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Flexible Supplier Selection of WASPAS based on Hesitant Cloud Language

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Abstract: To ensure the continuity and stability of the supply chain under the sudden crisis, flexible supplier selection has taken up an important position in the operation decision of enterprises. Considering the differences of different expert decision-making and decision-making results that contain fuzziness, randomness and hesitation, the flexible supplier selection was studied by using the method of combining hesitant fuzzy language with normal cloud model and hesitant cloud linguistic term set was established. The weights were calculated according to the decision quality and aggregated with the evaluation results. Finally, WASPAS was used for scheme sorting to select the best supplier. The validity and applicability of the model were verified by a case study, which provided a scientific basis for enterprise decision makers to avoid interruption risk.

Keywords: Flexible supplier selection; Hesitant fuzzy language; Normal cloud model; WASPAS

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1. Introduction

In the past two years, a variety of disasters have occurred frequently, and the global supply chain has encountered a "perfect storm," with various supply chains have been affected to different degrees, and even appears the interruption phenomenon. The supply chain elasticity management trend has been irreversible. At present, there is no unified definition of a flexible supply chain. Most scholars believe that when the supply chain is threatened by natural disasters, man-made disasters or technology, logistics and information flow will face disruption. However, flexible supply chain can help enterprises to recover to a normal state, or even to a higher level, so as to gain competitive advantages in the dynamic and changeable business environment [1].

Existing research methods of flexible supplier selection mainly focus on mathematical programming model, artificial intelligence method, multi-attribute decision making method and fuzzy decision making method, etc., focusing on dealing with the uncertainty of index weight [2-11]. However, these methods often ignore the differences among experts. Due to the differences in knowledge background, experience, preferences and so on, experts have different evaluations on the same index. Yang Xiao-jun et al. [11] combined hesitant fuzzy language and normal cloud model and proposed a new multi-indicator group decision making method based on hesitant cloud linguistic term set. This method can simultaneously describe the fuzziness, randomness, hesitation and difference of subjective evaluation in the decision-making process, and calculate the weight according to the decision quality, so as to improve the reliability of evaluation results.

Weighted aggregated sum product assessment (WASPAS) is a commonly used multi-criteria decision making method. It is a combination of weighted sum model (WSM) and weighted product model (WPM), which is more accurate than WSM and WPM. It can effectively improve the accuracy of decision target selection, and the calculation is simple. In this paper, the flexible supplier selection model is constructed by combining WASPAS on the basis of hesitant cloud linguistic term set, which provides an effective basis for enterprise decision makers to avoid interruption risk.

2. Flexible supplier selection model of WASPAS based on hesitant cloud language

Flexible supplier selection is a multi-attribute decision making problem. The evaluation index contains both quantitative data and qualitative language description. Among them, the qualitative indicators are evaluated by the expert group. Based on the comprehensive evaluation information, the appropriate decision method is selected to sort the scheme and determine the best supplier.

Assume that the decision-maker of the enterprise is given the index $C_j(j = 1,2, \dots, m)$ is the weight of $\omega_j(j = 1,2, \dots, m)$. Collect raw data of each supplier$S_q(q = 1,2, \dots, n)$ and classify the information. The quantitative data are standardized, while the qualitative language description is evaluated and converted by experts$Z_i(i = 1,2, \dots, k)$ with reference to the hesitant cloud linguistic term set.

2.1. Flexible supplier evaluation index system

In recent years, supplier selection has become a key strategic issue, and it is of great significance to select a scientific and reasonable evaluation index. Based on literature analysis and combined with the actual situation of the enterprise, this paper selects nine elastic indicators, including quality, price, delivery time, service, technology, environmental friendliness, supplier absorbency, supplier adaptability and supplier resilience.

(1) Quality

Quality is the guarantee of quality, but also an important guarantee to survive in the fierce competition of the market economy tide, and can be measured from the following aspects of quality: performance, characteristics, reliability, durability, compliance, maintainability, aesthetic, perceived quality.

(2) Price

Enterprises in the premise of ensuring product quality, should choose a reasonable price, so as to improve the product market share.

(3) Delivery time

The 21st century is the era of the pursuit of aging and personalization, the user's demand for aging is more intense. Shortening the delivery time can maximize the customer's expectations, and improve the capital turnover rate, so as to form a virtuous circle, to achieve a win-win situation for customers and enterprises.

(4) Service

Comprehensive and high quality service is an effective means to attract customers. Different services should be provided according to the needs of customers, so as to improve customer satisfaction. Service levels are usually measured by service efficiency, the skill of the staff at the service, service equipment, and reliability rate.

