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Research Article

An Evaluating Method with Combined Assigning-Weight Based on Maximizing Variance

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This paper proposes a combined assigning-weight approach to determine attribute weights in the multiattribute decision problems. The approach combines subjective weights and objective weights of attributes based on maximizing variance. Objective weights are determined by rough set method and subjective weights by Analytic Hierarchy Process. This new combination method may integrate the merits of both subjective and objective weighting methods. Empirical study shows that the new method can lead to more reasonable weighting results and decision.

1. Introduction

During the process of multiattribute decisions, it is necessary to establish a set of index systems for evaluating attributes and determine relative weights for the attributes. The weights of attributes represent the relative importance among them [1]. They also reflect status and effect of each attribute during the process of evaluation and decision-making. Determining weights of indexes is related to reliability and correctness of order on schemes. Therefore, it has been a hotspot in the field of decision-making and evaluation theory and multiple attribute decision-making has received a great deal of attention from researchers in many disciplines [2]. Generally speaking, there are two kinds of methods determining attribute weights including subjective assigning-weight and objective assigning-weight [3]. In the strict sense, there is no absolute objective assigning-weight method. The standard is whether the weights are determined by experts or not. In fact, even if it is an objective method, there are also some subjective factors in the entire process of a method.

Objective assigning-weight method takes advantage of information of each attribute to determine weights of attributes. It does not depend on subjective judgment of decision-makers to assign the weights. The weights are assigned to attributes by a mathematical method directly. Objective methods contain entropy evaluation [4, 5], principal component analysis [6], similarity scale based on alternative [7], goal programming [8, 9], centroid method [10], satisfactory degree of alternative [11], two-phase method [12], case-based reasoning [13], genetic algorithms [14], rough set [15, 16], fuzzy preference [17], interval-valued intuitionistic fuzzy decision [18], and so forth.

Subjective assigning-weight method gives weight to attributes according to experience of decision-makers and subjective importance to each attribute [19]. Subjective weights reflect accumulated experience of decision-makers and subjective judgment to present decision-making background. Variability of environment requires us to grasp importance of each attribute neatly when we make a decision. Thus, subjective methods can solve the problems. They include expert survey [20], dare score [21], importance ranking of attributes [13], point estimation [22], binomial coefficient [23], and judge matrix [24].

Determining weights by subjective weight method can utilize decision-makers' experience and knowledge. But its flexibility and mutability lead to much more subjective randomness. Hence, it is very important to avoid subjective randomness while giving play to its advantages. At the same time, objective weight method is inconsistent with actual importance of attributes sometimes because it does not

consider decision-makers' subjective willing. Besides, it is difficult to give clear explanation to the results. Considering advantages and disadvantages of subjective and objective method, respectively, many scholars brought forward methods combining subjective and objective weights [25], interactive assignment [26], combined TOPSIS [27, 28], and so forth. However, how to choose methods determining subjective and objective weights or what methods are appropriate to combine the two kinds of methods for overcoming the shortages which occur in either a subjective approach or an objective approach is still argued. In this paper, we will study a combined assigning-weight method based on maximizing variance to determine attribute weights, where objective weights of attributes are determined by rough set theory and subjective weights by AHP. Lastly, empirical study will demonstrate the feasibility of our method.

The remainder of the paper is organized as follows. Determining subjective weights for attributes based on Analytic Hierarchy Process is introduced in Section 2. Determining objective weights for attributes based on rough set is introduced in Section 3. Combined assigning-weights for attributes based on variance maximization is described in Section 4. Empirical study is presented in Section 5. Finally, conclusive results are drawn in Section 6.

