Technological and Economic Development of Economy
ISSN: 2029-4913 / eISSN: 2029-4921
2022 Volume 28 Issue 2: 559–580
https://doi.org/10.3846/tede.2022.16634

A PROBABILISTIC LINGUISTIC VIKOR METHOD TO SOLVE MCDM PROBLEMS WITH INCONSISTENT CRITERIA FOR DIFFERENT ALTERNATIVES

Xingli WU [1], Huchang LIAO [1*], Edmundas Kazimieras ZAVADSKAS [2], Jurgita ANTUCHEVIČIENĖ [3]

[1]*Business School, Sichuan University, Chengdu, China*
[2]*Institute of Sustainable Construction, Vilnius Gediminas Technical University, Vilnius, Lithuania*
[3]*Department of Construction Management and Real Estate, Vilnius Gediminas Technical University, Vilnius, Lithuania*

Received 03 November 2021; accepted 17 February 2022

Abstract. VIKOR is a well-defined multiple criteria decision-making (MCDM) method since it reflects different risk attitudes of decision-makers by measuring the overall performance of an alternative under all criteria as "group value" and the worst performance of the alternative under all criteria as "individual regret", but it cannot deal with MCDM problems where the criteria of different alternatives are inconsistent (different) and the decision information is uncertain. To address these problems, we present a probabilistic linguistic VIKOR method by combining with probabilistic linguistic term sets which portrays uncertain information such as individual hesitancy and incomplete belief flexibly. In addition, we introduce the aspired and tolerable values of criteria as reference points to measure the closeness degrees of alternatives to the ideal solution. To compare group values and individual regrets of different alternatives, we develop a vector normalization method that considers the number of criteria. The robustness of the aggregation results of group values and individual regrets is improved based on the extended Borda rule, which takes into account both values and ranks of alternatives in the aggregation. A case study of personnel evaluation demonstrates the effectiveness of the proposed method for solving MCDM problems with inconsistent criteria and uncertain decision information.

Keywords: multiple criteria decision making, VIKOR, inconsistent criteria, probabilistic linguistic term set, personnel selection.

JEL Classification: C51, C61, D81, L00.

Introduction

Decision-making processes often need to measure the performance of several or even thousands of alternatives (which also refer to as candidates, or reasons for action) against multiple irreplaceable criteria (which also refer to as goals, indicators, or attributes) in order to classi-

*Corresponding author. E-mail: *liaohuchang@163.com*

fy, select or rank them (Cinelli et al., 2020). These so-called multiple criteria decision-making (MCDM) problems are common in our daily life (Hashemkhani Zolfani et al., 2021). For example, building redevelopment decisions depends on existing state, development possibilities, and impact (Antucheviciene et al., 2011); water resource development planning alternatives are measured from cost, water quality, and feasibility of implementation (Roozbahani et al., 2018); personnel selection needs to take into account candidates' personality, education, experience and skills to achieve a company's goals (Kilic et al., 2020). In most of these MCDM problems, there are not obvious dominance relations between alternatives under different criteria because the performance of each alternative is usually inconsistent regarding different criteria. To enhance comparability among alternatives, MCDM theory provides a series of preference models that can reflect the value systems of decision makers. It aims to aggregate the performance of alternatives under different criteria into their comprehensive performance, so as to find compromise solutions that have the best comprehensive performance, although they cannot satisfy all criteria at the same time.

