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Decision-Refillable-Based Shared Feature-Guided Fuzzy Classification for Personal Thermal Comfort

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Abstract: Different types of buildings in different climate zones have their own design specifications and specific user populations. Generally speaking, these populations have similar sensory feedbacks in their perception of environmental thermal comfort. Existing thermal comfort models do not incorporate personal thermal comfort models for specific populations. In terms of an algorithm, the existing work constructs machine learning models based on an established human thermal comfort database with variables such as indoor temperature, clothing insulation, et al., and has achieved satisfactory classification results. More importantly, such thermal comfort models often lack scientific interpretability. Therefore, this study selected a specific population as the research object, adopted the 0-order Takagi–Sugeno–Kang (TSK) fuzzy classifier as the base training unit, and constructed a shared feature-guided new TSK fuzzy classification algorithm with extra feature compensation (SFG-TFC) to explore the perception features of the population in the thermal environment of buildings and to improve the classification performance and interpretability of the model. First, the shared features of subdatasets collected in different time periods were extracted. Second, the extra features of each subdataset were independently trained, and the rule outputs corresponding to the key shared features were reprojected into the corresponding fuzzy classifiers. This strategy not only highlights the guiding role of shared features but also considers the important compensation effect of extra features; thereby, improving the classification performance of the entire classification model. Finally, the least learning machine (LLM) was used to solve the parameters of the "then" part of each basic training unit, and these output weights were integrated to enhance the generalization performance of the model. The experimental results demonstrate that SFG-TFC has better classification performance and interpretability than the classic nonfuzzy algorithms support vector machine (SVM) and deep belief network (DBN), the 0-order TSK, and the multilevel optimization and fuzzy approximation algorithm QI-TSK.

Keywords: thermal comfort model; interpretability; shared feature; fuzzy classification

Citation: Xu, Z.; Lu, W.; Hu, Z.; Yan, W.; Xue, W.; Zhou, T.; Jiang, F. Decision-Refillable-Based Shared Feature-Guided Fuzzy Classification for Personal Thermal Comfort. *Appl. Sci.* **2023**, *13*, 6332. https://doi.org/10.3390/app13106332

Academic Editor: Cesare Biserni

Received: 27 March 2023
Revised: 28 April 2023
Accepted: 3 May 2023
Published: 22 May 2023

1. Introduction

People spend approximately 90% of their time indoors [1]. Thermal comfort is one of the main factors affecting building energy and work performance [2]. The study of building comfort is beneficial for reducing building energy consumption and improving building environment satisfaction [3].

In the past few decades, many experts and scholars have conducted in-depth research on thermal comfort models using different methods [4–8]. For example, D. Enescu reviewed the most used thermal comfort models and indicators with their variants and discussed their usage in control problems referring to energy management in indoor applications [4]. S. Carlucci et al. analyzed the adaptive models in ASHRAE Standard 55 [9], the European EN 15251 [10], the Dutch ISSO 74 [11] and the Chinese GB/T 50785 [12], then identified the main sources of uncertainty around the application of adaptive models, and analyzed the difference between the adaptive comfort models quantitatively [5]. Zhu et al. summarized the progress in the literature concerning the dynamic characteristics and comfort assessment of airflow in four main sections. It will hopefully aid the understanding of human thermal comfort perception of indoor airflow [6]. X. Zhou et al. studied the thermal comfort effects of asymmetric radial environments under different exposure durations, they proposed relational equations with consideration of exposure duration [7]. M. Luo et al. transferred the developments in human metabolic science to the built environmental context. They led to the conclusion that the algorithm of human metabolism will affect thermal comfort modeling with precision [8]. These methods can be roughly classified into two categories.

The approaches in the first category use statistical methods to study thermal comfort models. Among them, the predicted mean voting (PMV) model established by Fanger [13] and the adaptive thermal comfort model proposed by de Dear et al. [14] are the most representative. However, PMV does not have self-learning ability. Although the adaptive thermal comfort model proposed by de Dear et al. can self-learn and self-correct, its self-correction ability is limited. Its accuracy drops dramatically for new climate conditions or building types. In addition, the thermal comfort of building occupants may be affected by factors not included in these models (such as gender, age, health status [15,16], and long-term and short-term adaptation [17,18]).

The approaches in the second category mainly use machine learning algorithms to study thermal comfort models. Many scholars have applied machine learning algorithms to thermal comfort research [19]. Although thermal comfort models based on machine learning algorithms outperform traditional thermal comfort models [20], the commonly used artificial neural network (ANN), support vector machine (SVM), and random forest (RF) all have poor semantic interpretability and, thus, have difficulty describing the importance of each input variable. Recently, some scholars have conducted research on thermal comfort from the perspective of fuzzy logic reasoning [21,22]. For example, C. Li et al. presented a type-2 fuzzy method based on a data-driven strategy for the modeling and optimized the thermal comfort parameters. The proposed method can be used to realize a comfortable and energy-saving environment in a smart home or intelligent buildings [21]. J. Menyhárt et al. determined a new comfort index using fuzzy logic based on the responses of subjects, it can evaluate a new personalized ventilation system [22].

In terms of the input parameters, these models use the same environmental and personal factors as in the PMV model. or add new features, such as skin temperature [23] and time [24]; however, they do not consider usage scenarios or population features. Therefore, thermal comfort models face the following challenges:

(1) Test scenarios (climate, building type, and user population) and feature dimensions:

Researchers have confirmed that the season, climate, and building type impact human thermal adaptability and thermal expectations [25]. Most of the recent research focuses on the Mediterranean climate region [26,27]. In addition, due to inconsistent observation indicators for subjects in different research or scenarios, the feature dimensions of the datasets are usually inconsistent, and previous thermal comfort models are not suitable for datasets with multiple different feature dimensions. Therefore, for different climatic regions, it is necessary to develop thermal comfort models that can be applied to multiple datasets of different feature dimensions to enable a prediction using personal thermal comfort models in a wider range of scenarios.

(2) Research on the shared features of specific populations:

For a particular type of building, the long-term user population generally has the same or similar shared features, such as age, activity level, clothing level [28], and human behavior [29]. This kind of specific observation population has similarities and correlations regarding the impact of shared features on the final decision's results. Therefore, it is particularly important to identify shared features that are relatively easy to observe and greatly impact the final decision classification among these features. However, the recent research on personal thermal comfort models has not addressed the impact of shared features of specific populations on comfort.

(3) Semantic interpretability of thermal comfort models:

The choice of algorithm is one of the main factors affecting the accuracy of machine learning-based thermal comfort models [30]. According to previous studies of thermal comfort models, many machine learning-based models have difficulty expressing the relationship between input variables and model outputs; hence, these models are called "black box models". Although these algorithms can achieve a good performance in the learning process, they do not have good scientifically derived semantic interpretability.

