# An Integrated Framework of Product Kansei Decision-Making Based on Hesitant Linguistic Fuzzy Term Sets

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**Abstract.** Kansei adjectives have the advantage of close to consumers' perception of a product. But consumers may show hesitation and opinion discrepancy while expressing their preferences through comparative Kansei adjectives. To address this, this article investigates hesitant linguistic expression and its application in product Kansei decision-making. An integrated framework is firstly presented based on hesitant fuzzy linguistic term sets (HFLTSs), which involves a consensus model for assessing consistency of consumers' preferences, particle swarm optimization (PSO) method for adjusting Kansei opinions when agreement fails, and the technique for order preference by similarity to an ideal solution (TOPSIS) for yielding ranked product solutions. An example of charging piles design was used to illustrate the necessity of considering consumers' hesitation in Kansei decision-making. With the proposed method, the consensus level of consumers' preferences is enhanced from 0.8339 to 0.9052, and the overall satisfaction degree is also improved. Furthermore, the results of Kansei decision-making through optimizing Kansei preferences are significantly different from that without optimization. This improvement demonstrates that hesitance and consensus change will influence design decision-making and they should be considered in product Kansei decision-making. The given example shows the validity and suitability of the proposed approach.

**Keywords:** Kansei engineering · Product Kansei decision-making · Hesitant fuzzy linguistic term sets · Consensus reaching · Particle swarm optimization

## 1 Introduction

In today's rapid growing and competitive market, consumer-centered approach has attracted increasing attentions of many companies as a vital strategy for product development. It can help enterprises to enhance their market competitiveness and save time and costs during product development. The core of consumer-centered approach is to have a better understanding of consumers' requirements, which includes two aspects:


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physiological and psychological. The former mainly involves functional attributes of products while the latter refers to subjective needs and feelings [1]. It is widely believed that similar products will have equivalent function, and it may be difficult for consumers to differentiate products only by their function [2, 3]. Moreover, good quality products are not enough for a company to survive in the increasing competitive market [4]. In this regard, satisfying consumers' needs not only depends on the reliability and physical quality of products, but also the affective aspects evoked by various product design elements [5]. One of the influential factors is attractive product appearance, which can affect consumers' intuitive perception and first impression, generate affective resonance, and lure them into making purchase decisions. The unique emotional value related to beauty or aesthetics of a product is also used to attract the attention of potential consumers [6].

To study the affective influence on consumers, Kansei Engineering (KE) has been proposed and used to link emotions to product properties [7, 8]. Covering the meanings of sensibility, impression and emotion, Kansei means all the senses of an individual's subjective impression and recognition from a certain artifact, environment, or situation, as described by Nagamachi [9]. KE methodology aims to integrate consumers' psychology and translate them into appropriate product design elements [10]. It has been proven that this technique is capable of testing the different feeling and shows their relation with characteristics of real production requirements by associating with consumers' physiological and psychological feelings [11]. For decades, KE has been developed as a consumer-oriented technique and connected to the industrial world to create numerous successful products and innovations [12].

An important KE type is KE modeling for assessing consumers' feeling of Kansei words [7]. It mainly involves attribute classification, preference modeling, and priority analysis [13]. When performing these operations, a common practice taken by many researchers is to convert users' Kansei preferences to numerical values for quantifying qualitative perception. However, it may result in loss of information because consumers tend to prefer Kansei adjectives or words to express their preferences rather than numerical values [14, 15]. Another common practice is that users' preferences are depicted by discrete concrete numbers or fuzzy numbers. Nevertheless, this may not accurately reflect the true intentions of users due to respondent bias when users are unable or unwilling to provide accurate answers. The third issue for Kansei assessment is hesitance in making preference, which reflects consumers' uncertainty about comparative linguistic terms. For example, a consumer's perception may be irresolute and swing between "very comfortable" and "comfortable", but the exact description cannot be given and the final perception may be "no worse than comfortable". In this situation, both "comfortable" and "very comfortable" should be used for preference representation. The three issues mentioned above are the key to elevating the quality of design decision-making and affect consensus reaching of group opinions.

In general, Kansei preference data is better to be treated as semantic variables than SD method [16], and using fuzzy linguistic term sets to deal with consumers' Kansei preference as continuous variables is more in line with their perception. Besides, hesitance and opinion discrepancy often happen when consumers make a choice. However, these problems have got little attention in product Kansei decision-making process.

Aiming at these issues of product Kansei decision-making, this paper presents an integrated framework based on hesitant fuzzy linguistic term sets (HFLTSs), which involves a consensus model for assessing consistency of consumers' preferences, particle swarm optimization (PSO) method for adjusting Kansei opinions when agreement fails, and the technique for order preference by similarity to an ideal solution (TOPSIS) for yielding ranked product solutions. Accordingly, the remainder of the paper is organized as follows: Sect. 2 introduces preliminaries of the proposed method, including linguistic variables and HFLTSs. In Sect. 3, an integrated framework is proposed. Then, a numerical example is provided to illustrate the detailed implementation of the proposed method in Sect. 4. Finally, Sect. 5 makes the concluding remarks and contribution of this paper.