MCDM approaches can be divided into three categories: 1) value theory-based methods such as the TOPSIS[1] (Chen & Hwang, 1992) and VIKOR (Opricovic, 1998), 2) outranking methods such as the ELECTRE (Roy, 1968) and PROMETHEE (Brans & Vincke, 1985), and 3) rule-based approaches (Greco et al., 2016). The first type is based on the multiple criteria value theory (Keeney & Raiffa, 1976), which refers to the conversion (namely a normalization process) of criterion values on inconsistent criterion dimensions into the values of the same dimension by means of marginal value functions, thus enabling the comparison or aggregation operation of the performances of alternatives under different criteria (Dyer & Smith, 2021). Outranking methods are based on the pairwise comparisons of alternatives, while rule-based approaches apply decision rules to construct preference models. Compared with these two categories of MCDM methods, value theory-based methods have solid rationality axioms and have the advantages of being computationally simple and easy to understand (Zheng & Lienert, 2018). They have been widely used in many fields, such as manufacturing, construction management, performance evaluation, health-care management, renewable energy management, emergency management, and human resource management (Mardani et al., 2016; Komazec & Petrović, 2019; S. Lin et al., 2021b). TOPSIS and VIKOR are the most widely used value theory-based methods. Both of them aim to find the optimal or compromise solutions[2] closest to the ideal solution by coordinating multiple conflicting criteria through distance measures, so they are also known as distance-based methods. The comparative analysis of VIKOR and TOPSIS shows the advantages of VIKOR in terms of aggregation and normalization techniques (Opricovic & Tzeng, 2004).

Through a balance between "group values" determined by the "majority" rule and "individual regrets" determined by the "opponent" rule, the compromise solutions found by VIKOR can satisfy the requirements of decision-makers with different risk attitudes (An-

[1] TOPSIS-Technique for order preference by similarity to ideal solution; VIKOR-Vlsekriterijumska optimizacija I kompromisno resenje in Serbian, meaning multi-criteria optimization with compromise solution; ELECTRE-Elimination et choix traduisant larealité in French, meaning elimination and choice expressing the reality; PROMETHEE-Preference ranking organization method for enrichment evaluations.

[2] Compromise is an agreement reached through mutual concessions (Ou-Yang et al., 2009).

tucheviciene et al., 2012; Su et al., 2020). Especially, when decision-makers pay more attention to the opponent rule, the compromise solutions determined by VIKOR not only have good overall performance, but also do not perform too badly under each criterion. Although previous studies have enhanced the theory and applications of the VIKOR method, there are still challenges to overcome:

1) The VIKOR method and its extensions are designed to solve the MCDM problems where all alternatives are measured by the same set of criteria. In many practical MCDM problems, however, different alternatives are associated with different criteria, meaning that the same set of criteria cannot be used to measure the performances of all alternatives (Anvari et al., 2014; Jing et al., 2019). For example, when evaluating the research ability of talents in the field of natural science, we can focus on the number of publications indexed by science citation index (SCI) database in web of science (WoS), while when evaluating the research ability of talents in the field of social science, we would better focus on the number of publications indexed by social science citation index (SSCI) database in WoS. The criteria for measuring the profitability of a company's different projects (e.g., technical support, technology services and software development projects) differ, and the criteria for evaluating the profitability of the same project at different stages of development differ. The criteria for evaluating the strength of different types of hospitals, such as general hospitals, specialty hospitals and rehabilitation hospitals, are different. As far as we know, there is little literature on solving such type of MCDM problems with different sets of criteria for different types of alternatives.
2) Although the VIKOR method has advantages over the TOPSIS method in theory, TOPSIS has obtained more applications than VIKOR. One reason is that the compromise-ranking approach used in the traditional VIKOR method is not intuitive, and the existence of multiple compromise solutions increases the difficulty of decision-making (Liao & Wu, 2020). Specifically, although the VIKOR method can meet the requirements of decision-makers with different risk attitudes, it is difficult to determine the relative importance of the majority rule and opponent rule, and the result is sensitive to this parameter.
3) The traditional VIKOR method aims to address quantitative forms of decision information and has limitations to deal with uncertain linguistic information. In complex decision-making environments, decision information, including the performance of alternatives under different criteria, is difficult to collect directly and often needs to be assessed by experts in a subjective manner. Consequently, researchers (Bausys & Zavadskas, 2015; Liao et al., 2015; Awasthi et al., 2018; Abdel-Baset et al., 2019; Çalı & Balaman, 2019) have focused on extending the application of VIKOR by combining linguistic approaches, in which linguistic models were used to represent decision information. Experimental studies on subjective probabilistic judgment theory (Tversky & Kahneman, 1974; Machina & Schmeidler, 1992) have shown that evaluators tend to provide beliefs about possible "guesses" on "events" in their judgments under uncertain conditions by means of subjective probabilities expressed in numerical values (Tversky & Kahneman, 1974). In MCDM problems, "subjective probability" can be regarded as