To address these issues, the following steps are performed in this study: (1) extracting key shared features that greatly impact classification performance from the features of specific scenarios and specific populations and highlighting the guiding role of these key shared features in the performance of the final model; (2) strengthening the guiding role of the shared features of a specific population in the classification while considering the compensatory effect of extra features on human thermal comfort; and (3) constructing a highly interpretable fuzzy classifier to mine the effect of the thermal environment on human thermal comfort; thereby, better guiding building environmental design.

The features of a specific population can be roughly classified into shared features and extra features. The shared features do not change with external conditions and are easily acquired using conventional acquisition methods. The extra features may change with changes in the external environment or have feature information that is difficult to acquire. Therefore, in the modelling process, it is necessary to strengthen the guiding role of shared features in the final decision, to fully consider the impact of extra features on the classification, and to ensure that the antecedent parameters of each rule, the output of each rule, and the outputs of the model are all interpretable; thereby, making the thermal comfort model applicable to more usage scenarios. The contributions of this study can be summarized as follows:

(1) Rich practical application scenarios

In contrast to previous studies in which data were collected for various climatic regions using various methods, this study collects comprehensive data on a specific population in a specific scenario in a specific climatic region (see Section 4.1 for details), not only supplementing the thermal comfort database but also enriching the application scenarios of thermal comfort models by processing datasets of different feature dimensions.

(2) Model optimization, construction, and training

Both shared features and extra features of the specific population impact the final decision of the model. This study highlights the guiding role of shared features through training on and the information reuse of shared features of the specific population. Moreover, the model is trained separately on extra features, taking into account the impact of these extra features on the final classification results. Finally, through the integrated optimization of the output weights, the stability and generalization performance of the model are improved.

(3) Enhancement of semantic interpretability

The predicted results of previous thermal comfort models constructed by machine learning algorithms are difficult to interpret and analyze. In the process of building environmental design, it is necessary to understand the factors and indicators that affect the thermal comfort results to understand the mechanism underlying the impact of the building environment on human thermal comfort. The Takagi–Sugeno–Kang (TSK) algorithm selected in this study has a natural ability to address uncertainty, and the features in the rules of the model, the output of the rules, and the output of the model are all semantically interpretable.

The sections of this study are arranged as follows: The Section 1 introduces the relevant research background, current situation, research content, and framework of the thesis. The Section 2 introduces the basic knowledge of this study. The Section 3 discusses the constructed model. The Section 4 presents the experimental analysis and discussion. The Section 5 summarizes this study.

2. Related Knowledge

This study uses mainly the classic 0-order TSK fuzzy classifier and the least learning machine (LLM). They are briefly introduced first in this section.

2.1. Classic 0-Order TSK Fuzzy Classifier

Due to the high classification performance and high interpretability of the 0-order TSK fuzzy classifier, it has been widely used in daily life [31–35]. The classifier is briefly described as follows:

The output y^k of the k-th fuzzy rule is expressed as follows:

Rule k: If x_1 is $B_1^k \wedge x_2$ is $B_2^k \wedge ... \wedge x_D$ is B_D^k, then $y^k = p_0^k$, $k = 1, 2, \ldots, K$

where the input vector is $x = [x_1, x_2, \ldots, x_D]^T$ (D is the number of features), each component x_i is a fuzzy linguistic variable, $\mathrm{F}_{B_i^k}(x_i)(i = 1, 2, \ldots, D, k = 1, 2, \ldots, K)$ is the corresponding membership function, and $B_i^k(k = 1, 2, \ldots, K)$ is the fuzzy subset of the input vector x_i under the k-th rule. Rule k refers to the k-th rule, $\wedge$ is the fuzzy connection operator, K is the total number of fuzzy rules, and p_0^k represents the output of the k-th fuzzy rule.

The fuzzy membership function $\mathrm{F}^k(\boldsymbol{x})$ can be written as [33]:

$$\mathrm{F}^k(\boldsymbol{x}) = \prod_{i=1}^{D} \mathrm{F}_{B_i^k}^k(x_i) \tag{1}$$

where the normalized fuzzy membership function $\widetilde{\mathrm{F}^k}(\boldsymbol{x})$ can be written as [33]:

$$\widetilde{\mathrm{F}^k}(\boldsymbol{x}) = \mathrm{F}^k(\boldsymbol{x}) \bigg/ \sum_{k\prime=1}^{K} \mathrm{F}^{k\prime}(\boldsymbol{x}) \tag{2}$$

Usually, we use the Gaussian fuzzy membership function as the fuzzy membership function, and its expression is as follows [33]:

$$\mathrm{F}_{B_i^k}(x_i) = \exp(-(x_i - c_i^k)^2 / 2\delta_i^k) \tag{3}$$

where two parameters c_i^k and δ_i^k can be obtained by the fuzzy c-means (FCM) algorithm [36] and their expressions are as follows [33]:

$$c_i^k = \sum_{i=1}^{N} \mathrm{F}^k(x_i) x_{ij} \bigg/ \sum_{i=1}^{N} \mathrm{F}^k(x_i) \tag{4}$$

$$\delta_i^k = h.\sum_{i=1}^{N} \mathrm{F}^k(x_i)(x_{ij} - c_i^k)^2 \bigg/ \sum_{i=1}^{N} \mathrm{F}^k(x_i) \tag{5}$$

where the fuzzy membership degree $\mathrm{F}^k(x_i)$ is obtained by FCM, $i = 1, 2, \ldots, N$, and h is a scale parameter that can be manually tuned or optimized using the learning strategy [37].

Each rule is used to process the input vector through a series of steps, and the final output value of the TSK fuzzy classifier can be expressed as [33]:

$$y_0 = \sum_{k=1}^{K} \mathrm{F}^k(\boldsymbol{x}) p_0^k / \sum_{k\prime=1}^{K} \mathrm{F}^{k\prime}(\boldsymbol{x}) \quad (6)$$

2.2. Least Learning Machine (LLM)

According to the literature [38,39], the LLM was first conceptually proposed as a fast learning algorithm for single-layer or multilayer feedforward neural networks. For the i-th input sample, the input layer is $\boldsymbol{x}_i = (x_{i1}, \ldots, x_{iD})$. In the hidden layer, $g(\boldsymbol{w}_i, b_i, \boldsymbol{x}_i)$ is the activation function, and $\boldsymbol{w}_i$ and b_i are the weight parameter and the bias value, respectively. $\beta_1, \beta_2, \ldots, \beta_K$ are the output parameters of the output layer.