2. Determine Subjective Weights for Attributes Based on Analytic Hierarchy Process

Analytic Hierarchy Process (AHP) was put forward by American Operation Researcher Sasty in the mid 1970s, which is a simple and practical method of system analysis and evaluation combining qualitative and quantitative analyses. The basic thinking to process decision-making problems is to simplify decision-making problems with multiobjective, multicriteria, and difficulty to be standardized into single target problems with multihierarchies, calculate the importance of each element in the same hierarchy to that in upper hierarchy by pairwise comparison, and acquire the weights of indexes finally. Basic steps of evaluating problems for AHP are shown as follows.

Step one: establish index hierarchy-structure. Divide indexes on a problem into different hierarchies, and determine the relation among indexes of every hierarchy.

Step two: construct judge matrix B. In multiple attributes, if there are many evaluating indexes, it is very difficult to determine the importance of each index directly. AHP requires decision-makers to judge relative importance of every index in a hierarchy and calibrate number for the judgment to form judge matrix.

Step three: calculate sequence weights. Calculate the importance of pairwise indexes for judge matrix and obtain weight of each index in the same hierarchy.

Step four: consistency check. When comparing the importance of pairwise indexes, it is not possible to meet consistency requirements because of some errors. In order to make sure of the feasibility of weight determination in AHP, consistency check needs to be done for judging results.

There are two core ideas in AHP. One is that indexes are divided into different hierarchies, namely, by establishing a hierarchy-structure model of a problem, transferring a complex problem use to a sequence calculation in hierarchies. Two is that AHP solves the problem that it is difficult to judge relative importance of multiple factors according to the idea of pairwise comparison. Because AHP can solve the sequencing problem of indexes in complex system, it is widely used in many fields.

3. Determine Objective Weights for Attributes Based on Rough Set

Rough set was a theory of data analysis brought forward by Polish Mathematician Professor Pawlak in 1982. By utilizing rough set method to analyze decision-making table, we can evaluate the importance of given attributes, construct the reduction of attribute set, and eliminate redundant attributes from decision-making table. At the same time, we also can produce clustering rules from decision-making table and apply it to make decisions.

Since Professor Pawlak proposed the theory of rough set, it has been widely used to process uncertain, imprecise, and incomplete information in the fields of artificial intelligence, cognitive science, and especially intelligent information processing as an effective mathematical tool. In recent years, some scholars have been introducing rough set theory into decision-making science for determining weights of all kinds of index objectively according to the characteristics that rough set can acquire property involved in data themselves while it does not depend on a priori knowledge [29]. When assigning weights in decision-making of management, rough set theory is widely used and developed in many fields.

3.1. Importance of Attributes. In rough set theory, $S = (U, C, V, f)$ is defined as an information system, where $U = \{x_1, x_2, \ldots, x_n\}$ is a discourse domain and C is a condition attribute set. $f : U \times C \rightarrow V$ is an information function which endows the attribute of every object with an information value, where $V = \cup V_a$, $a \in C$, and V_a denotes the range of attribute a. Subset $P \subseteq C$ of every attribute decides a binary indistinguishable relation IND(P):

$$\begin{aligned} &\mathrm{IND}(P) \\ &\quad = \{(x, y) \in U \times U \mid \forall a \in P,\ f(x, a) = f(y, a)\}. \end{aligned} \tag{1}$$

The relation IND(P) composes one partition of U, denoted by $U/\mathrm{IND}(P)$, simply denoted by $U/P = \{P_1, P_2, \ldots, P_k\}$. Any element $P_i = [x]_P = \{y \mid \forall a \in P, f(x, a) = f(y, a)\}$ is named as an equivalence class in U/P.

A decision-making table is defined as $S = (U, C, D, V, f)$, where $U = \{x_1, x_2, \ldots, x_n\}$ is a discourse domain, C is a condition attribute set, D is a decision-making attribute set, $f : U \times (C \cup D) \rightarrow V$ is an information function, $F = C \cup D$, $V = \cup V_a$, $a \in F$, and V_a denotes a range of attribute a. If decision-making attribute is removed in decision-making table, the table will become an information system, which means the difference between information system and

decision-making table is whether decision-making attributes are involved or not.