(5) Technology

Technology is an important condition to ensure the survival of enterprises in the rapidly changing market. Usually, the technology level can be measured according to the production technology level, the number of professional and technical personnel, and the ability of new product research and development.

(6) Environmental friendliness

Adapting to the trend of the green era can not only promote the sustainable development of the society, but also improve the competitiveness of enterprises. Generally, the green level of an enterprise is judged by energy consumption rate, air pollution rate and recoverable rate.

(7) Supplier absorbency

Supplier absorbency refers to the absorptive capacity of emergency situations to effectively resist risks and prevent supply chain disruptions. And it can be evaluated according to whether there is a spare plant area, whether there is a safety stock, whether there is a reserve of employees, whether there are multiple sources of supplies, and the level of risk awareness of employees.

(8) Supplier adaptability

The adaptability of suppliers is flexibility. They adapt to the outside world through their own changes and take the best measures in case of interruption to reduce losses. Adaptability can be measured by the presence of multi-skilled employees, the presence of multi-functional equipment, and the presence of professional management experts.

(9) Supplier resilience

Resilience refers to the rapid return of a supply chain to its original level or even higher after a disruption to prevent a permanent disruption or collapse. Resilience level can be judged according to whether there are spare funds to resume production, whether there are complete repair equipment's, and whether there are professional repair technicians.

2.2. Expert decision weight

2.2.1. hesitant cloud language

Definition 1 [7-8]: Let U be a quantitative domain expressed numerically, C be a qualitative concept on the domain U, and the existence of quantitative value $\mathrm{x} \in \mathrm{U}$ is a random realization on the qualitative concept C, that is, qualitative uncertainty is dealt with quantitatively. And the membership degree $\mu(\mathrm{x}) \in [0,1]$ for C is a random number with stable tendency, namely $\mu: \mathrm{U} \to [0,1], \forall \mathrm{x} \in \mathrm{U}, \mathrm{x} \to \mu(\mathrm{x})$. Then the distribution of membership degree $\mu(\mathrm{x})$ in the domain U is called cloud for short, denoized as $\mathrm{C(U)}$, and each $(\mathrm{x}, \mu(\mathrm{x}))$is called a cloud droplet.

Definition 2 [9]: The characteristics of clouds are characterized by three numerical parameters that describe their qualitative concepts, namely, expectation Ex, entropy En, and hyperentropy He. Among them,Ex represents the central value of the conceptual domain of qualitative language, En represents the fuziness of qualitative concept, and He represents the random change of entropy dispersion and membership degree, that is, the normal cloud model is denote as $\mathrm{L}(Ex, En, \mathrm{He})$.

Definition 3 [10]: Set the $\mathrm{L} = \{l_0, \ldots, l_n\}$ is a finite and ordered complete set of discrete linguistic terms on the domain, where l_i represents a linguistic term constructed by a normal cloud model. Then a hesitant linguistic term set H_L is defined as an ordered finite subset of the language term set L.

Among them, Yang Xiao-jun et al. adapted the cloud model of linguistic terms established by using interval survey and membership function fitting method to form a new complete set of linguistic terms L defined by the normal cloud model, as shown in **Table 1** [11].

The context-free syntax and conversion function are used to convert semantic information into hesitant cloud language. The conversion function f is defined as follows [10]:

$$\mathrm{f}(l_k) = \{l_k | l_k \in L\}$$
$$\mathrm{f}(at\ most\ l_k) = \{l_j | l_j \in L\ and\ l_j \le l_k\}$$
$$\mathrm{f}(lower\ than\ l_k) = \{l_j | l_j \in L\ and\ l_j < l_k\}$$
$$\mathrm{f}(at\ least\ l_k) = \{l_j | l_j \in L\ and\ l_j \ge l_k\}$$
$$\mathrm{f}(greater\ than\ l_k) = \{l_j | l_j \in L\ and\ l_j > l_k\}$$
$$\mathrm{f}(between\ l_i\ and\ l_k) = \{l_j | l_j \in L\ and\ l_i \le l_j \le l_k\}$$

Table 1. The complete set of linguistic terms defined by the normal cloud model L