Therefore, for a given training set $\mathrm{O} = \{(\boldsymbol{x}_i, t_i) | \boldsymbol{x}_i \in \mathbb{R}^D, t_i \in \mathbb{R}, i = 1, 2, 3, \ldots, N\}$, $\boldsymbol{x}_i$ represents the i-th input sample, and t_i represents the label corresponding to the i-th sample. We let $\mathbf{X} = [\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_N]^T$, $\mathbf{T} = [t_1, t_2, \ldots, t_N]^T$, and the number of hidden-layer nodes be K. Then, the output is $\mathbf{H} = [\boldsymbol{h}_1, \boldsymbol{h}_2, \ldots, \boldsymbol{h}_K]$, where $\boldsymbol{h}_k$ is the output of the k-th hidden-layer node ($\boldsymbol{h}_k = g(\boldsymbol{w}_k, b_k, \boldsymbol{x}_i)$). The final output is $f(\mathbf{X}) = \sum_{k=1}^{K} \boldsymbol{\beta}_k \mathbf{h}_k = \mathbf{H}\boldsymbol{\beta}$, where $\boldsymbol{\beta} = [\beta_1, \beta_2, \ldots, \beta_K]^T$ [38]. According to [38], $\boldsymbol{\beta} = (\frac{1}{\eta}\mathbf{I} + \mathbf{H}^T\mathbf{H})^{-1}\mathbf{HT}$, where η is a constant, $\mathbf{I}$ is a D-dimensional identity matrix, and $\mathbf{T}$ is the label set.

3. The Proposed Fuzzy Classifier: SFG-TFC

As mentioned above, building a thermal comfort model is not an easy task. In recent years, most of the work on thermal comfort models has been focused on machine learning algorithms. One representative work is the data-driven thermal comfort model based on the support vector machine algorithm [15]. This is a model with self-learning and self-tuning capabilities using the support vector machine (SVM) algorithm. This model focuses on variables such as indoor temperature, clothing insulation, metabolic rate, and wind speed. It is very similar to our study. More importantly, compared to SVM, the fuzzy system constructed by our model not only has good classification performance, but also has good interpretability.

In our study, data are collected from specific people in specific climate regions and in specific scenarios. Subdatasets of M time nodes are obtained under laboratory simulation scenarios and are randomly ordered, and each subdataset contains shared features and extra features. For each time node, the collected datasets can be divided into a shared feature dataset and an extra feature dataset. As shown in Figure 1, the SFG-TFC training structure is divided into the following steps: First, the key shared features that greatly impact decision-making are obtained using the method of information gain, fuzzified, and output by rules. Second, the extra features of each subset are fuzzified and output by rules, and the rule output matrix of key shared features is reprojected to each independent base training unit. Finally, the output weights of the optimized model are integrated to improve the generalization performance of the model. In the modelling process, one of the difficulties and objectives of this study is to strengthen the guiding role of the key shared features in human thermal comfort while considering the enhancing effect of extra features on the final classification performance.

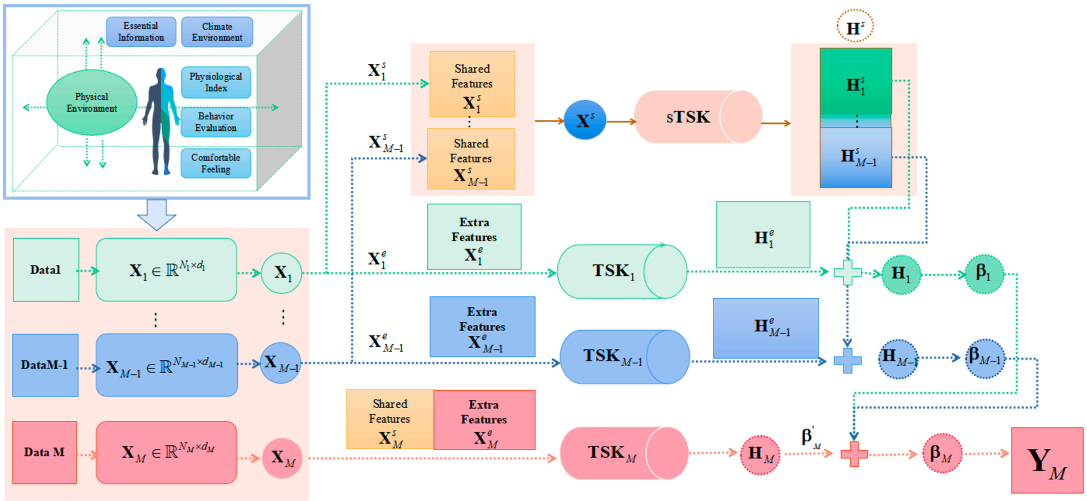

Figure 1. The training structure of SFG-TFC.

3.1. Construction of the Basic Training Units

Each base training unit is described as follows [39].

A. According to FCM, the membership value of each feature is obtained as follows [35]:

$$\mathrm{F}(x_{ij}) = \prod_{r=1}^{C} \mathrm{F}(x_{ij}^{r}) \tag{7}$$

where $i = 1, 2, \ldots, N, j = 1, 2, \ldots, D, r = 1, 2, \ldots, C$, C is the number of the fuzzy partitions.

B. The rule output ω is expressed as follows [39]:

$$\omega_{ik} = \prod_{j=1}^{D} \mathrm{F}(x_{ij}) \cdot \boldsymbol{\varphi}(j, k) \tag{8}$$

where $i = 1, 2, \ldots, N, j = 1, 2, \ldots, D, k = 1, 2, \ldots, K$, and $\boldsymbol{\varphi}$ is a randomly generated (0, 1) matrix, N is the number of training samples and K is the number of rules.

C. The rule output matrix $\mathbf{H}$ is expressed as follows:

$$\mathbf{H} = \begin{bmatrix} \omega_{11} & \cdots & \omega_{1K} \\ \vdots & \ddots & \vdots \\ \omega_{N1} & \cdots & \omega_{NK} \end{bmatrix}_{N \times K} \tag{9}$$

where N is the number of training samples and K is the number of rules.

D. According to the LLM, the final output $\mathbf{Y}$ of each base training unit is expressed as follows [39]:

$$\mathbf{Y} = \mathbf{H} \times \boldsymbol{\beta} \tag{10}$$

3.2. Fuzzy Modeling Based on Shared Features

Since the thermal comfort perception of a specific population has similar perception features, these features usually do not change over time, and the corresponding features in each training sample are similar. Therefore, starting from the shared features of a specific population, the association between the shared features and personal thermal comfort data can be mined.