In decision-making table $S = (U, C, D, V, f)$, for $\forall A \subseteq C$, suppose that $U/A = \{A_1, A_2, \ldots, A_m\}$ expresses the partition of condition attribute set A to discourse domain U. $\forall X \subseteq U$, noted as $A^*(X) = \cup\{A_j \mid A_j \subseteq X\}$, $A^*(X)$ is called as lower approximate set on A of X in U.

In decision-making table $S = (U, C, D, V, f)$, for $\forall A \subseteq C$, suppose that $U/A = \{A_1, A_2, \ldots, A_m\}$ expresses the partition of condition attribute set A to discourse domain U and $U/D = \{D_1, D_2, \ldots, D_h\}$ denotes the partition of decision-making attribute set D to discourse domain U and call $\mathrm{POS}_A(D) = U_{D_i \in U/D} A * (D_i)$ as positive region on decision-making attribute set D of condition attribute set A in discourse domain U.

In accordance with the above-mentioned definitions, we can define the concept for importance of attribute a. In information system $S = (U, C, V, f)$, for $\forall a \subseteq C$, assuming $U/\{a\} = \{A_1, A_2, \ldots, A_m\}$, importance of attribute a is defined as follows:

$$\mathrm{Sig}(\{a\}) = \sum_{i=1}^{m} \frac{|A_i| \, |U - A_i|}{|U| \, (|U| - 1)}. \tag{2}$$

3.2. Determine Attribute Weights. In discernibility matrix based HU, $|A_i||U - A_i|$ denotes the total amount of discernibility elements produced by attribute $\{a\}$ in discernibility matrix. Total amount size of discernibility elements produced by attribute $\{a\}$ is conducted as heuristic information; namely, if the bigger is the total amount size of discernibility elements produced by an attribute $\{a\}$, it means the higher is important level of attribute $\{a\}$. In our paper, it is also used to measure importance of attributes in information system.

In information system $S = (U, C, V, f)$, for $\forall c_i \subseteq C$, define weights of attribute c_i in information system as the following equation [30]:

$$W(\{c_i\}) = \frac{\mathrm{Sig}(\{c_i\})}{\sum_{j=1}^{|C|} (\{c_i\})}. \tag{3}$$

Evidently, the attribute weights are only determined by (3) rather than experts. Therefore, it is an objective method.

4. Method Combining Subjective and Objective Assigning-Weight Based on Maximizing Variance

Assuming a decision-making problem with multiple attributes, its scheme set is $X = \{x_1, x_2, \ldots, x_n\}$, and $F = \{f_1, f_2, \ldots, f_n\}$ is an attribute set. $y_{ij} = f_i(x_j)$, $(i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n)$, is the value of scheme x_j to attribute f_i. r_{ij} is the result of standardizing decision-making matrix $Y = (y_{ij})_{m \times n}$. If weight vectors $w = (w_1, w_2, \ldots, w_m)^\tau$ are determined, we can calculate evaluating result of every scheme as follows [31]:

$$Z_i = \sum_{i=1}^{m} w_i r_{ij}. \tag{4}$$

Subjective and objective assigning-weight methods have their advantages and disadvantages. In this paper, we first use rough set theory and AHP to determine objective weights and subjective weights of attributes, respectively, and then assign weights combining subjective weights and objective weights based on maximizing variance.