## 2 Preliminaries

### 2.1 Linguistic Variables

The essential part of fuzzy linguistic approach are fuzzy sets as they provide a means of modeling vagueness underlying most natural linguistic terms [17, 18]. For Kansei decision-making problems, adjectives of emotional connotations can be regarded as a fuzzy set $U$ defined by its membership function $\mu : U \rightarrow [0, 1]$, where $U$ is a nonempty set [19]. With fuzzy sets, fuzzy linguistic approach can be founded based on linguistic variables introduced by Zadeh [20–22], which takes words or sentences to model the linguistic information. A linguistic variable is formally defined as follows.

**Definition 1** [20]. A linguistic variable is characterized by a quintuple $(L, T(L), U, S, M)$ in which $L$ is the name of the variable; $T(L)$ denotes the term set of $L$, i.e., the set of names of linguistic values of $L$, with each value being a fuzzy variable that is denoted generically by $X$ and ranging across a universe of discourse $U$, which is associated with the base variable $u$; $S$ is a syntactic rule (which usually takes the form of a grammar) for the generation of the names of values of $L$; and $M$ is a semantic rule for associating its meaning with each $L$, $M(X)$, which is a fuzzy subset of $U$. With triangular fuzzy numbers, the composition of a quintuple of Kansei adjective "comfortable" is illustrated in Fig. 1.

Using ordered linguistic term sets, Xu [23] defined a set of linguistic terms as $S = \{s_\alpha | \alpha \in \{-\tau, \cdots, 0, \cdots, \tau\}\}$ with 0 as the symmetric center and odd number of linguistic terms. Let $\tau = 3$ then we can get a Likert-7 scale which is often used in measuring consumers' Kansei preferences, shown as follows:

$S = \{s_{-3}$: not at all, $s_{-2}$: low, $s_{-1}$: slightly, $s_0$: neutral, $s_1$: moderately, $s_2$: very, $s_3$: extremely$\}$.

With ordered finite subset of consecutive linguistic terms, it is obvious that $s_\alpha \leq s_\beta \Leftrightarrow \alpha \leq \beta$. If a negation operator exists, then we can have $\mathrm{Neg}(s_\alpha) = s_{-\alpha}$.

In order to preserve all given information, Xu [24] further extended the discrete linguistic term set $S$ to the continuous linguistic term set $\overline{S} = \{s_\alpha | \alpha \in [-t, t]\}$, where $t$ is a sufficiently large positive integer. In general, the linguistic terms $s_\alpha (s_\alpha \in S)$ are given by decision makers while the extended linguistic terms $\bar{s}_\alpha (\bar{s}_\alpha \in \bar{S})$ only appear in operations.

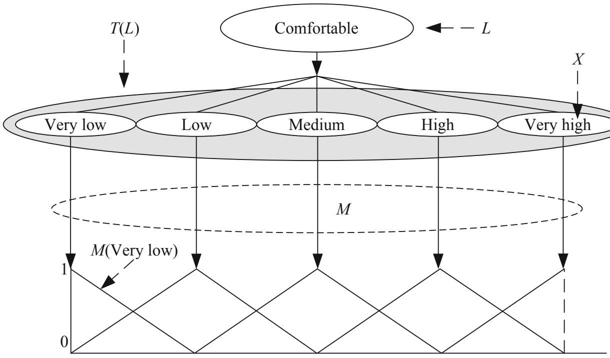


**Fig. 1.** A quintuple of the Kansei adjective "comfortable"

Let $\mu, \mu_1, \mu_2 > 0$, $s_\alpha, s_\beta \in \bar{S}$. The basic operation rules of linguistic variables are as follows [25].

(1) $s_\alpha \oplus s_\beta = s_{\alpha+\beta}$;
(2) $\mu s_\alpha = s_{\mu\alpha}$;
(3) $(\mu_1 + \mu_2)s_\alpha = \mu_1 s_\alpha \oplus \mu_2 s_\beta$;
(4) $\mu(s_\alpha \oplus s_\beta) = \mu s_\alpha \oplus \mu s_\beta$.

### 2.2 HFLTSs

For product Kansei decision-making, consumers' preferences may sway or hesitate between two or more options. In such situation, singleton linguistic term may be not suitable to represent their judgment. To denote the hesitancy over several linguistic terms, HFLTSs are employed to represent and aggregate consumers' Kansei preferences.

**Definition 2** [26]. Let $S$ be a linguistic term set, $S = \{s_\alpha | \alpha \in \{-\tau, \cdots, 0, \cdots, \tau\}\}$. An HFLTS, $H_S$, is an ordered finite subset of the consecutive linguistic terms of $S$.

Using the example from the previous section, we can get two different HFLTSs as:

$$H_S^1 = \{s_{-1} : \text{ slightly}, \ s_0 : \text{ neutral}\},$$
$$H_S^2 = \{s_1 : \text{ moderately}, \ s_2 : \text{ very}, \ s_3 : \text{ extremely}\}.$$

The basic operations and computations that will be performed on the HFLTS in this paper are as follows.