Linguistic term	Normal cloud model
$l_0: non(none)$	(0.00,1.00,0.20)
$l_1: vl(very\ low)$	(1.97,4.57,0.22)
$l_2: low$	(12.46,10.62,0.34)
$l_3: sl(slightly\ low)$	(30.83,10.30,0.33)
$l_4: med(medium)$	(50.58,11.09,0.56)
$l_5: sh(slightly\ high)$	(71.05,10.27,0.41)
$l_6: high$	(87.43,12.42,0.41)
$l_7: vh(very\ high)$	(97.75,10.54,0.27)
$l_8: max(maximum)$	(100.00,1.00,0.20)

2.2.2. Comprehensive uncertainty and average difference degree

(1) Comprehensive uncertainty

Definition 4 [11]: In order to define the fuzziness, randomness and hesitation contained in the decision result itself, it is assumed that $H_L = \{l_i, \dots, l_{i+k}\}(\mathrm{i} \geq 0, \mathrm{k} \geq 0, \mathrm{i} + \mathrm{k} \leq \mathrm{n})$ is a function defined in $\mathrm{L} = \{l_0, \dots, l_n\}$, and the comprehensive uncertainty of H_L is:

$$UD_i = \alpha \frac{k}{|L| - 1} + \beta \frac{\sum_{j=0}^{k} En_{i+j}}{\sum_{p=0}^{n} En_p} + \gamma \frac{\sum_{j=0}^{k} He_{i+j}}{\sum_{p=0}^{n} He_p} \quad (1)$$

Where α, β and γ represent the weight coefficients of hesitance, fuzziness and randomness, respectively, and $\alpha > 0$, $\beta > 0$, $\gamma > 0$, $\alpha + \beta + \gamma = 1$. $0 \leq \mathrm{UD} \leq 1$, the smaller the UD_i is, the more confident the decision maker is in the evaluation of the index or scheme, and the decision result is more accurate. However, when the UD_i is 1, it indicates that the decision maker's information is invalid.

(2) Average difference degree

Definition 5 [11-12]: Considering the different knowledge background, experience and preference of each expert, the evaluation results of the same indicator may also be different. Assume expert $Z_1, \dots, Z_k$ evaluates the semantic information of indicators respectively, and obtains the $H_L^1, \dots, H_L^k$, the average difference degree of expert Z_i is:

$$AD_i = \frac{1}{k-1} \sum_{j=1, j \neq i}^{k} d\left(H_L^i, H_L^j\right) \quad (2)$$

Among them,

$$\mathrm{Aver}(H_L) = \frac{1}{|H_L|} \sum_{l_i \in H_L} l_i = \frac{1}{|H_L|} \sum_{l_i \in H_L} lnd(l_i) \quad (3)$$

$$\mathrm{d}(H_L^1, H_L^2) = \frac{1}{|L|-1} \left|\mathrm{Aver}(H_L^1) - \mathrm{Aver}(H_L^2)\right| \quad (4)$$

The smaller AD_i is, the closer the decision result of expert Z_i is to that of other experts. $\mathrm{Aver}(H_L)$ represents the mean value of H_L, and $\mathrm{d}(H_L^1, H_L^2)$ represents the distance between H_L^1 and H_L^2.

2.2.3. Determine decision weights

Due to the differences in knowledge background, experience and preference, different experts often have different evaluations on the same indicator. Meanwhile, due to the different fields of expertise, the same

$$\omega_i^* = \rho \frac{1-AD_i}{\sum_{i=1}^{k}(1-AD_i)} + (1-\rho) \frac{1-UD_i}{\sum_{i=1}^{k}(1-UD_i)} \quad (5)$$

expert has different degrees of certainty in the evaluation of different indicators. The smaller the average difference degree and the comprehensive uncertainty degree are, the more accurate the decision result is, and the greater the weight is. The AD_i and the UD_i are calculated by using the term set H_L after semantic transformation. Finally, the decision weights ω_i^* of experts are calculated synthetically:

2.3. WASPAS ranking of schemes

The multi-criteria decision-making method can identify the most promising scheme among a series of alternatives based on the previously established criteria [13]. In this paper, the WASPAS method is adopted to select suppliers. The main steps are as follows [14-15] :

(1) Construct weighted normalized matrix

(2) WSM total relative importance $Q_i^{(1)}$

$$Q_i^{(1)} = \sum_{j=1}^{n} x_{ij}\omega_{ij} \tag{6}$$

(3) WPM total relative importance $Q_i^{(2)}$

$$Q_i^{(2)} = \prod_{j=1}^{n} (x_{ij})^{\omega_j} \tag{7}$$

(4) Calculate the WASPAS final result

$$Q_i = \lambda \sum_{j=1}^{n} x_{ij}\omega_{ij} + (1-\lambda) \prod_{j=1}^{n} \left(x_{ij}\right)^{\omega_j} \quad ,\lambda = 0, \dots ,1 \tag{8}$$

Where the parameter $\lambda \in [0,1]$, when $\lambda = 0$, WASPAS completely degenerates to WPM; When $\lambda = 1$, WASPAS is converted to WSM. The scheme is sorted by the size of Q_i. The larger the value of Q_i, the better the scheme is.