Suppose the subjective weights are $V = (v_1, v_2, \ldots, v_m)^\tau$ $v_j \geq 0$, $\sum_{j=1}^{m} v_j = 1$ in accordance with rough set theory and the objective weights are $U = (u_1, u_2, \ldots, u_m)^\tau$ $u_j \geq 0$, $\sum_{j=1}^{m} u_j = 1$ in accordance with rough set theory. In order to absorb advantages of subjective and objective assigning-weight methods, combine two kinds of weights to integrated weight $w = \alpha U + \beta V$, where $w = (w_1, w_2, \ldots, w_m)^\tau$, α and β are linear combining coefficients, $\alpha \geq 0$, $\beta \geq 0$, and simultaneously α and β meet unit restriction $\alpha^2 + \beta^2 = 1$. If subjective weights $V = (v_1, v_2, \ldots, v_m)^\tau$ and objective weights $U = (u_1, u_2, \ldots, u_m)^\tau$ are made certain, integrative weights $w = (w_1, w_2, \ldots, w_m)^\tau$ depend on α and β. We deduce how to determine α and β according to maximizing variance as follows.

In multiple decision-making, if there is no evident difference for the j attribute to all decision-making schemes, the attribute will have no effect on sequencing results of decision-making schemes. So, the weight of the attribute is zero. However, if there is evident difference for an attribute to all decision-making schemes, the attribute will have big effect on sequencing results of decision-making schemes. So, the attribute should be given bigger weight. In statistics, variance is an important factor reflecting difference degree. Based on the principle of maximizing variance, weight vectors should have the total variance of all m attributes to all n decision-making schemes to be maximized. Thus, construct the following linear programming model [32]:

$$\begin{aligned} \max \quad Z &= \sum_{j=1}^{m} \sum_{i=1}^{n} \left(r_{ij} - \overline{r_{ij}}\right)^2 w_j \\ &= \sum_{j=1}^{m} \sum_{i=1}^{n} \left(r_{ij} - \overline{r_{ij}}\right)^2 \left(\alpha u_j + \beta v_j\right) \\ \text{s.t.} \quad & \alpha^2 + \beta^2 = 1 \\ & \alpha, \beta > 0. \end{aligned} \tag{5}$$

In the above model, $\overline{r_{ij}}$ denotes arithmetic mean of n attribute values of attribute i; namely,

$$\overline{r_{ij}} = \frac{1}{n} \sum_{i=1}^{n} r_{ij}, \quad j = 1, 2, \ldots, m. \tag{6}$$

In order to solve the above-mentioned optimization problem, construct *Lagrange* function as follows [33]:

$$L(\alpha, \beta) = \sum_{j=1}^{m} \sum_{i=1}^{n} (r_{ij} - \overline{r_{ij}})^2 \left(\alpha u_j + \beta v_j\right) + \lambda \left(\alpha^2 + \beta^2 - 1\right), \tag{7}$$

Table 1: AHP hierarchy for choosing location of a logistic park.

Goal	Criteria	Subcriteria	Alternative
C: location selection of logistic	$C1$: traffic environment	$C11$: relying city	$L1$: location 1
		$C12$: traffic condition	$L2$: location 2
		$C13$: geological condition	$L3$: location 3
	$C2$: benefit	$C21$: land prices and construction costs	$L4$: location 4
		$C22$: improvement to urban transport	$L5$: location 5
		$C23$: facilitation of distribution	$L6$: location 6
	$C3$: matching function	$C31$: situation surrounding existing facilities	$L7$: location 7
		$C32$: situation surrounding businesses	$L8$: location 8
		$C33$: possibility of attracting talent	
	$C4$: development potential	$C41$: trade logistics development potential	
		$C42$: development prospect relying on environment	
		$C43$: development prediction of trade and economy	

where λ is *Lagrange* multiplier. Let $\partial L/\partial\alpha = 0$, $\partial L/\partial\beta = 0$ [34]; then

$$\sum_{j=1}^{m}\sum_{i=1}^{n}\left(r_{ij}-\overline{r_{ij}}\right)^2 u_j + 2\lambda\alpha = 0,$$
$$\sum_{j=1}^{m}\sum_{i=1}^{n}\left(r_{ij}-\overline{r_{ij}}\right)^2 v_j + 2\lambda\beta = 0. \tag{8}$$