(1) The upper bound $H_{S+}$ and lower bound $H_{S-}$:

$$H_{S+} = \max\{s_i | s_i \in H_S\}, \ H_{S-} = \min\{s_i | s_i \in H_S\}.$$

(2) The envelope $\mathrm{env}(H_S)$ of the HFLTS:

$$\mathrm{env}(H_S) = [H_S^-, H_S^+].$$

In order to operate correctly when comparing two HFLTSs, Zhu and Xu [27] proposed a method to add linguistic terms in a HFLTS:

$$\bar{H}_S = \xi H_{S+} \oplus (1 - \xi) H_{S-} \tag{1}$$

where $\xi(\xi \in [0, 1])$ is an optimized parameter. $\xi = 1$ and $\xi = 0$ correspond with the optimism and pessimism rules, respectively. Without loss of generality, we set $\xi = 0.5$ in this paper.

## 3 An Integrated Framework for Kansei Decision-Making

On account of the function of HFLTSs for aggregating consumers' Kansei preferences, an integrated framework of product Kansei decision-making is proposed, including a consensus model, PSO and TOPSIS. The flow chart of the proposed framework is shown in Fig. 2.

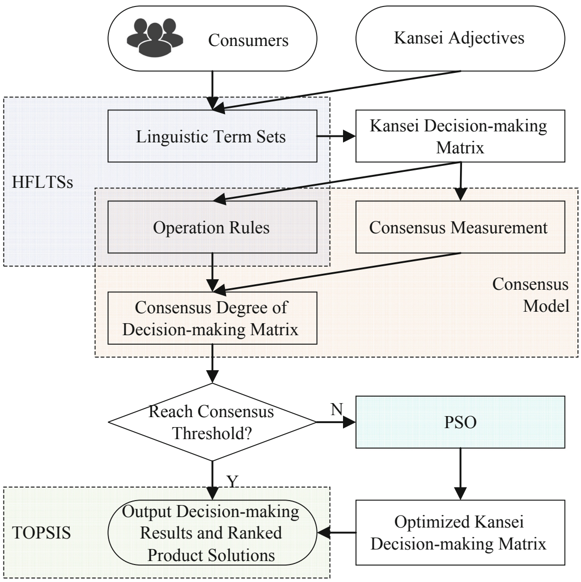


**Fig. 2.** The integrated framework of the proposed method

In the framework with HFLTSs employed, a consensus model is built to gauge their consistency, as is expected that the final decision should be reached based on a wide enough agreement. When disagreement fails to meet an acceptable consensus degree, PSO will be adopted to adjust the Kansei opinions and finally the ranked product solutions will be output with TOPSIS. The following expounds the details of the framework.

### 3.1 Consensus Model

Let $D = \{d_1, d_2, \cdots, d_q\}$ $(q \geq 2)$ be a set of consumers who are invited to participate in product Kansei decision-making about a set of product design alternatives $X = \{x_1, x_2, \cdots, x_n\}$ $(n \geq 2)$. Assume that the set of Kansei indicators is $C = \{c_1, c_2, \cdots, c_m\}$ $(m \geq 2)$. A linguistic term set, $S = \{s_\alpha | \alpha \in \{-\tau, \cdots, 0, \cdots, \tau\}\}$, is used to collect consumers' preference information. Then we have the decision matrix of HFLTS:

$$A^{(k)} = [H_{ij}^{(k)}]_{n \times m} \tag{2}$$

where $k = 1, 2, \cdots, q$; $H_{ij}^{(k)}$ represents the judgment of product alternative $x_i$ given by consumer $d_k$ in terms of Kansei indicator $c_j$.

In product Kansei decision-making process, the opinions of consumers will be aggregated when they reach a certain level of agreement or consensus to assure a high reliability of decision-making result. In order to evaluate the consistency of decision matrix, similarity function is an effective tool, which is usually used to build mathematical consistency model by measuring the proximity of consumers' preferences [28].

For a Kansei indicator, suppose that $H_S^1 = \{s_{\delta_l^1} | s_{\delta_l^1} \in S\}$ and $H_S^2 = \{s_{\delta_l^2} | s_{\delta_l^2} \in S\}$ are two HFLTSs given by two consumers, and $l(H_S^k)(k = 1, 2)$ represents the number of elements in $H_S^k$. Then the Euclidean distance between $H_S^1$ and $H_S^2$ can be defined as [29]:

$$D(H_S^1, H_S^2) = \left( \frac{1}{L} \sum_{l=1}^{L} \left( \frac{\left| \delta_l^1 - \delta_l^2 \right|}{2\tau + 1} \right)^2 \right)^{1/2} \tag{3}$$

where $L = l(H_S^1) = l(H_S^2)$ (otherwise, the shorter one should be extended by adding the linguistic terms given as Eq. (1)).