2.4. Flexible supplier selection process

Step 1. Normalize the processing of quantitative indicators. The commonly used normalized treatment methods include standardized treatment method, extreme value treatment method, linear proportion method, normalized treatment method, vector standard method, efficiency coefficient method. Through the evaluation of the properties of the six indexes of monotonicity, difference ratio invariance, translation independence, scaling independence, interval stability and total constancy, it is found that the standardized treatment method, extreme value treatment method and efficiency coefficient method are better than other methods [16]. In this paper, the extremum treatment method is used for normalization processing, which can be calculated according to Equation (9) or (10) :

$$x_{ij}^* = \frac{M_j - x_{ij}}{M_j - m_j} \quad (i = 1,2, \dots, m; j = 1,2, \dots, n) \tag{9}$$

$$x_{ij}^* = \frac{x_{ij} - m_j}{M_j - m_j} \quad (i = 1,2, \dots, m; j = 1,2, \dots, n) \tag{10}$$

Where, it is assumed that the number of suppliers is m, the number of indicators is n, and x_{ij} represents the j_{th} index value of the i_{th} supplier, $M_j = max\{x_{ij}\}$, $m_j = \min\{x_{ij}\}$. Equation (9) for the case that indicator x_{ij} is very small, namely, a cost-type indicator, while indicator x_{ij} is very large, namely, a benefit-type indicator, Formula (10) is adopted.

Step 2. Use hesitant cloud semantics to transform qualitative indicators. The experts conduct semantic evaluation on the qualitative indicators, and transform them into hesitating cloud language through the transformation function. Whereinto, the decision results of k experts on supplier S_q in C_j index are

$H_L^1, H_L^2, \ldots, H_L^k$.

Step 3. Determine the decision weights of experts. Formulas (1) ~ (4) are used to calculate the comprehensive uncertainty UD_i and average difference AD_i of experts respectively, and then the decision weights ω_i^* of experts are calculated according to formula (5).

Step 4. Calculate comprehensive cloud model. Equation (11) is used to calculate comprehensive cloud model $s_1, s_2, \ldots, s_k$ of $H_L^1, H_L^2, \ldots, H_L^k$[17].

$$s_i = \left(\frac{1}{n}\sum_{i=1}^{n} Ex_i, \frac{1}{6}\left(\max(Ex_i + 3En_i) - \min\left(Ex_j - 3En_j\right)\right), \frac{1}{n}\sum_{i=1}^{n} He_i\right) \tag{11}$$

Step 5. Calculate the weighted comprehensive cloud model. Combined with the expert decision weight ω_i^* and the comprehensive cloud model S_i, the formula below is used to calculate the weighted comprehensive cloud model $S_1^*, S_2^*, \ldots, S_k^*$[17].

$$S_i^* = \sum_{i=1}^{n} \omega_i^* s_i = \left(\sum_{i=1}^{n} \omega_i^* Ex_i, \sqrt{\sum_{i=1}^{n}(\omega_i^* En_i)^2}, \sqrt{\sum_{i=1}^{n}(\omega_i^* He_i)^2}\right) \tag{12}$$

Step 6. Construct a comprehensive evaluation matrix. After the normalization of equation (9) or (10), the weighted comprehensive cloud model S_i^* is combined with the standardized objective data indicators to form a new comprehensive matrix to obtain the final comprehensive evaluation matrix.

Step 7. Sort alternative. According to the WASPAS method, formula (6) ~ (8) is used to calculate the total relative importance Q_i, and the alternative schemes are ranked.

3. Case study

Taking a manufacturer as an example, three suppliers (S_1, S_2, S_3) were selected as alternative suppliers after prequalification examination. According to the nine elastic indexes of quality (C_1), price (C_2), delivery time (C_3), service (C_4), technology (C_5), environmental friendliness (C_6), supplier absorbency (C_7), supplier adaptability (C_8) and supplier resilience (C_9), the relevant data were collected. where, C_2 and C_3 are quantitative indexes, as shown in **Table 2**. The other qualitative indexes were evaluated by experts (Z_1, Z_2, Z_3, Z_4) respectively.