the belief degree of an evaluator in the chosen linguistic term. For example, one may express that "the probability that a product is good is 80% and the probability that the product is bad is 20%". Additionally, subjective probability can be expressed as the frequency of a linguistic term when multiple evaluators evaluate an object. For example, in response to the evaluation of a product's quality, 50% of the evaluators rated the quality as "good", 30% rated the quality as "very good" and 20% rated the quality as "between good and very good". To represent such type of complex linguistic information, Pang et al. (2016) defined the probabilistic linguistic term set (PLTS), which is a generic linguistic representation model for describing evaluation information given by individuals or groups. The PLTS has gained the attention of researchers (Liao et al., 2020). Although researchers (M. Lin et al., 2021a; Gou et al., 2021) have introduced PLTSs to the VIKOR method to solve MCDM problems, they failed to avoid the inability of the VIKOR method in solving the problem of inconsistent criterion sets and the low robustness of decision results.

This study aims to propose a probabilistic linguistic VIKOR method to solve MCDM problems where the criteria for different alternatives may be different and the decision information of alternatives cannot be quantified. The motivations and contributions of this study include:

1) When different alternatives are measured by different sets of criteria, the positive ideal solution and negative ideal solution, defined in the traditional VIKOR method, cannot be determined by comparing the values of different alternatives under the same set of criteria. To solve this problem, an aspired value and a tolerable value can be introduced for each criterion (Ou-Yang et al., 2009). The aspired value represents decision-makers' aspired performance of alternatives under a criterion, that is, when the performance of an alternative equals or exceeds the aspired value, decision-makers are completely satisfied with the alternative. On the contrary, the tolerable value represents decision-makers' critical performance of alternatives under a criterion, that is, decision-makers are completely dissatisfied with an alternative if its performance is equal to or lower than the tolerable value. The closer the performance of an alternative to the aspired (or tolerable) value for each of its criteria is, the closer the alternative to the positive (or negative) ideal solution is. In this sense, by measuring the distances between the values of an alternative and the aspired (or tolerable) values, we can get how close each alternative to the positive (or negative) ideal solution is, and thus define the group values and individual regrets of alternatives. In addition, a normalization process considering the number of criteria is proposed to make the group values and individual regrets of different alternatives to the same scale. The problem of measuring different alternatives with different criteria is resolved.
2) According to the majority rule and opponent rule, the group values and individual regrets of alternatives can be obtained to represent their overall performances, respectively, and the two subordinate rankings of alternatives can be determined. The values can reflect the actual differences in performance between alternatives, while the ranks can reflect the preference relations between alternatives (Wu et al., 2018). In order to improve the robustness of aggregation results, we propose an aggregation method to

integrate the subordinate values and ranks of alternatives to determine their compromise degrees and overall ranking, which avoids the poor robustness of the results due to considering only the subordinate values and the poor accuracy of the results due to considering only the subordinate ranks. The second challenge of the traditional VIKOR method is overcome.

3) We use PLTSs to describe the performance of alternatives under each criterion. To compare the performance of alternatives with the aspired and tolerable values, we adjust different PLTSs to the same probability distribution without losing any information, and then apply a probabilistic linguistic distance measure to determine how close each alternative is to the positive (or negative) ideal solution. The third challenge mentioned above is addressed.