First, the key shared feature dataset $\mathbf{X}^s$ is extracted using the method of information gain. The dataset is divided into a corresponding number of subdatasets

$\mathbf{X}_1, \ldots, \mathbf{X}_{M-1}, \mathbf{X}_M (\mathbf{X}_i \in \mathbb{R}^{N_i \times D_i}, i = 1, 2, \ldots, N)$ according to different sampling nodes. A total of $M-1$ subdatasets $\mathbf{X}_1, \ldots, \mathbf{X}_{M-1}$ are randomly selected, and the share features for a specific population $\mathbf{X}_1^s, \ldots, \mathbf{X}_{M-1}^s$ are organized ($\mathbf{X}_i^s \in \mathbb{R}^{N_i \times D^s}$) and merged into a shared feature dataset $\mathbf{X}^{s'} = \begin{pmatrix} \mathbf{X}_1^s \\ \ldots \\ \mathbf{X}_{M-1}^s \end{pmatrix}$, where $\mathbf{X}^{s'} \in \mathbb{R}^{(N_1+N_2\ldots+N_{M-1}) \times D^{s'}}$. For the shared feature dataset, the key shared features that greatly impact the final decision are obtained through the method of information gain and organized into a key shared feature dataset $\mathbf{X}^s = (\mathbf{X}^s \in \mathbb{R}^{(N_1+N_2\ldots+N_{M-1}) \times D^s}$ and $D^s \leq D^{s'}$). The specific method is as follows: First, the matrix $\mathbf{\Phi}$ randomly assigns an initial value (from 0 to 1) to each element of the shared feature dataset $\mathbf{X}^s$, and then features are selected based on the information determination ratio (IDR). In this study, the IDR is set to 80%, namely, when a feature contains more than 80% valid information, all the information of the feature is selected; otherwise, the information of the feature is not selected.

Next, a shared TSK fuzzy classifier (sTSK) to be trained on the key shared feature dataset $\mathbf{X}^s$ is constructed. According to the basic model introduced in Section 3.1, as shown in Figure 1, the sTSK is trained on the key shared feature dataset $\mathbf{X}^s$ to obtain the rule output matrix of the key shared features $\mathbf{H}^s = \begin{pmatrix} \mathbf{H}_1^s \\ \mathbf{H}_2^s \\ \ldots \\ \mathbf{H}_{M-1}^s \end{pmatrix}$, $\mathbf{H}^s \in \mathbb{R}^{N \times K^s}$, where $\mathbf{H}_i^s$ represents the rule output matrix of the i-th subdataset in the sTSK. Therefore, $\mathbf{H}^s$ contains the rule output information of the key shared features of each subdataset.

3.3. Reuse of Information for Shared Features

As shown in Figure 1, the TSK base training units are trained autonomously on extra features from each subdataset $\mathbf{X}_i^e$ to obtain the corresponding rule output matrices. The rule output matrix $\mathbf{H}^s$ of the efficient key shared features in Section 3.2 is reprojected to each independent TSK base training unit and fused with the rule output matrix of extra features $\mathbf{H}^e$. The main process includes the following steps:

(1) Training on extra features

The 0-order TSK fuzzy classifier is trained on the extra features $\mathbf{X}_1^e, \ldots, \mathbf{X}_{M-1}^e$ separately. This method not only enables the effective information of the extra features of each subdataset sample to be fully retained and utilized but also solves the problem of having different numbers of samples and feature dimensions in each subdataset. In this manner, the rule output matrices of the extra features $\mathbf{H}_1^e, \ldots, \mathbf{H}_{M-1}^e$, $\mathbf{H}_i^e \in \mathbb{R}^{N_i \times K^e}$ are obtained.

(2) Reuse of key shared features

The *i-th* sample set in the rule output matrix of the shared features $\mathbf{H}^s = \begin{pmatrix} \mathbf{H}_1^s \\ \mathbf{H}_2^s \\ \ldots \\ \mathbf{H}_{M-1}^s \end{pmatrix}$ is reprojected to the corresponding rule output matrix of the extra features $\mathbf{H}_i^e$ to obtain the rule output matrix of each base training unit $\mathbf{H}_i = \left[\mathbf{H}_i^e \vdots \mathbf{H}_i^s \right]$, $\mathbf{H}_i^e \in \mathbb{R}^{N_i \times (K^s+K^e)}$; thereby, reprojecting the key shared features. The reprojection of the key shared features enables the key shared features to be used in each base training unit, which ensures the guiding role of the key shared features in model decision-making.

(3) Calculation of the output weights

According to Formula (10), the output weights of the $M-1$ base training units $\boldsymbol{\beta}_i$, $\boldsymbol{\beta}_i \in \mathbb{R}^{(K^s+K^e) \times L}$, are calculated.

3.4. Integration of the Output Weights

The subdataset $\mathbf{X}_M$ is subjected to basic unit training. According to Formulas (7)–(10), the membership function value F_M, the rule output matrix $\mathbf{H}_M$, and the output weight $\boldsymbol{\beta}_{M'}$ are obtained. Next, the output weights of the previous $M-1$ base training units $\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, \ldots, \boldsymbol{\beta}_{M-1}$ are integrated into the current base training unit $\boldsymbol{\beta}_{M'}$ to obtain the final output weights $\boldsymbol{\beta}_M$, improving the stability and generalization performance of the model where θ is a small constant that can be set in advance and $\boldsymbol{\beta}_i$ denotes the i-th output weights of each TSK base training unit.

Hence, the final output $\mathbf{Y}_M$ is obtained.

The output weights of the $M-1$ base training units are used to integrate and optimize the model decision-making of the M base training units to give the SFG-TFC model more stable generalization performance.

3.5. Algorithms

This section presents the SFG-TFC algorithm. The specific training steps are specified in Algorithm 1.

Algorithm 1: Training Algorithm of SFG-TFC

Input: The training set $\mathbf{X}_1, \ldots, \mathbf{X}_{M-1}, \mathbf{X}_M$,where,$\mathbf{X}_i = \left[x_1^i, x_2^i, \ldots, x_{N_i}^i\right]^T$

The corresponding class label set $\mathbf{T}_1, \ldots, \mathbf{T}_{M-1}, \mathbf{T}_M$, where, $\mathbf{T}_i = \left[t_1^i, t_2^i, \ldots, t_{N_i}^i\right]^T$

Output weight parameter θ, rule number K

Step1: Acquisition and processing of shared features

Step 1(a): the key shared feature dataset $\mathbf{X}^s$ is extracted by the method of information gain

Step 1(b): Perform sTSK training on $\mathbf{X}^s$

Step 1(c): Calculation rule output matrix $\mathbf{H}^s = \begin{pmatrix} \mathbf{H}_1^s \\ \mathbf{H}_2^s \\ \cdots \\ \mathbf{H}_{M-1}^s \end{pmatrix}$

Step2: Re-projection of key shared features

Step 2(a): Conduct TSK base unit training for additional features $\mathbf{X}_1^e, \ldots, \mathbf{X}_{M-1}^e$ to obtain the rule output matrix of additional features $\mathbf{H}_1^e, \ldots, \mathbf{H}_{M-1}^e$.