Table 2. Raw data of each supplier

	S_1	S_2	S_3
C_2	25	23	27
C_3	8	10	6

Step 1. C_2 and $C_3$are both quantitative indicators and cost-type indicators. Through the extreme value processing method, Formula (9) is used to conduct normalized data processing, as shown in **Table 3**.

Table 3. Standardization of raw data of each supplier

	S_1	S_2	S_3
C_2	0.5	1	0
C_3	0.5	0	1

Step 2. Experts conduct semantic evaluation on qualitative indicators, and transform them into hesitant

cloud language through the transformation function. And the evaluation value of the definition of normal cloud model is obtained by referring to Table 1, as shown in **Table 4**.

Table 4. Expert subjective evaluation of the value of each supplier

		C_1	C_4	C_5	C_6	C_7	C_8	C_9
Z_1	S_1	$\{l_4\}$	$\{l_6\}$	$\{l_6, l_7\}$	$\{l_4, l_5\}$	$\{l_5, l_6\}$	$\{l_5, l_6, l_7\}$	$\{l_6\}$
	S_2	$\{l_5, l_6\}$	$\{l_5, l_6\}$	$\{l_6\}$	$\{l_5, l_6\}$	$\{l_6\}$	$\{l_7, l_8\}$	$\{l_5, l_6\}$
	S_3	$\{l_3, l_4, l_5\}$	$\{l_4, l_5\}$	$\{l_4, l_5, l_6\}$	$\{l_4, l_5, l_6\}$	$\{l_6, l_7\}$	$\{l_6\}$	$\{l_5, l_6, l_7\}$
Z_2	S_1	$\{l_5, l_6\}$	$\{l_6, l_7\}$	$\{l_6\}$	$\{l_3, l_4, l_5\}$	$\{l_6\}$	$\{l_5, l_6\}$	$\{l_5, l_6\}$
	S_2	$\{l_3, l_4, l_5, l_6\}$	$\{l_6\}$	$\{l_7\}$	$\{l_5\}$	$\{l_5, l_6\}$	$\{l_6, l_7\}$	$\{l_6\}$
	S_3	$\{l_4\}$	$\{l_5\}$	$\{l_5, l_6, l_7\}$	$\{l_5, l_6\}$	$\{l_6, l_7, l_8\}$	$\{l_6, l_7\}$	$\{l_6, l_7\}$
Z_3	S_1	$\{l_4, l_5, l_6\}$	$\{l_7\}$	$\{l_5, l_6, l_7\}$	$\{l_4\}$	$\{l_6, l_7\}$	$\{l_6, l_7\}$	$\{l_4, l_5\}$
	S_2	$\{l_5\}$	$\{l_5, l_6, l_7\}$	$\{l_6, l_7\}$	$\{l_4, l_5, l_6\}$	$\{l_5\}$	$\{l_7\}$	$\{l_6, l_7\}$
	S_3	$\{l_6\}$	$\{l_6\}$	$\{l_6\}$	$\{l_5\}$	$\{l_7\}$	$\{l_5, l_6, l_7\}$	$\{l_6\}$
Z_4	S_1	$\{l_5\}$	$\{l_5, l_6\}$	$\{l_5, l_6\}$	$\{l_4, l_5\}$	$\{l_6\}$	$\{l_7\}$	$\{l_5\}$
	S_2	$\{l_5, l_6\}$	$\{l_4, l_5, l_6, l_7\}$	$\{l_5, l_6\}$	$\{l_5, l_6\}$	$\{l_5, l_6, l_7\}$	$\{l_6, l_7, l_8\}$	$\{l_6\}$
	S_3	$\{l_4, l_5\}$	$\{l_4, l_5, l_6\}$	$\{l_6\}$	$\{l_5\}$	$\{l_6, l_7\}$	$\{l_6\}$	$\{l_6, l_7, l_8\}$

Step 3. Formulas (1) ~ (4) are used to calculate the comprehensive uncertainty UD_i (**Table 5**) and average difference AD_i (**Table 6**) of experts respectively, and then the decision weights ω_i^* (**Table 7**) of experts are calculated according to formula (5). Wherein, take $\alpha = 0.5, \beta = 0.3, \gamma = 0.2, \rho = 0$.