Let $w_j (j = 1, 2, \cdots, m)$ represent the weight of Kansei criteria. The distance between two product Kansei decision matrices $A^{(k)} = [H_{ij}^{(k)}]_{n \times m}$ and $A^{(l)} = [H_{ij}^{(l)}]_{n \times m}$ can be described as:

$$d(A^{(k)}, A^{(l)}) = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{m} w_j d(H_{ij}^{(k)}, H_{ij}^{(l)}) \tag{4}$$

Accordingly, the consensus degree between $A^{(k)}$ and $A^{(l)}$ can be computed as:

$$CON(A^{(k)}, A^{(l)}) = 1 - d(A^{(k)}, A^{(l)}) \tag{5}$$

Then the consensus level of all consumers whose judgements are represented in the set $(A^{(1)}, A^{(2)}, \cdots, A^{(q)})$ can be obtained as follows:

$$CONS = \frac{1}{q(q-1)} \sum_{\substack{k=1 \\ k \neq l}}^{q} \sum_{l=1}^{q} CON(A^{(k)}, A^{(l)}) \tag{6}$$

### 3.2 PSO for Consensus Reaching by Adjusting Consumers' Preferences

Agreement of the majority of consumers is essential for design decision-making. However, it is likely not to reach a consensus easily due to cognitive discrepancy. Comparing to ask consumers to change their opinions, it is more effective to employ intelligent algorithms to search for satisfactory solutions of consumers' opinions that meet a consensus threshold instead of finding the optimal value. With the advantage of ease of implementation, high degree of stability and fast convergence to acceptable solutions [30–32], PSO is suitable for consensus optimization. As a population based self-adaptive, stochastic optimization technique [33], all population members in PSO survive from the beginning of a trial until the end rather than are selected and evolve in evolutionary algorithms. Due to that particle interactions result in iterative improvement of the quality of problem solutions over time with few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions [34], the PSO techniques are taken to seek consensus with adjustment of consumers' preferences. Each candidate solution in PSO, called a particle, flies in the $N$-dimensional search space according to a speed. Suppose that there are $M$ particles in the swarm, and then particle $p_j$ has a position $p_j = (p_{1j}^T, p_{2j}^T, \cdots, p_{mj}^T)^T$ and a velocity $v = (v_{1j}, v_{2j}, \cdots, v_{mj})$, where $p_{1j}^T, p_{2j}^T, \cdots, p_{mj}^T$ represents the automatically adjusted preferences of consumers. The velocity decides the flying distance and direction, and Eq. (6) is used as target optimization function. Thus, the velocity and location updating of a particle can be calculated as follows:

$$\begin{cases} v_{\alpha\beta}(t+1) = \omega v_{\alpha\beta}(t) + c_1 r_{1\beta}(t)(pbest_{\alpha\beta}(t) - x_{\alpha\beta}(t)) + c_2 r_{2\beta}(t)(gbest_\beta - x_{\alpha\beta}(t)) \\ x_{\alpha\beta}(t+1) = x_{\alpha\beta}(t) + v_{\alpha\beta}(t+1) \end{cases} \tag{7}$$

where $t$ is the iteration number; $v_{\alpha\beta}(t)$, $x_{\alpha\beta}(t)$ represent the velocity and position of particle $\alpha$ in the $\beta$ dimension, respectively; $pbest_{\alpha\beta}(t)$ is the current best position of particle $\alpha$; $gbest_\beta$ shows the best fit that any particle of the swarm has ever achieved; $r_{1\beta}(t)$ and $r_{2\beta}(t)$ are two random numbers ranging from 0 and 1; $c_1$ and $c_2$ are two positive constants, denoting the cognitive and social components respectively; $\omega$ is the inertia of the particle which is employed to improve the convergence of the swarm. Linearly Decreasing Inertia Weight (LDW) is often used to enhance the global exploration ability for searching in a larger space by increasing the value of $\omega$ when the evolution speed of the swarm is fast, and maintain the particles searching in a small space to find the optimal solution more quickly by decreasing the value of $\omega$ if the evolution speed of particles slows down. $\omega$ can be calculated as follows [35]:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{t\_\max} \times t \tag{8}$$

where $t\_\max$ is the maximal iteration generations of PSO; $\omega_{\max}$ and $\omega_{\min}$ represent the maximum and minimum of $\omega$ respectively. Generally, $\omega$ linearly decreases from 0.9 to 0.4.

### 3.3 TOPSIS

When consumers' preferences come to an agreement, the TOPSIS [36] method will be employed to determine the orders of product alternatives. The basic principle of TOPSIS is to calculate the distance between each HFLTS and the hesitant fuzzy linguistic positive ideal solution, and the distance between each HFLTS and the hesitant fuzzy linguistic negative ideal solution, respectively. The closer to the positive ideal solution and the farther from the negative ideal solution, the better the alternative.

Kansei adjectives utilized to describe consumers' perceptions reflect their expectations about a product. They are benefit-type criteria. Hence, for each HFLTS in $A^{(k)} = [H_{ij}^{(k)}]_{n\times m}$, utilizing the upper bound $H_{S+}$ and lower bound $H_{S-}$, the hesitant fuzzy linguistic positive ideal solution $A_+$ and the hesitant fuzzy linguistic negative ideal solution $A_-$ can be defined as follows:

$$\begin{cases} A_+ = \{H_S^{1+}, H_S^{2+}, \cdots, H_S^{m+}\} \\ A_- = \{H_S^{1-}, H_S^{2-}, \cdots, H_S^{m-}\} \end{cases} \tag{9}$$

where $H_S^{j+}(j = 1, 2\cdots, m) = \max\limits_{\substack{i=1,2,\cdots,n \\ k=1,2,\cdots,q}} \{s_{\delta_l} | s_{\delta_l} \in H_{ij}^{(k)}\}$, $H_S^{j-}(j = 1, 2\cdots, m) = \min\limits_{\substack{i=1,2,\cdots,n \\ k=1,2,\cdots,q}} \{s_{\delta_l} | s_{\delta_l} \in H_{ij}^{(k)}\}$.