In addition, according to $\alpha^2 + \beta^2 = 1$, we can calculate values of α and β as follows:

$$\alpha = \frac{1}{\sqrt{1+\sum_{j=1}^{m}\sum_{i=1}^{n}\left(r_{ij}-\overline{r_{ij}}\right)^2 u_j / \sum_{j=1}^{m}\sum_{i=1}^{n}\left(r_{ij}-\overline{r_{ij}}\right)^2 v_j}},$$
$$\beta = \frac{1}{\sqrt{1+\sum_{j=1}^{m}\sum_{i=1}^{n}\left(r_{ij}-\overline{r_{ij}}\right)^2 v_j / \sum_{j=1}^{m}\sum_{i=1}^{n}\left(r_{ij}-\overline{r_{ij}}\right)^2 u_j}}. \tag{9}$$

After getting the values of α and β, it is easy to obtain integrative weights $w = \alpha U + \beta V$. Then, normalize $w = (w_1, w_2, \ldots, w_m)^\tau$ and acquire the result $w_0 = (w_{01}, w_{02}, \ldots, w_{0m})^\tau$ as the final value of each weight. We can calculate comprehensive evaluating result of every scheme,

$$Z_i = \sum_{i=1}^{m} w_{0i} r_{ij}. \tag{10}$$

Because the method combines subjective assigning-weight and objective assigning-weight, its weights both mix decision-maker's preference and ensure objectivity of decision-making. Furthermore, combined assigning-weight method based on maximizing variance can make evaluating values of schemes more discrete, and it is available for decision-maker to make a decision clearly.

5. Empirical Analysis

There are three kinds of methods to choose location of a logistic park, including linear programming, multiple attributes evaluation, and heuristic algorithm. When making the planning of regional logistic system, there are often some alternative schemes. Decision-making of a logistic park implies choosing an optimal one from alternative schemes. Accordingly, multiple attribute decision-making is often used to evaluate schemes. Process of location decision-making for a logistic park includes selecting evaluating indexes, determining index weights, index normalization, calculating comprehensive evaluating results, and making decision. In this paper, taking logistic center selection of a city as an example, we illustrate how to apply combined assigning-weight method to choose location of a logistic park.

5.1. Construct Index Systems of Evaluation and Mark Them. Firstly, according to the factors influencing the location of a logistic park, choose four indexes including traffic environment, benefit, matching function, and development potential as criteria layer. Each of the criteria involves its decision-making indexes. There are four hierarchies for AHP. The highest layer is goal and then criteria and subcriteria; the lowest layer is alternatives in AHP hierarchies. Assume there are eight alternatives in decision-making (see Table 1).

According to these indexes, experts mark 5, 4, 3, 2, and 1 to express excellent, good, average, poor, and poorer for each index. After calculating arithmetic mean of marks from experts, we can obtain average value of each index for every alternative (see Table 2).

5.2. Determine Subjective Weights of Indexes. Subjective weights are determined by AHP. In AHP, its fundamental problem is to find largest eigenvalue and corresponding eigenvectors of judge matrix. In practice, there are two calculation methods including accurate calculation and approximate calculation. In this paper, we use sum-product method of approximate calculation. We give an example of how to

Table 2: Initial evaluating values of indexes for alternatives.

Alternative	$C11$	$C12$	$C13$	$C21$	$C22$	$C23$	$C31$	$C32$	$C33$	$C41$	$C42$	$C43$
$L1$	3.98	3.96	4.04	3.24	4.03	4.23	3.45	3.50	4.25	4.56	4.50	4.45
$L2$	3.56	3.87	4.04	3.87	4.14	4.86	2.87	3.12	4.32	4.85	4.23	4.38
$L3$	4.56	4.78	4.08	4.56	4.56	4.13	4.28	4.29	4.52	4.12	3.93	4.65
$L4$	4.02	3.98	4.21	4.21	3.87	3.87	3.56	4.45	3.87	3.53	4.65	4.12
$L5$	4.03	4.23	3.96	4.02	4.06	4.81	2.96	3.26	4.51	4.82	4.12	3.86
$L6$	3.04	3.67	3.87	3.35	3.02	3.02	4.65	4.89	3.03	2.78	4.86	4.66
$L7$	3.89	376	4.02	4.03	3.86	3.98	3.63	4.86	2.98	3.28	3.69	4.68
$L8$	4.76	4.23	4.56	3.98	4.02	4.03	3.97	4.52	4.56	3.67	4.46	4.07