Table 5. Expert comprehensive uncertainty UD_i

		C_1	C_4	C_5	C_6	C_7	C_8	C_9
Z_1	S_1	0.0844	0.0798	0.2047	0.2177	0.2131	0.3380	0.0798
	S_2	0.2131	0.2131	0.0798	0.2131	0.0798	0.1427	0.2131
	S_3	0.3457	0.2177	0.3600	0.3600	0.2047	0.0798	0.3380
Z_2	S_1	0.2131	0.2047	0.0798	0.3457	0.0798	0.2131	0.2131
	S_2	0.4880	0.0798	0.0624	0.0708	0.2131	0.2047	0.0798
	S_3	0.0844	0.0708	0.3380	0.2131	0.2850	0.2047	0.2047
Z_3	S_1	0.3600	0.0624	0.3380	0.0844	0.2047	0.2047	0.2177
	S_2	0.0708	0.3380	0.2047	0.3600	0.0708	0.0624	0.2047
	S_3	0.0798	0.0798	0.0798	0.0708	0.0624	0.3380	0.0798

Z_4	S_1	0.0708	0.2131	0.2131	0.2177	0.0798	0.0624	0.0708
	S_2	0.2131	0.4849	0.2131	0.2131	0.3380	0.2850	0.0798
	S_3	0.2177	0.3600	0.0798	0.0708	0.2047	0.0798	0.2850

Table 6. Expert average difference degree AD_i

		C_1	C_4	C_5	C_6	C_7	C_8	C_9
Z_1	S_1	0.2292	0.0833	0.0833	0.0417	0.0833	0.0833	0.1250
	S_2	0.0625	0.0417	0.0833	0.0417	0.0625	0.0833	0.0833
	S_3	0.1042	0.1042	0.1250	0.2708	0.0417	0.0208	0.0625
Z_2	S_1	0.1042	0.0833	0.0417	0.0417	0.0417	0.1250	0.0833
	S_2	0.1042	0.0417	0.1250	0.0417	0.0625	0.0833	0.0417
	S_3	0.1042	0.0625	0.0417	0.1458	0.0417	0.0625	0.0625
Z_3	S_1	0.1042	0.1250	0.0417	0.0417	0.0833	0.0833	0.1250
	S_2	0.0625	0.0417	0.0833	0.0417	0.1042	0.0417	0.0833
	S_3	0.2292	0.1458	0.0417	0.1042	0.0417	0.0208	0.0625
Z_4	S_1	0.1042	0.1250	0.0833	0.0417	0.0417	0.1250	0.0833
	S_2	0.0625	0.0417	0.1250	0.0417	0.0625	0.0417	0.0417
	S_3	0.1042	0.0625	0.0417	0.1042	0.0417	0.0208	0.1042

Table 7. Expert decision weights ω_i^*

		C_1	C_4	C_5	C_6	C_7	C_8	C_9
Z_1	S_1	0.2343	0.2581	0.2458	0.2499	0.2416	0.2463	0.2492
	S_2	0.2544	0.2546	0.2581	0.2501	0.2580	0.2474	0.2416
	S_3	0.2472	0.2455	0.2274	0.2118	0.2490	0.2580	0.2450
Z_2	S_1	0.2553	0.2509	0.2626	0.2417	0.2582	0.2448	0.2507
	S_2	0.2272	0.2638	0.2499	0.2591	0.2500	0.2437	0.2582
	S_3	0.2632	0.2637	0.2466	0.2504	0.2442	0.2417	0.2537
Z_3	S_1	0.2464	0.2499	0.2463	0.2585	0.2420	0.2546	0.2411
	S_2	0.2640	0.2459	0.2509	0.2407	0.2496	0.2612	0.2420
	S_3	0.2346	0.2448	0.2630	0.2689	0.2578	0.2423	0.2618
Z_4	S_1	0.2640	0.2411	0.2453	0.2499	0.2582	0.2543	0.2590
	S_2	0.2544	0.2357	0.2411	0.2501	0.2424	0.2477	0.2582
	S_3	0.2550	0.2460	0.2630	0.2689	0.2490	0.2580	0.2395

Step 4. Equation (11) is used to calculate comprehensive cloud model $s_1, s_2, \ldots, s_k$ of $H_L^1, H_L^2, \ldots, H_L^k$, as shown in **Table 8**.