For ranking the product design schemes according to the idea of TOPSIS, the distance between each HFLTS and the positive ideal solution $A_+$ (denoted by $d(A_j^{(i)}, A_+)$), and the distance between each HFLTS and the negative ideal solution $A_-$ (denoted by $d(A_j^{(i)}, A_-)$) are computed using Eq. (4) respectively. Then the Kansei satisfaction degree of a product design alternative can be defined as:

$$\eta(x_i) = \frac{1}{q}\sum_{j=1}^{q} \frac{(1-\theta)d(A_j^{(i)}, A_-)}{\theta d(A_j^{(i)}, A_+) + (1-\theta)d(A_j^{(i)}, A_-)} \tag{10}$$

where the parameter $\theta$ denotes the risk preferences of the decision maker: $\theta > 0.5$ means that the decision maker is pessimists; while $\theta < 0.5$ means the opposite. Without loss of generality, we choose $\theta = 0.5$.

## 4 Case Study

A case study of charging piles design for electric vehicles was used to determine the proposed method's ability for reaching consensus in product Kansei decision-making process. To collect consumers' Kansei needs effectively, various charging piles were involved in this research, covering current production and concept design. 43 Kansei adjectives about product samples were collected from websites, literatures, product manuals, magazines, experts, industrial designers, experienced users and dissertations. Adjectives with antonyms were paired up and others were endowed with right antonyms, and based on this we used an NDSM-GA based approach which was discussed in our previous research [37] to cluster consumers' Kansei needs into several categories and clarify primary adjectives. Finally, we obtained 4 Kansei adjectives to evaluate consumers' response about product design alternatives, shown as follows: (1) technological; (2) dynamic; (3) modern; (4) futuristic. 3 industrial designers were asked one each to

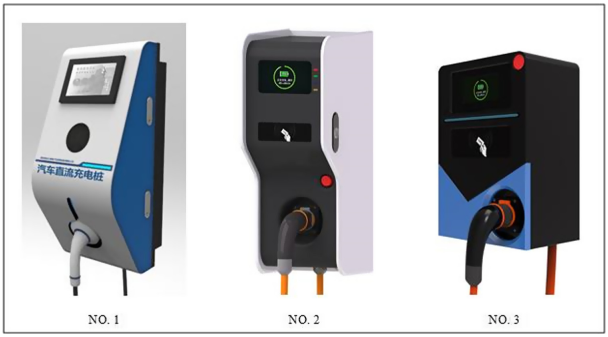


**Fig. 3.** Charging piles design solutions

give a design solution according to consumers' Kansei needs and the requirement of the principal, who requested the product to be processed by sheet metal (seen in Fig. 3).

Through questioning the designers, the styling features of 3 product solutions were articulated to consumers. 5 consumers who intended to buy or use charging piles were randomly selected and invited to give their preferences about the alternatives according to the Kansei indices, which were represented through linguistic terms of $S = \{s_{-3}$: not at all, $s_{-2}$: low, $s_{-1}$: slightly, $s_0$: neutral, $s_1$: moderately, $s_2$: very, $s_3$: extremely$\}$.

The Kansei decision-making matrices are shown below:

$$A^{(1)} = \begin{bmatrix} \{s_2, s_3\} & \{s_2, s_3\} & \{s_3\} & \{s_1, s_2\} \\ \{s_1\} & \{s_2, s_3\} & \{s_1, s_2\} & \{s_2\} \\ \{s_1, s_2\} & \{s_0\} & \{s_2\} & \{s_1\} \end{bmatrix};$$

$$A^{(2)} = \begin{bmatrix} \{s_2\} & \{s_3\} & \{s_2, s_3\} & \{s_2\} \\ \{s_1, s_2\} & \{s_1, s_2\} & \{s_1\} & \{s_0, s_1, s_2\} \\ \{s_2\} & \{s_0, s_1\} & \{s_{-2}\} & \{s_1\} \end{bmatrix};$$

$$A^{(3)} = \begin{bmatrix} \{s_0\} & \{s_1\} & \{s_{-1}, s_0\} & \{s_1, s_2\} \\ \{s_1, s_2\} & \{s_1, s_2\} & \{s_1\} & \{s_0, s_1\} \\ \{s_0, s_1, s_2\} & \{s_0, s_1\} & \{s_1, s_2\} & \{s_1, s_2\} \end{bmatrix};$$

$$A^{(4)} = \begin{bmatrix} \{s_1, s_2\} & \{s_{-1}, s_0\} & \{s_2, s_3\} & \{s_1\} \\ \{s_2\} & \{s_1, s_2\} & \{s_0, s_1, s_2\} & \{s_1\} \\ \{s_1, s_2\} & \{s_{-1}\} & \{s_2\} & \{s_0\} \end{bmatrix};$$

$$A^{(5)} = \begin{bmatrix} \{s_{-2}\} & \{s_0, s_1\} & \{s_2\} & \{s_{-1}, s_0\} \\ \{s_1, s_2\} & \{s_0\} & \{s_1, s_2\} & \{s_0, s_1\} \\ \{s_1, s_2\} & \{s_0\} & \{s_{-1}, s_0\} & \{s_1, s_2\} \end{bmatrix}.$$