calculate subjective weights of criteria hierarchy with four indexes.

Firstly, determine judge matrix B and normalize it to $\overline{B}$; namely,

$$B = \begin{bmatrix} 4 & 5 & \frac{1}{2} & 1 \\ 5 & 6 & 1 & 2 \\ \frac{1}{3} & 1 & \frac{1}{6} & \frac{1}{5} \\ 1 & 3 & \frac{1}{5} & \frac{1}{4} \end{bmatrix}, \tag{11}$$

$$\overline{B} = \begin{bmatrix} 0.3871 & 0.3333 & 0.2679 & 0.2899 \\ 0.4839 & 0.4000 & 0.5357 & 0.5797 \\ 0.0323 & 0.0667 & 0.0893 & 0.0580 \\ 0.0968 & 0.2000 & 0.1071 & 0.0725 \end{bmatrix}.$$

Then, calculate sequence weights:

$$\overline{W} = \begin{bmatrix} 0.4764 \\ 0.2462 \\ 1.9993 \\ 1.2781 \end{bmatrix}, \qquad W = \begin{bmatrix} 0.1191 \\ 0.0615 \\ 0.4998 \\ 0.3195 \end{bmatrix}, \tag{12}$$

$$BW = \begin{bmatrix} 0.4835 \\ 0.2484 \\ 2.1038 \\ 1.3537 \end{bmatrix}.$$

Thirdly, calculate largest eigenvalue of judge matrix BW:

$$\begin{aligned} \lambda_{\max} &= \sum_{i=1}^{n} \frac{(BW)_i}{nw_i} \\ &= \frac{0.4835}{4 \times 0.1191} + \frac{0.2484}{4 \times 0.0615} \\ &\quad + \frac{2.1038}{4 \times 0.4998} + \frac{1.3537}{4 \times 0.3195} \\ &= 4.1356. \end{aligned} \tag{13}$$

Table 3: Subjective weight of each index.

Goal	Criteria	Subcriteria
C: location selection of logistic	$C1 = 0.1191$	$C11 = 0.0244$
		$C12 = 0.0422$
		$C13 = 0.0525$
	$C2 = 0.0615$	$C21 = 0.0205$
		$C22 = 0.0266$
		$C23 = 0.0145$
	$C3 = 0.4998$	$C31 = 0.1999$
		$C32 = 0.1749$
		$C33 = 0.1250$
	$C4 = 0.3195$	$C41 = 0.1023$
		$C42 = 0.1757$
		$C43 = 0.0415$

Fourthly, calculate consistency check CI:

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1} = \frac{4.1356 - 4}{4 - 1} = 0.0453. \tag{14}$$

Look RI up from random consistency index table, RI = 0.89; then calculate consistency ratio CR:

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} = \frac{0.0453}{0.89} = 0.0509 < 0.1. \tag{15}$$

Consequently, we can judge that there is satisfied consistency with the judge matrix and calculate relative weights of four indexes in criteria hierarchy. In the same way, determine weight of each index in subcriteria hierarchy (see Table 3).

5.3. Determine Objective Weights of Indexes. Objective weight of each index is determined by rough set theory. Firstly, discretize initial evaluating value of each index. The rule is that the excellent is in [4.5, 5.0], marked by 5; good in [4.0, 4.5), marked by 4; average in [3.5, 4.0), marked by 3; poor in [3.0, 3.5), marked by 2; poorer less than 3.0, marked by 1. According to the rule, the values in Table 2 are discretized as Table 4.