Table 8. Comprehensive cloud model S_i

	C_1	C_4	C_5	C_6
S_1	（50.5800，	（87.4300，	（92.5900，	（60.8150，
S_2	11.0900，0.5600）	12.4200，0.4100）	13.2000，0.3400）	14.0917，

	S_3				0.4850）
Z_1		（79.2400，14.0750，0.4100）	（79.2400，14.0750，0.4100）	（87.4300，12.4200，0.4100）	（79.2400，14.0750，0.4100）
		（50.8200，16.9883，0.4333）	（60.8150，14.0917，0.4850）	（69.6867，17.8967，0.4600）	（69.6867，17.8967，0.4600）
Z_2	S_1	（79.2400，14.0750，0.4100）	（92.5900，13.2000，0.3400）	（87.4300，12.4200，0.4100）	（50.8200，16.9883，0.4333）
	S_2	（59.9725，20.7933，0.4275）	（87.4300，12.4200，0.4100）	（97.7500，10.5400，0.2700）	（71.0500，10.2700，0.4100）
	S_3	（50.5800，11.0900，0.5600）	（71.0500，10.2700，0.4100）	（85.4100，14.8550，0.3633）	（79.2400，14.0750，0.4100）
Z_3	S_1	（69.6867，17.8967，0.4600）	（97.7500，10.5400，0.2700）	（85.4100，14.8550，0.3633）	（50.5800，11.0900，0.5600）
	S_2	（71.0500，10.2700，0.4100）	（85.4100，14.8550，0.3633）	（92.5900，13.2000，0.3400）	（69.6867，17.8967，0.4600）
	S_3	（87.4300，12.4200，0.4100）	（87.4300，12.4200，0.4100）	（87.4300，12.4200，0.4100）	（71.0500，10.2700，0.4100）
Z_4	S_1	（71.0500，10.2700，0.4100）	（79.2400，14.0750，0.4100）	（79.2400，14.0750，0.4100）	（60.8150，14.0917，0.4850）
	S_2	（79.2400，14.0750，0.4100）	（76.7025，18.6767，0.4125）	（79.2400，14.0750，0.4100）	（79.2400，14.0750，0.4100）
	S_3	（60.8150，14.0917，0.4850）	（69.6867，17.8967，0.4600）	（87.4300，12.4200，0.4100）	（71.0500，10.2700，0.4100）

Continue table 8. Comprehensive cloud model S_i

		C_7	C_8	C_9
Z_1	S_1	（79.2400，14.0750，0.4100）	（85.4100，14.8550，0.3633）	（87.4300，12.4200，0.4100）
	S_2	（87.4300，12.4200，0.4100）	（98.8750，10.5400，0.2350）	（79.2400，14.0750，0.4100）
	S_3	（92.5900，13.2000，0.3400）	（87.4300，12.4200，0.4100）	（85.4100，14.8550，0.3633）
	S_1	（87.4300，12.4200，0.4100）	（79.2400，14.0750，0.4100）	（79.2400，14.0750，0.4100）

Z_2	S_2	（79.2400，14.0750，0.4100）	（92.5900，13.2000，0.3400）	（87.4300，12.4200，0.4100）
	S_3	（95.0600，13.2000，0.2933）	（92.5900，13.2000，0.3400）	（92.5900，13.2000，0.3400）
Z_3	S_1	（92.5900，13.2000，0.3400）	（92.5900，13.2000，0.3400）	（60.8150，14.0917，0.4850）
	S_2	（71.0500，10.2700，0.4100）	（97.7500，10.5400，0.2700）	（92.5900，13.2000，0.3400）
	S_3	（97.7500，10.5400，0.2700）	（85.4100，14.8550，0.3633）	（87.4300，12.4200，0.4100）
Z_4	S_1	（87.4300，12.4200，0.4100）	（97.7500，10.5400，0.2700）	（71.0500，10.2700，0.4100）
	S_2	（85.4100，14.8550，0.3633）	（95.0600，13.2000，0.2933）	（87.4300，12.4200，0.4100）
	S_3	（92.5900，13.2000，0.3400）	（87.4300，12.4200，0.4100）	（95.0600，13.2000，0.2933）

Step 5. Combined with the expert decision weight ω_i^* and the comprehensive cloud model S_i, formula (12) is used to calculate the weighted comprehensive cloud model $\mathrm{S}_1^*, \mathrm{S}_2^*, \ldots, \mathrm{S}_\mathrm{k}^*$, as shown in **Table 9**.