Step 2(b): Project the corresponding relevant information in the rule output matrix $\mathbf{H}^s$ of the shared feature to the corresponding base training unit again. Calculate the rule output matrix of each base training unit $\mathbf{H}_i = \left[\mathbf{H}_i^e \vdots \mathbf{H}_i^s\right]$

Step 2(c): Calculate the output weight of M-1 training base units $\boldsymbol{\beta}_i$

Step 3: Integration of output weights

Step 3(a): Generate the M-th rule output matrix $\mathbf{H}_M$

Step 3(b): Optimize output weight $\boldsymbol{\beta}_M = \boldsymbol{\beta}_{M'} + \sum\limits_{i=1}^{M-1} \frac{\theta}{M-1} \boldsymbol{\beta}_i$

Output:

The prediction function of SFG-TFC: $\mathbf{Y}_M = \mathbf{H}_M \times \boldsymbol{\beta}_M$

Remark 1. *The datasets are collected at different time spans, and the features still have similarities or differences over time. The associations between similar features (shared features) and different features (extra features) are clarified to characterize their impact on the final personal comfort.*

Remark 2. *The reasons for the enhanced classification performance of Algorithm 1 are analyzed from the perspective of feature enhancement and model optimization. First, this study analyzes the dataset features and classifies the features of each dataset into shared features and extra features. Then, the shared features play a guiding role, the extra features have a compensation effect, and the integrated output weight guarantees the classification performance of the model.*

Remark 3. *The output weight parameter θ and the number of rules K are important parameters that affect the performance of Algorithm 1. In repeated experiments in this study, the output weight parameter is 0.005, and the number of rules is 10–20.*

4. Experiment and Discussion

4.1. Dataset and Experimental Setup

This study applied thermal comfort information for a specific population in a laboratory scenario that simulates a specific scenario. The specific scenario simulated in this study is an office or learning environment of an office building in a tropical humid climate region in southern North Asia (as shown in Figure 2). Relevant instruments are arranged inside and outside the experimental chamber in advance to measure and record the subjects' basic conditions, sampling conditions, physical environment, physiological parameters, subjective perception, and self-assessment (as shown in Figure 3).

Figure 2. Sampling situation.

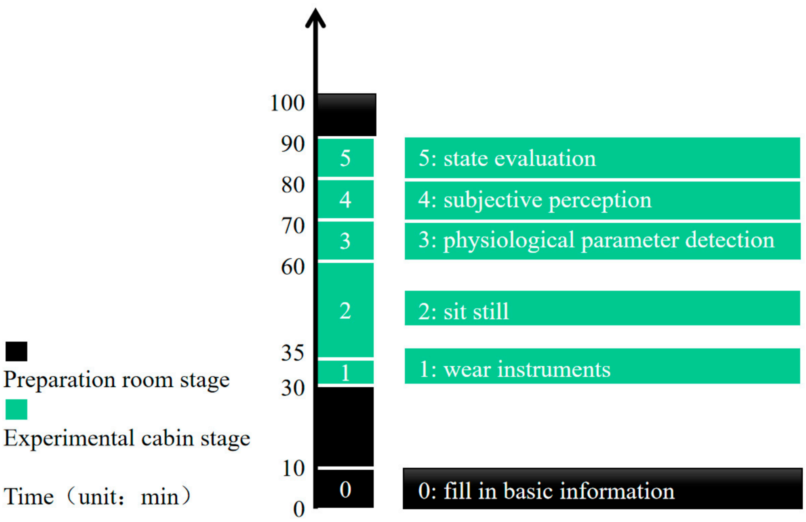

Figure 3. Schematic diagram of the experimental flow.

Sampling population: The subjects are healthy (all without cardiovascular or cerebrovascular diseases or sensory disorders) young people of approximately 20 (20 $\pm$ 2) years old who have lived in Zhangjiagang City (31°43′12″–32°02′ N, 120°21′57″–120°52′ E) for at least one year and are fully adapted to the local climatic conditions.

Sampling time: This sampling was carried out in three time periods (April 2020, April 2021, and December 2021). April is in a transitional climate with comfortable weather, while December is in an extreme climate. Choosing both comfortable and extreme climate experiments can truly demonstrate the participants' feelings towards the environment. The total number of samples collected in the three periods are 48, 108, and 255, respectively.

Sampling procedure: All subjects were required to complete a 90-min experiment. The experimental process was as follows: First, each subject fills in basic personal information and sampling condition information on a sampling information form in the preparation room and enters the experimental chamber after sitting quietly for 30 min. After entering the experimental chamber, the subject reads a book or browses the internet to simulate a relaxed working state for 30 min while wearing a device to adapt to the indoor environment. In 60–90 min, the staff record the physiological parameters of the volunteers and the physical parameters of the indoor environment at that time, and then the subject completes a subjective perception and self-assessment evaluation form. The staff ensure that the form has been properly filled in before the subject is allowed to leave the sampling room.

4.1.1. Sampling Features

The features that affect personal thermal comfort are classified into six categories: basic conditions, sampling conditions, physiological parameters, physical environment, environmental perception, and self-assessment. Each category contains multiple observation indicators. All six categories of indicators are present at each time node. The shared features and extra features are identified from these indicators. Figure 4 summarizes the features observed in this study.