The 4 Kansei indices were given equal weight by investigating consumers' opinions. Using Eq. (1)–Eq. (6), the consensus matrix can be obtained as:

$$CON = \begin{bmatrix} 1 & 0.86363 & 83287 & 0.86980 & 0.79250 \\ 0.86363 & 1 & 0.83630 & 0.82562 & 0.80895 \\ 0.83287 & 0.83630 & 1 & 0.84212 & 0.84917 \\ 0.86980 & 0.82562 & 0.84212 & 1 & 0.81783 \\ 0.79250 & 0.80895 & 0.84917 & 0.81783 & 1 \end{bmatrix}$$

The consensus threshold value was set as 0.9, and the overall consensus of consumers was 0.8339, which did not reach the specific threshold and the Kansei decision-making matrices should be adjusted using PSO.

Generally, particle swarm size ranges from 10 to 50 depending on different applications and problems [30], and here its value was set as 10. $c_1$ and $c_2$ belong to the range of [0, 4], and $c_1 = c_2 = 2$ may be preferable. $t\_max$ was set to 500. By asking consumers' advice, the adjustment space of consumers' preferences was set to [− 0.5, 0.5]. Yet the adjusted value should fall in the range of $-3$ and 3. There were 120 parameters that would be adjusted and searched in the bound. The adjustment rules are as follows: (1) if there is only one element in an HFLTS, it will be extended to three equal elements; (2) if there are two or three elements, the lower bound and the upper bound will be extended by $-0.5$ and 0.5 respectively, and the intermediate elements are calculated according to Eq. (1).

After 100 operations by using PSO, the optimal consensus value distribution was obtained, shown in Fig. 4. Figure 5 shows the convergence process of the algorithm and Fig. 6 depicts the mean deviation change in one of the operations. It can be seen that the optimal consensus value was found in each generation and mean deviation between the optimal matrix and the original matrix did not outnumber 0.07.

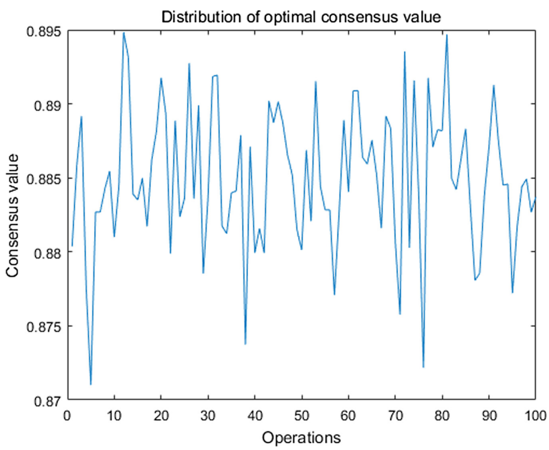


**Fig. 4.** Distribution of optimal consensus value in 100 operations

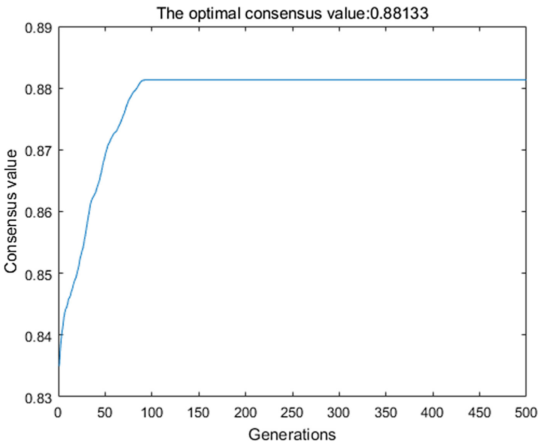


**Fig. 5.** The change curve of optimal consensus value

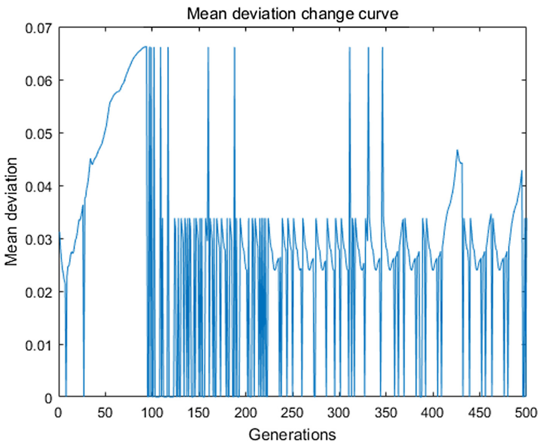


**Fig. 6.** Mean deviation change curve

However, the optimization results failed to meet the expected requirement of consensus threshold. In terms of the mean deviation and consumers' suggestion, the adjustment space was extended to $[-0.6, 0.6]$ and the consensus value was recalculated, shown in Fig. 7. The results show that the optimal consensus degree reached the threshold requirement in operations of 4, 12, 20, 28, 31, 41, 43, 46, 52, 60, 66, 68, 72, 76, 79, 83 and 86. The maximum appears in the 43th operation which equals to 0.9052. The distribution of mean deviation shown in Fig. 8 demonstrates that the overall deviation between the optimal matrix and the original matrix does not exceed 0.032.

