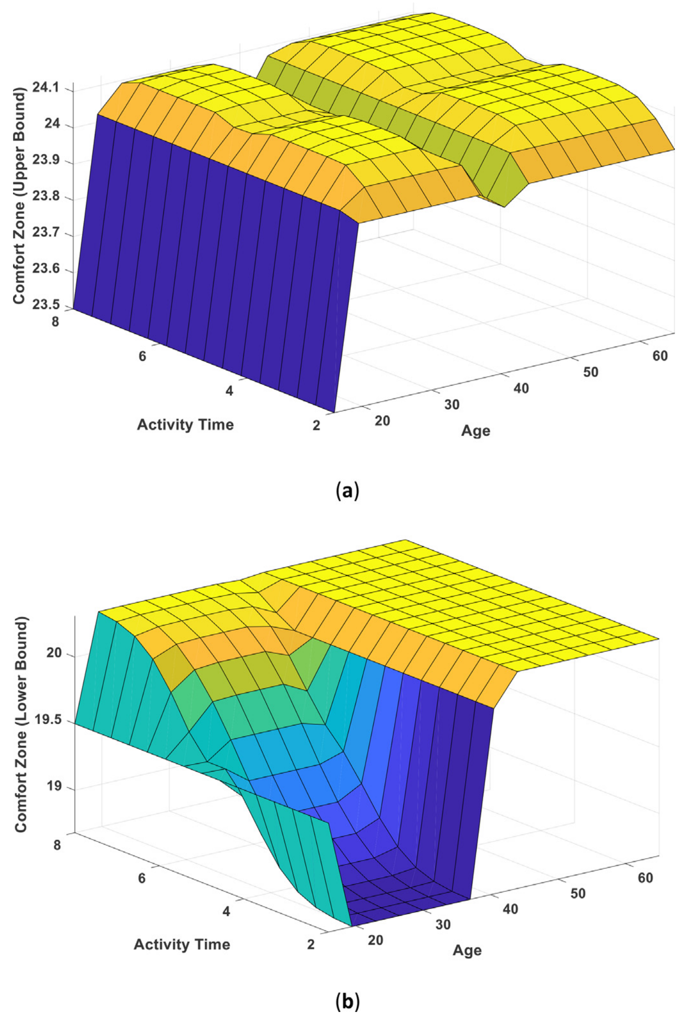

Fig. 11. The fuzzy control surface. (**a**): Upper bound, (**b**): Lower bound.

If the design is complex and so the modelling and simulations are expected to be more vulnerable to errors, therefore the usage of assumed level of comfort in simulation tools could significantly increase the likelihood of BPG. This is the area where artificial intelligence based tools have been left out in being used as an additional tool for simulations and building operations. The need for such tools is mostly sensed in architectural technology that explores new boundaries in data processing and performance-driven design. The interface developed in this study can also be used to exchange data between various simulation tools, a concept that is widely known as coupling [49]. This interface is used to make a decision on thermal comfort boundaries and could set more contextualised and accurate temperature for simulation tools.

6. Conclusion

This study is driven by a necessity to use an expandable model that interprets the relationships between critical factors affecting thermal comfort. This study suggests how thermal comfort data gathered through a simple questionnaire can be interpreted and used for simulation tools and building control systems. The following are notable:

- With a very simple questionnaire and sample of 100 users, this study approached thermal comfort prediction from local assessment perspective.
- With variables of indoor air temperature, age, clothing insulation and working hours, the model shows capacity to reduce the previous models' inaccuracy. Compared to the ASHRAE model, it can quantify the effects of each input variable on building users' thermal comfort.
- This research demonstrates meaningful relationship in critical thermal comfort elements and the method is practical enough to predict the value of comfort level based on data and the predefined rules.
- A combination of Association Rule Mining and Fuzzy Logic Systems approach with expandable capacity is used with RMSE values of 1.2291 and 0.8153 of accuracy in data interpretation and decision making.
- The developed interface can be used for open source programs and has the ability to expand and include more variables into the database.

Conflicts of interest

None.

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