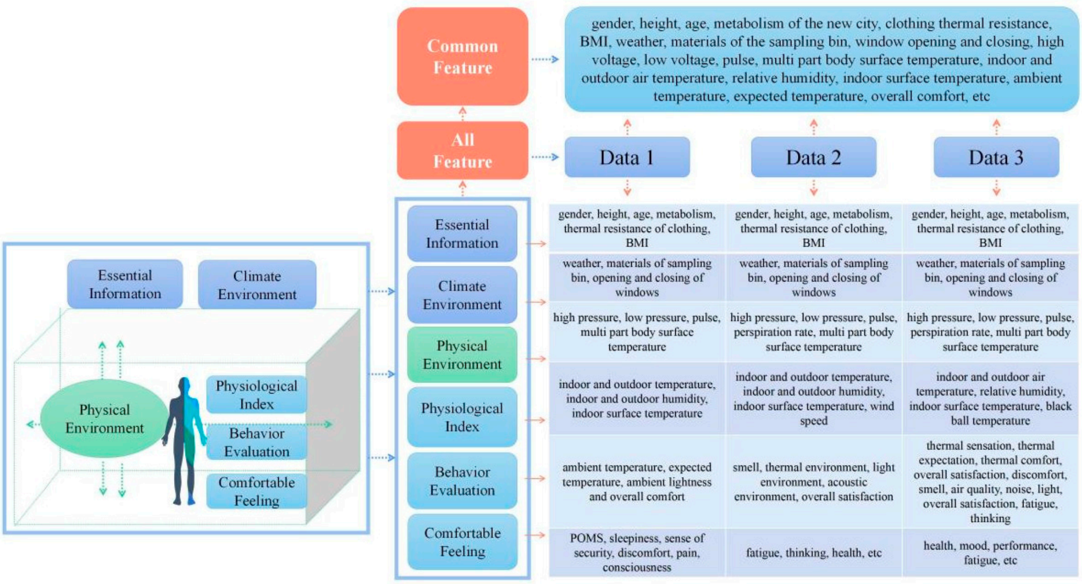

Figure 4. Selected features for the development of SFG-TFC personal thermal comfort models. Data1, Data2 and Data3 were collected in April 2020, April 2021, and December 2021, respectively.

4.1.2. Sampling Labels

In the thermal sensation vote (TSV) scale, which is the most widely accepted scale in recent comfort research, thermal comfort is categorized into seven standards. In the sampling process, this scale is used to obtain the thermal statuses of individuals. In the process of data sorting, the sample labels with individual TSV values of −1, 0, and 1 are defined as comfortable, and the sample labels with individual TSV values less than −1 or greater than 1 are defined as uncomfortable; thereby, constructing binary classification samples, as shown in Figure 5.

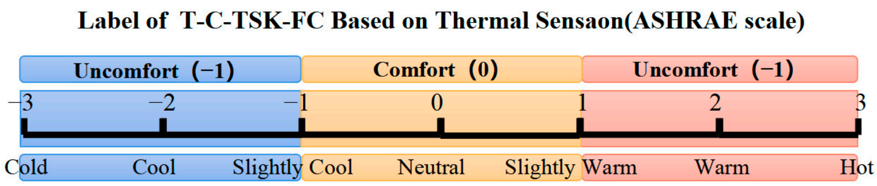

Figure 5. Schematic diagram of thermal sensation classification.

In this study, the datasets sampled using time nodes are processed and grouped, and finally, a training sample of the comfort level of the indoor environment is obtained. Table 1 describes the three experimental datasets in detail. Two of the datasets are used for training, and the remaining dataset is used for testing.

Table 1. Dataset descriptions.

Groups	No. of Samples	No. of Shared Features	No. of Total Features	No. of Classes
Data1 *	48	10	23	2
Data2 *	109	10	34	2
Data3 *	255	10	82	2

* Data1, Data2, and Data3 are the datasets collected in April 2020, April 2021, and December 2021, respectively.

4.1.3. Parameter Settings

The main parameters of this experiment include the number of fuzzy rules K, the number of cluster centers C, coefficient η, and coefficient θ, which can be set in advance. The settings are shown in Table 2.

Table 2. Experimental parameter settings.

Parameters	Values
Number of fuzzy rules K	10~20
C	5
η	(0, 0.1)
θ	(0.005, 0.010)

4.2. Description of the Comparison Algorithms

In this study, the classic algorithms SVM [40] and DBN [41], the 0-order TSK [39], and the multilevel optimization and fuzzy approximation algorithm QI-TSK [42] are used as comparison algorithms to further verify the rationality and superiority of the method proposed in this study. Among the above algorithms, SVM and DBN are classic nonfuzzy machine learning algorithms, and 0-order TSK and QI-TSK are both fuzzy classification algorithms. To further evaluate the classification performance of SFG-TFC, this study compares the proposed algorithm with the abovementioned algorithms. Table 3 describes these algorithms in detail.

4.3. Performance Comparison

(1) Classification performance

Figure 6 shows the classification performance of SFG-TFC. From the training results, SFG-TFC has high and stable classification performance. According to the comparison results, SFG-TFC outperforms the nonfuzzy algorithms DBN and SVM in terms of classification performance. Compared with the classic fuzzy algorithms TSK and QI-TSK, SFG-TFC shows better classification performance. Therefore, SFG-TFC effectively utilizes the shared features of the specific population, strengthens the guiding role of the shared features, and takes into account the compensatory effects of extra features to ensure the classification ability of the final model.

Table 3. Algorithm descriptions.

Compared Algorithms		Main Descriptions of SFG-TFC
Algorithms	**Main Descriptions**	
DBN	(1) In a hierarchical structure with multiple hidden layers, only nodes of adjacent layers are connected. (2) The process of feature learning has better feature expression.	(1) Fuzzy inference of shared features: The method of information gain is used to extract the key shared features from the subdatasets and perform fuzzy inference on the key shared features to obtain the rule output matrix of the key shared features. (2) Information reprojection of the shared features: The rule output matrix of the key shared features is reprojected to the rule output matrix of the extra features of each base training unit to strengthen the guiding role of the key shared features in determining human thermal comfort while considering the learning and coordination of the extra features. (3) Output weights: The output weight information of all basic training units is integrated to improve the generalization performance. (4) Fuzzy rules: These rules have high usability and interpretability.
SVM	(1) A generalized linear classifier that binarily classifies data based on supervised learning. The decision boundary of the classifier is the largest-margin hyperplane for the learning samples. (2) A few support vectors determine the final result.	
0-TSK	(1) The output is a constant. (2) Fuzzy rules are highly interpretable.	
Q I-TSK	(1) The basic construction unit of QI-TSK-fc (td > 1) is composed of an optimized zero-order TSK fuzzy classifier. Each basic building unit is consistent with the adjacent basic building unit. (2) Fuzzy rules and features are highly interpretable. (3) The algorithm does not need to be iterated.	

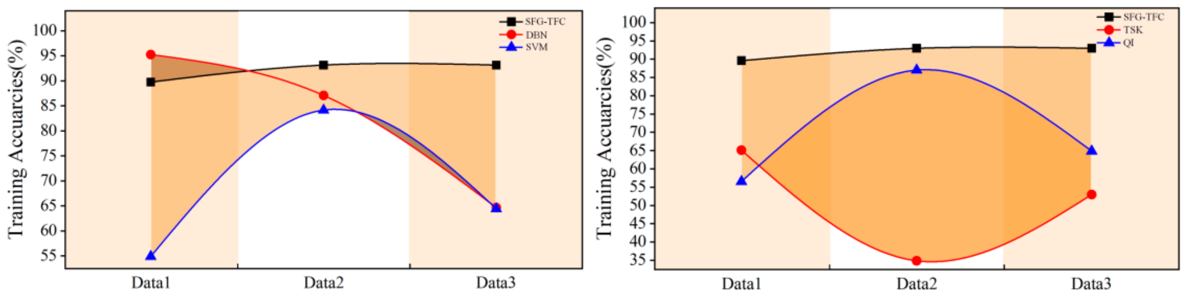

Figure 6. Schematic diagram of the classification performance.