The adjusted Kansei decision-making matrices are listed as follows:

$$A_t^{(1)} = \begin{bmatrix} \{s_{1.4}, s_{1.9}, s_{2.4}\} & \{s_{1.4}, s_{1.9}, s_{2.4}\} & \{s_{2.4}, s_{2.4}, s_{2.4}\} & \{s_{1.6}, s_{1.6}, s_{1.6}\} \\ \{s_{1.6}, s_{1.6}, s_{1.6}\} & \{s_{1.4}, s_{1.9}, s_{2.4}\} & \{s_{1.6}, s_{1.6}, s_{1.6}\} & \{s_{1.4}, s_{1.4}, s_{1.4}\} \\ \{s_{1.393513}, s_{1.3967565}, s_{1.4}\} & \{s_{0.128705}, s_{0.128705}, s_{0.128705}\} & \{s_{1.4}, s_{1.4}, s_{1.4}\} & \{s_{1.3984}, s_{1.3984}, s_{1.3984}\} \end{bmatrix}$$

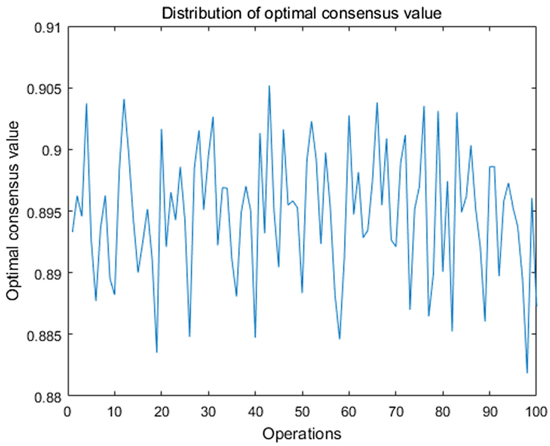


**Fig. 7.** Distribution of optimal consensus value in 100 operations after extending the adjustment space

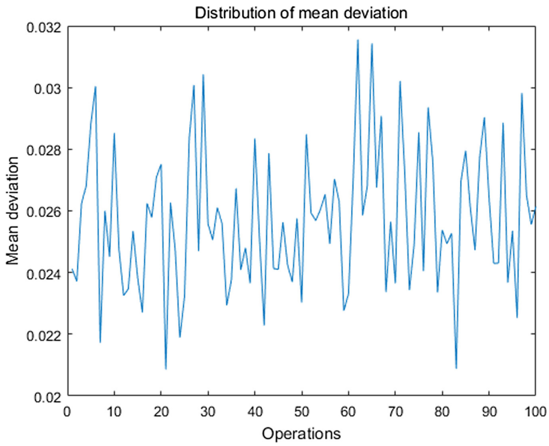


**Fig. 8.** Distribution of mean deviation in 100 operations after extending the adjustment space

$$A_t^{(2)} = \begin{bmatrix} \{s_{1.4}, s_{1.4}, s_{1.4}\} & \{s_{2.4}, s_{2.4}, s_{2.4}\} & \{s_{2.400927}, s_{2.400927}, s_{2.400927}\} & \{s_{1.4}, s_{1.4}, s_{1.4}\} \\ \{s_{1.6}, s_{1.6}, s_{1.6}\} & \{s_{0.609128}, s_{1.2445585}, s_{1.879989}\} & \{s_{1.6}, s_{1.6}, s_{1.6}\} & \{s_{0.6}, s_{1}, s_{1.4}\} \\ \{s_{1.4}, s_{1.4}, s_{1.4}\} & \{s_{-0.01036}, s_{0.19482}, s_{0.4}\} & \{s_{-1.4}, s_{-1.4}, s_{-1.4}\} & \{s_{1.398742}, s_{1.398742}, s_{1.398742}\} \end{bmatrix}$$

$$A_t^{(3)} = \begin{bmatrix} \{s_{0.6}, s_{0.6}, s_{0.6}\} & \{s_{1.6}, s_{1.6}, s_{1.6}\} & \{s_{-0.4}, s_{0.1}, s_{0.6}\} & \{s_{1.6}, s_{1.6}, s_{1.6}\} \\ \{s_{1.6}, s_{1.6}, s_{1.6}\} & \{s_{0.605709}, s_{1.2481525}, s_{1.890596}\} & \{s_{1.6}, s_{1.6}, s_{1.6}\} & \{s_{0.6}, s_{0.99972}, s_{1.39944}\} \\ \{s_{0.6}, s_{1}, s_{1.4}\} & \{s_{-0.01046}, s_{0.19477}, s_{0.4}\} & \{s_{1.253859}, s_{1.3269295}, s_{1.4}\} & \{s_{1.393535}, s_{1.3967675}, s_{1.4}\} \end{bmatrix}$$