Table 9. Weighted comprehensive cloud model S_i^*

	C_1	C_4	C_5	C_6
S_1	（68.0089,6.8162,0.2296）	（89.3290，6.2974，0.1181）	（86.1918，6.8170，0.1916）	（55.7535，7.0626，0.2476）
S_2	（72.7003,6.7876,0.2071）	（82.3196，7.5032，0.2001）	（89.3290，6.3006，0.1811）	（74.8185，7.1007，0.2111）
S_3	（60.5286,6.7749,0.2403）	（72.2118，6.9161，0.2208）	（82.8970，7.1639，0.2055）	（72.8120，6.4840，0.2106）

Continue table 9. Weighted comprehensive cloud model S_i^*

	C_7	C_8	C_9
S_1	（69.8892，6.7952，0.2305）	（88.8657，6.6134，0.1740）	（74.7175，6.3884，0.2144）
S_2	（72.3789，7.6433，0.2073）	（96.1045，5.9513，0.1427）	（86.7000，6.5066，0.1975）
S_3	（62.6882，6.9132，0.2774）	（88.1877，6.6083，0.1920）	（90.0716，6.7103，0.1784 ）

Step 6. The qualitative indicators in the weighted comprehensive cloud model S_i^* are all benefit indicators. Through the extreme value processing method, formula (10) is used for normalized data processing, and a

new comprehensive matrix is formed with the normalized objective data indicators to obtain the final comprehensive evaluation matrix $\boldsymbol{V_L}$.

$$V_L = \begin{bmatrix} 0.6146 & 0.5 & 0.5 & 1 & 0.5123 & 0 & 0.7431 & 0.0856 & 0 \\ 1 & 1 & 0 & 0.5907 & 1 & 1 & 1 & 1 & 0.7804 \\ 0 & 0 & 1 & 0 & 0 & 0.8948 & 0 & 0 & 1 \end{bmatrix}.$$

Step 7. Given that the weights of indicators $C_j(j = 1,2,\dots,9)$ given by enterprise decision makers are $\omega_j(j = 1,2,\dots,9) =$ （0.2,0.25,0.1,0.05,0.05,0.05,0.1,0.1,0.1. Combined with the WASPAS method, the total relative importance Q_i is calculated by using equations (6) ~ (8). When λ is the optimal value, the value of Q_i is the largest, and the ranking accuracy of the decision target is higher. According to multiple calculations and empirical studies, when λ is 0.5 (that is, when the weighted method model is equal to the weighted product model), the ranking accuracy of the decision target is optimal [18-20].

Table 10. WASPAS decision target ranking

supplier	WSM	WPM	Total Evaluation Score	ranking
S_1	0.4564	6.4011	3.4288	2
S_2	0.8756	7.9495	4.4126	1
S_3	0.2447	2.9942	1.6195	3

The scheme is sorted by the size of Q_i. The larger the value of Q_i, the better the scheme is. It can be seen from **Table 10** that the order of the three suppliers is S_2>S_1>S_3, that is, the best supplier is supplier 2.

4. Sensitivity analysis

Sensitivity analysis studies and predicts the influence of the changes of these attributes on the output value of the model by making the attributes in the model vary within the possible value range. Sensitivity analysis can reflect the reliability and applicability of the selected method. Generally, the parameter λ is changed from 0 to 1 and increased by 0.1 successively. After sensitivity analysis, the final evaluation score of alternative solutions is obtained (**Table 11**). By observing the table, it is found that the ranking of schemes has not changed. No matter how the parameter changes and the best supplier is still supplier 2.

Table 11. Alternative evaluation score sheet

supplier	λ and the total evaluation score										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
S1	6.4011	5.8066	5.2122	4.6177	4.0232	3.4288	2.8343	2.2398	1.6453	1.0509	0.4564
S2	7.9495	7.2421	6.5347	5.8273	5.1199	4.4126	3.7052	2.9978	2.2904	1.5830	0.8756
S3	2.9942	2.7193	2.4443	2.1694	1.8944	1.6195	1.3445	1.0696	0.7946	0.5197	0.2447

5. Conclusion

Flexible supplier selection was studied by using hesitating fuzzy language and normal cloud model. The term set of hesitating cloud language was established, and the qualitative linguistic value was transformed into the uncertain quantitative model of numerical description. The weights were calculated according to the decision quality and aggregated with the evaluation results. Finally, WASPAS was used to sort alternative schemes, and the conclusions are as follows:

(1) Considering the differences in decision-making among expert groups due to different knowledge backgrounds, experiences and preferences, as well as the fuzziness, randomness and hesitation of decision-making results due to different expertise of experts. And the weight of experts is calculated according to the quality of decision.

(2) A flexible supplier selection model considering the difference and fuzziness is established, and the validity and applicability of the model are verified by a case study of a factory.

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