(2) Generalization performance

Figure 7 demonstrates that the generalization performance of SFG-TFC is stable. The generalization ability of SFG-TFC is comparable to those of the nonfuzzy algorithms DBN and SVM. Compared with the classic fuzzy algorithms 0-order TSK and QI-TSK, SFG-TFC exhibits better generalization performance. This study demonstrates that this advantage may stem from the integration of all output weights at multiple time nodes in the final training process, which optimizes the final output weights; thereby, improving the generalization performance of the model. Therefore, the method of integrating the output weights of all basic training units improves the stability and generalization performance of the SFG-TFC model.

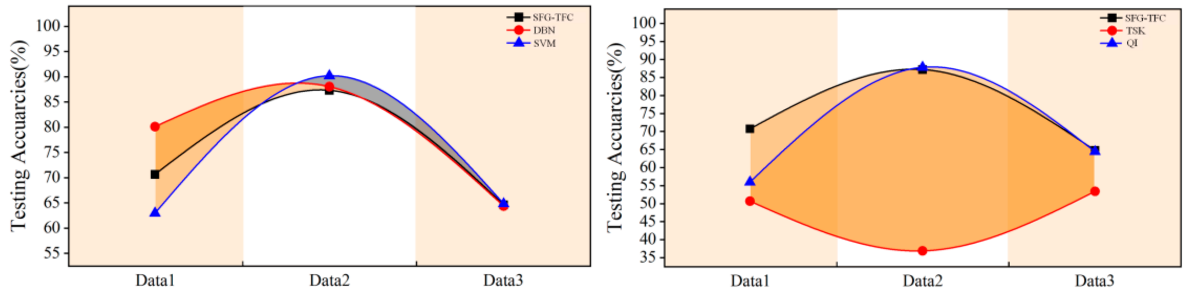

Figure 7. Schematic diagram of the generalization performance.

(3) Shared feature-guided optimization

Figure 8 compares the thermal comfort models with and without the guidance of the shared features of the specific population and identifies the impact of the shared features on the classification and generalization performance. The thermal comfort model without the guidance of shared features is constructed as follows. The subdatasets obtained at the $M-1$ time nodes are trained using the basic training module to obtain the corresponding rule output matrix and output weights. The output weights of the training module are integrated to obtain the final output of the model. SFG-TFC has good classification accuracy. Hence, it is feasible to use the shared features of a specific population as guidance.

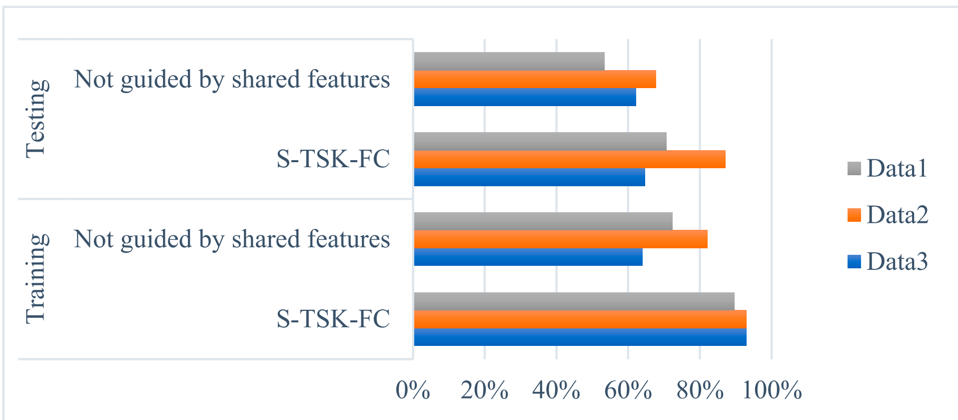

Figure 8. Performance comparison of SFG-TFC with and without shared feature guidance.

(4) Optimization of the output weights

To further verify the rationality of the output weight integration method proposed in this study, we construct a thermal comfort model that does not integrate the output weight information of the first $M-1$ base training units into the M-th training unit and compare it with the SFG-TFC to observe the impact of these two model construction methods on classification and generalization performance. According to Figure 9, SFG-TFC exhibits better classification and generalization performance than the thermal comfort model without integrating the output weights. The experimental results demonstrate that the output weight integration method proposed in this study makes the output weight of each basic training unit supervise the decision-making process of the model, which is stable and reasonable.

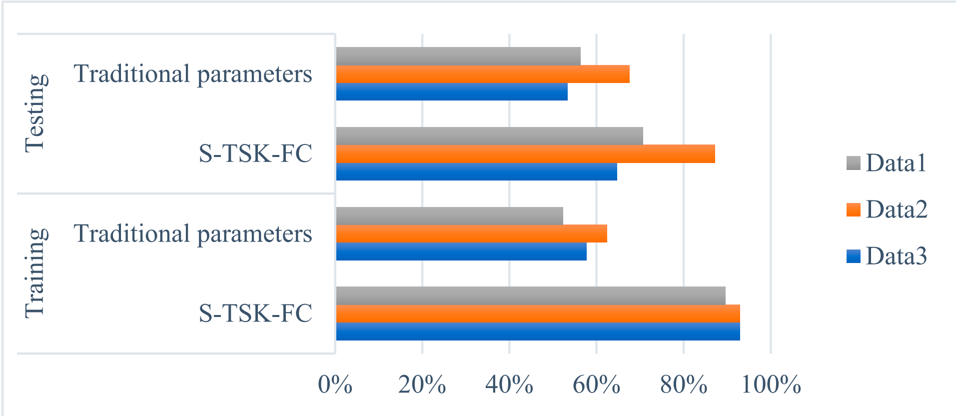

Figure 9. Performance comparison of the SFG-TFC with and without output weight integration.

4.4. Discussion

Advantages: The experimental results confirm the rationality of the proposed method of constructing the personal thermal comfort model based on the SFG-TFC model for a specific population guided by shared features and supplemented by extra features. Strategies such as fuzzifying key shared features, reprojecting the information of key shared features, and integrating the output weights are all effective, which improve the learning efficiency and the classification and generalization performance of the fuzzy classifier during the modelling process. In addition, the semantics of the outputs of the intermediate layers of SFG-TFC training, the output of each fuzzy rule, and the output of the final fuzzy classifier are all interpretable.