$$A_t^{(4)} = \begin{bmatrix} \{s_{1.6}, s_{1.6}, s_{1.6}\} & \{s_{-0.4}, s_{0.1}, s_{0.6}\} & \{s_{2.398064}, s_{2.399032}, s_{2.4}\} & \{s_{1.6}, s_{1.6}, s_{1.6}\} \\ \{s_{1.4}, s_{1.4}, s_{1.4}\} & \{s_{0.4}, s_{1.1455025}, s_{1.891005}\} & \{s_{0.6}, s_{1.193672}, s_{1.787344}\} & \{s_{1.119032}, s_{1.119032}, s_{1.119032}\} \\ \{s_{1.390762}, s_{1.395381}, s_{1.4}\} & \{s_{-0.4}, s_{-0.4}, s_{-0.4}\} & \{s_{1.4}, s_{1.4}, s_{1.4}\} & \{s_{0.6}, s_{0.6}, s_{0.6}\} \end{bmatrix}$$

$$A_t^{(5)} = \begin{bmatrix} \{s_{-1.4}, s_{-1.4}, s_{-1.4}\} & \{s_{0.6}, s_{1.1}, s_{1.6}\} & \{s_{2.6}, s_{2.6}, s_{2.6}\} & \{s_{-0.4}, s_{0.1}, s_{0.6}\} \\ \{s_{1.6}, s_{1.6}, s_{1.6}\} & \{s_{0.6}, s_{0.6}, s_{0.6}\} & \{s_{1.6}, s_{1.6}, s_{1.6}\} & \{s_{0.6}, s_{0.998952}, s_{1.397904}\} \\ \{s_{1.390743}, s_{1.3953715}, s_{1.4}\} & \{s_{0.129997}, s_{0.129997}, s_{0.129997}\} & \{s_{-0.4}, s_{-0.125955}, s_{0.274045}\} & \{s_{1.6}, s_{1.6}, s_{1.6}\} \end{bmatrix}$$

After getting the adjusted matrices of consumers' Kansei decision-making about charging piles design solutions, Eq. (9) and (10) will be used to determine their ranking orders. The positive ideal solution $A_+$ and the negative ideal solution $A_-$ of adjustment matrices are as follows:

$$\begin{cases} A_+ = [\{s_{2.4}\}, \{s_{2.4}\}, \{s_{2.6}\}, \{s_{1.6}\}] \\ A_- = [\{s_{-1.4}\}, \{s_{-0.4}\}, \{s_{-1.4}\}, \{s_{-0.4}\}] \end{cases}$$

Table 1 shows the satisfaction degrees of each product solution. In contrast, the satisfaction degrees calculated with the original matrix are also included in the table. Data from Table 1 displays that the ranking order of charging piles design solutions according to adjustment of consumers' preferences is $NO.1 \succ NO.2 \succ NO.3$, which is significantly different from that without optimization ($NO.2 \succ NO.1 \succ NO.\,3$). With the consensus level lifted from 0.8339 to 0.9052, the overall satisfaction degrees of consumers have also been improved. The satisfaction degrees of scheme 1 and 2 are promoted, while that of scheme 3 is slightly reduced.

**Table 1.** Comparison of satisfaction degrees

| Charging piles design solutions | Satisfaction degrees of adjusted HFLTSs | Satisfaction degrees of original HFLTSs |
|---|---|---|
| 1 | 0.71764 | 0.64303 |
| 2 | 0.70790 | 0.67383 |
| 3 | 0.53812 | 0.55172 |

## 5 Conclusion

As continuous linguistic variables are more in line with consumers' perception than concrete values or discrete Kansei adjectives, and hesitance and opinion difference exist extensively in Kansei decision-making process, it is conducive to employ HFLTSs to analyze consumers' preferences with the characteristics of uncertainty, imprecision and subjective vagueness. By studying the theories and operation rules of linguistic variables and HFLTSs, a consensus model is constructed to analyze the consistency of consumers' Kansei preferences. When disagreement fails to meet an acceptable consensus degree, PSO is deployed to adjust consumers' opinions aiming at lifting consensus level. With adjusted Kansei preferences, the final decision-making results are determined by HFLTSs-based TOPSIS. The case study of charging piles design for electric vehicles is taken as an example to verify the proposed method's ability in product Kansei decision-making process. Results show that with the consensus level lifted from 0.8339 to 0.9052, the overall satisfaction degrees of consumers have also been improved.

However, it should be noted that hesitance will affect preference consistency. The normalization of HFLTSs to ensure that the HFLTSs have the same number of linguistic terms mainly relies on the subjectivity of decision makers, but the determination of risk preference is an intractable task, which may distort the original preferences and will be further studied. Future research will focus on the development of Kansei decision-making software for dealing with consumers' perceptual opinions, and hesitance of online consumers' Kansei preference with big data technology.

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