In Table 2, twelve decision-making attributes are $C11$, $C12$, $C13$, $C21$, $C22$, $C23$, $C31$, $C32$, $C33$, $C41$, $C42$, and $C43$. Our aim is to calculate evaluating values of eight alternatives of location for a logistic park.

Table 4: Discretized initial evaluating values of indexes for alternatives.

Alternative	$C11$	$C12$	$C13$	$C21$	$C22$	$C23$	$C31$	$C32$	$C33$	$C41$	$C42$	$C43$
$L1$	3	3	4	2	4	4	3	3	4	5	5	4
$L2$	3	3	4	3	4	5	1	2	4	5	4	4
$L3$	5	5	4	5	5	4	4	4	5	4	3	5
$L4$	4	3	4	4	3	3	3	4	3	3	4	4
$L5$	4	4	3	4	4	5	1	2	5	5	4	3
$L6$	2	3	3	2	2	2	5	5	2	1	5	5
$L7$	3	3	4	4	3	3	3	5	1	2	3	5
$L8$	5	4	5	3	4	5	3	5	5	3	4	4

Table 5: Weight of each decision-making index based on rough set theory.

Attribute	Weight	Attribute	Weight	Attribute	Weight	Attribute	Weight
$C11$	0.0906	$C21$	0.0906	$C31$	0.0827	$C41$	0.0945
$C12$	0.0669	$C22$	0.0827	$C32$	0.0906	$C42$	0.0787
$C13$	0.0669	$C23$	0.0906	$C33$	0.0906	$C43$	0.0748

In light of rough set, information system is defined as $S = (U, C, V, f)$; for $\forall a \subseteq C$, let $U/\{a\} = \{L_1, L_2, \ldots, L_m\}$. Importance of attribute a is calculated by (2). Taking examples as $C11$ and $C12$, according to (2), we have

$$\begin{aligned} \frac{U}{\{C11\}} &= \{\{L1, L2, L5\}, \{L3\}, \{L4, L8\}, \{L7\}, \{L6\}\}, \\ \frac{U}{\{C11\}} &= \{\{L1, L6\}, \{L2, L4, L5, L8\}, \{L3, L7\}\}. \end{aligned} \tag{16}$$

Then, calculate the importance of attribute $C11$ as follows:

$$\begin{aligned} \operatorname{Sig}(\{C11\}) = {} & \frac{|\{L1, L2, L5\}|\,|U - \{L1, L2, L5\}|}{|U|\,(|U| - 1)} \\ & + \frac{|\{L3\}|\,|U - \{L3\}|}{|U|\,(|U| - 1)} \\ & + \frac{|\{L4, L8\}|\,|U - \{L4, L8\}|}{|U|\,(|U| - 1)} \\ & + \frac{|\{L7\}|\,|U - \{L7\}|}{|U|\,(|U| - 1)} \\ & + \frac{|\{L6\}|\,|U - \{L6\}|}{|U|\,(|U| - 1)} \\ = {} & \frac{3 \times 5}{8 \times 7} + \frac{1 \times 7}{8 \times 7} + \frac{2 \times 6}{8 \times 7} \\ & + \frac{1 \times 7}{8 \times 7} + \frac{1 \times 7}{8 \times 7} = \frac{48}{56}. \end{aligned} \tag{17}$$

The results of other attribute importance are shown in Table 5.

In information system $S = (U, C, V, f)$, for $\forall c_i \subseteq C$, weights of attribute c_i in information system are calculated by (3); weight of each index is shown in Table 6.