Disadvantages: In this study, the parameters of the thermal comfort model need to be set manually. Therefore, there is no way to obtain the hyperparameter combination of the parameters used. In addition, the datasets applied in this study is sourced from experimental cabin sampling. Due to the long duration of each sampling, the real-time status, cooperation level, and equipment accuracy of the subjects will affect the classification performance. Finally, the thermal comfort model in this study is only applicable to small sample datasets (i.e., the size of the training samples is usually small). If it is to be applied to large sample datasets, its relevant parameters still need to be further adjusted.

4.5. Analysis of the Semantic Interpretability

The interpretability of the TSK-FC classifier is crucial to facilitating building environmental design. This study introduces a form of rule representation that considers two types of features. First, c_i^k is normalized, and the corresponding coordinates are determined. In this study, the number of coordinates of all cluster centers is set equal to the corresponding number of fuzzy partitions. The interval range of a cluster center is defined by the average of its preceding cluster center and its succeeding cluster center (Figure 10). Each interval is assigned a corresponding semantic interpretation. For example, Data1 is selected as the final training data, Fi (i = 1,2, . . . ,10) are the key shared features, and Fi (i = 11,12, . . . ,23) are the extra features. Three rules are randomly selected from all fuzzy rules obtained by SFG-TFC. Taking F1 and F23 as examples, F1 and F23 each have five center points (that is 0.001, 0.490, 0.685, 0.735, 0.999 and 0.001, 0.632, 0.633, 0.830, 0.999), the corresponding fuzzy partitions are divided into (0.000,0.240), (0.240,0.588), (0.588,0.710), (0.710,0.867), (0.867,1.000) and (0.000,0.316), (0.316,0.633), (0.633,0.732), (0.732,0.915), (0.915,1.000), and the corresponding semantics are interpreted as *very low*, *low*, *medium*, *high*, and *extremely high*, respectively, which are identified by 1,2,3,4,5 respectively.

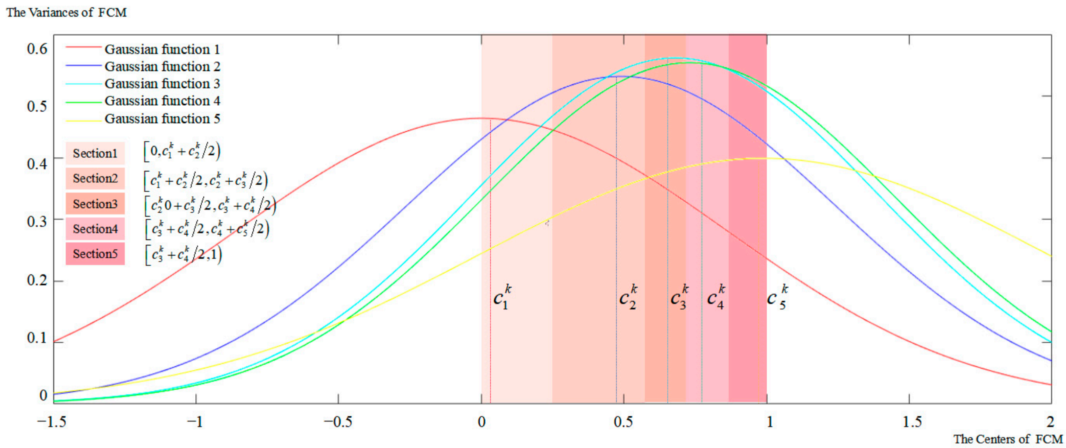

Figure 10. Division of fuzzy partitions.

Figure 11 summarizes this process in "if-then" form. Rule 1 can easily be expressed as follows:

IF						THEN
Features	Shared Features			Extra Features		y^k
	1	2	…	…	23	
Rule1	$e^{-\frac{1}{2}\left(\frac{x_1-0.685}{0.709}\right)^2}$ 3	$e^{-\frac{1}{2}\left(\frac{x_2-0.735}{0.717}\right)^2}$ 4	…	…	$e^{-\frac{1}{2}\left(\frac{x_{24}-0.633}{0.984}\right)^2}$ 3	0.475
Rule2	$e^{-\frac{1}{2}\left(\frac{x_1-0.001}{0.867}\right)^2}$ 1	$e^{-\frac{1}{2}\left(\frac{x_2-0.490}{0.750}\right)^2}$ 2	…	…	$e^{-\frac{1}{2}\left(\frac{x_{24}-0.632}{0.983}\right)^2}$ 2	−1.901
…	…			…		…
Rule19	$e^{-\frac{1}{2}\left(\frac{x_1-0.001}{0.867}\right)^2}$ 1	$e^{-\frac{1}{2}\left(\frac{x_2-0.685}{0.709}\right)^2}$ 3	…	…	$e^{-\frac{1}{2}\left(\frac{x_{24}-0.633}{0.984}\right)^2}$ 3	0.750

Figure 11. Partial rule descriptions.

5. Conclusions

According to fuzzy modeling, this study constructed a shared feature-guided personal thermal comfort model (SFG-TFC) with extra feature compensation for a specific population to observe the impact of different building environments on personal thermal comfort. The output of SFG-TFC is the comfort value of each subject, its classification and generalization performance are compared with actual feelings. The output results of the model reflect the participants' true reactions to the indoor environment under climate conditions in April or December. In contrast to previous research, this study classified the training features into shared features and extra features according to the features of the data and built different TSK fuzzy classifiers to be trained on the two types of features separately, which not only strengthened the guiding role of the shared features but also considered the important compensatory effect of the extra features, making the two types of features complementary in physical semantics. In addition, the output weights were integrated to improve the generalization performance of the model. Extensive experimental results verified the superiority and semantic interpretability of the model proposed in this study Relevant parameters (such as the number of rules in each basic training unit and the training depth) must be set in advance to make the model suitable for actual application scenarios. In future, we must also consider how to quantitatively characterize the association relationship between shared features and extra features.

Author Contributions: Methodology, W.L.; Software, Z.X.; Formal analysis, W.L., W.Y. and T.Z.; Investigation, Z.X. and W.X.; Data curation, Z.X.; Writing—original draft, Z.X., Z.H. and F.J.; Visualization, T.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Key Research and Development Program of China (No.2017YFC0703506); the national natural science foundation of Jiangsu, China under Grant BK20191200; the natural science foundation of Jiangsu Universities, China under Grant 19JKD520003; the Jiangsu Graduate Scientific Research Innovation Project under Grant KYCX21_3506 and KYCX22_3825; and the Suzhou Science and Technology Plan Project (SNG2022015).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data generated or analyzed in this research were included in this published article. Additionally, readers can access all data used to support conclusions of the current study from the corresponding author upon request.

Conflicts of Interest: The authors declare no conflict of interest.

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