5.4. Combine Subjective and Objective Weights. According to combined assigning-weight method based on maximizing variance, assume objective weight vector $U = (u_1, u_2, \ldots, u_m)^\tau$ $u_j \geq 0$, $\sum_{j=1}^{m} u_j = 1$ and the subjective weight vector $V = (v_1, v_2, \ldots, v_m)^\tau$ $v_j \geq 0$, $\sum_{j=1}^{m} v_j = 1$. Linear combination of two kinds of weights is expressed as integrate weight $w = \alpha U + \beta V$, where $w = (w_1, w_2, \ldots, w_m)^\tau$ and α and β are linear combining coefficients. According to the principle of maximizing variance, values of α and β are calculated as follows:

$$\begin{aligned} \alpha &= \frac{1}{\sqrt{1 + \sum_{j=1}^{m} \sum_{i=1}^{n} \left(r_{ij} - \overline{r_{ij}}\right)^2 u_j / \sum_{j=1}^{m} \sum_{i=1}^{n} \left(r_{ij} - \overline{r_{ij}}\right)^2 v_j}} \\ &= 0.7325, \\ \beta &= \frac{1}{\sqrt{1 + \sum_{j=1}^{m} \sum_{i=1}^{n} \left(r_{ij} - \overline{r_{ij}}\right)^2 v_j / \sum_{j=1}^{m} \sum_{i=1}^{n} \left(r_{ij} - \overline{r_{ij}}\right)^2 u_j}} \\ &= 0.6807. \end{aligned} \tag{18}$$

Calculate integrate weight $w = (w_1, w_2, \ldots, w_m)^\tau$ and normalize it. The final results of normalization for each attribute are shown in Table 7.

5.5. Evaluating Results of Location Selection for a Logistic Park. According to initial evaluating value of each index for alternatives and results of Table 7, calculate comprehensive evaluating results of each alternative by (10). The values are seen in Table 8. Because the score of alternative $L3$ is the highest, it can be chosen as the optimal scheme.

6. Conclusions

Most of multiattribute decision-making uses subjective or objective methods to determine weights. However, few

Table 6: Importance of attributes.

Attribute	$C11$	$C12$	$C13$	$C21$	$C22$	$C23$	$C31$	$C32$	$C33$	$C41$	$C42$	$C43$
Sig({Cij})	46/56	34/56	34/56	46/56	42/56	46/56	46/56	42/56	46/56	48/56	40/56	38/56

Table 7: Integrate weights of decision-making attributes.

Attribute	Weight	Attribute	Weight	Attribute	Weight	Attribute	Weight
$C11$	0.0587	$C21$	0.0568	$C31$	0.1392	$C41$	0.0982
$C12$	0.0550	$C22$	0.0557	$C32$	0.1312	$C42$	0.1255
$C13$	0.0600	$C23$	0.0539	$C33$	0.1071	$C43$	0.0588

Table 8: Evaluating results of alternatives.

Alternative	Comprehensive mark	Order of evaluating results
$L1$	3.9988	4
$L2$	3.9125	6
$L3$	4.3245	1
$L4$	4.0367	3
$L5$	3.9603	5
$L6$	3.9036	7
$L7$	3.8568	8
$L8$	4.2459	2

studies brought forward methods combining subjective and objective assigning-weight. In this paper, we brought forward a combined assigning-weight method when rough set and AHP are used to determine objective weights and subjective weights of multiattributes, respectively. For objective assigning-weight method by rough set, the bigger is the total amount size of discernibility elements produced by an attribute and the higher is the important level of the attribute. But it ignores the importance of each attribute itself because rough set determines weights according to actual values of indexes. AHP is a kind of typical subjective assigning-weight method. Wherefore, the assigning-weight method combing rough set and AHP can synthesize both of their merits. In addition, compared with other combining weight methods, the method with subjective and objective weight combination based on maximizing variance is more feasible because it considers different degree of each attribute itself. Finally, empirical study demonstrates feasibility of combining weight method. When attribute weights are entirely unknown and attribute values are continuous, the combining method is an effective evaluating tool of decision-making.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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