The paper is organized in the following way. A brief introduction of the VIKOR and PLTS is given in the next section. In Section 2, a probabilistic linguistic VIKOR method is proposed to solve the MCDM problems where the criteria of different alternatives may be inconsistent. Section 3 illustrates the proposed approach using a case study on the evaluation of scientific and technological talents. Finally, conclusions and directions for future research are provided.

1. Preliminaries

This section first describes the implementation steps of the classical VIKOR method, and then introduces the PLTS to represent uncertain evaluations.

1.1. The VIKOR method

The traditional VIKOR method can solve an MCDM problem with the purpose of ranking a set of alternatives (denoted as $A=\{a_1,a_2,\cdots,a_m\}$) or selecting one or more compromise alternatives, using the same set of criteria for each alternative, denoted as $C=\{c_1,c_2,\cdots,c_n\}$. The value of an alternative a_i under a criterion c_j is represented as an exact number x_{ij}. The steps of the traditional VIKOR method are as follows (Opricovic, 1998; Opricovic & Tzeng, 2004).

1) Determine the best and the worst values of each criterion by Eqs (1) and (2), respectively. $a^+=\{x_1^+,x_2^+,\cdots,x_n^+\}$ is the positive ideal solution, and $a^-=\{x_1^-,x_2^-,\cdots,x_n^-\}$ is the negative ideal solution.

$$x_j^+=\begin{cases}\max\limits_i x_{ij}, & \text{if criterion } c_j \text{ is in the benefit form}\\ \min\limits_i x_{ij}, & \text{if criterion } c_j \text{ is in the cost form}\end{cases}, \text{ for } j=1,2,\cdots,n; \tag{1}$$

$$x_j^-=\begin{cases}\min\limits_i x_{ij}, & \text{if criterion } c_j \text{ is in the benefit form}\\ \max\limits_i x_{ij}, & \text{if criterion } c_j \text{ is in the cost form}\end{cases}, \text{ for } j=1,2,\cdots,n. \tag{2}$$

2) Determine the group values G_i, $i = 1, 2, \ldots, m$, of alternatives by a weighted average aggregation operator (Eq. (3)), and determine the individual regrets R_i, $i = 1, 2, \ldots, m$, of alternatives by a maximization aggregation operator (Eq. (4)).

$$G_i=\sum_{j=1}^{n} w_j\,(x_j^+-x_{ij})\big/(x_j^+-x_j^-); \tag{3}$$

$$R_i = \max_j (w_j (x_j^+ - x_{ij}) \big/ (x_j^+ - x_j^-)), \tag{4}$$

where w_j, $j = 1, 2, \ldots, n$, are trade-off weights of criteria. $N(a_{ij}) = (x_j^+ - x_{ij}) \big/ (x_j^+ - x_j^-)$ represents the normalization value of a_i under criterion c_j. $N(\cdot)$ is a linear normalization function to measure the distance between the value of an alternative under a criterion and the best value of that criterion. The solution obtained with $\min_i G_i$ has the maximum group value (the majority rule), and the solution obtained with $\min_i R_i$ has the minimum individual regret (the opponent rule). The next step is to make a trade-off between these two rules to determine compromise solutions.

3) Compute the compromise degrees Q_i, $i = 1, 2, \ldots, m$, of alternatives by a weighted average aggregation operator:

$$Q_i = \eta(G_i - \min_i G_i) \big/ (\max_i G_i - \min_i G_i) + (1 - \eta)(R_i - \min_i R_i) \big/ (\max_i R_i - \min_i R_i), \tag{5}$$

where η is the weight of the majority rule used for ranking, and $\eta \in [0,1]$.

4) Rank alternatives according to the ascending orders of the three kinds of values, G_i, R_i, Q_i, $i = 1, 2, \ldots, m$, respectively. The compromise solutions are determined by the compromise-ranking method and should have high ranks in all three rankings.

Researchers have enhanced the VIKOR method from different perspectives. To solve inconsistent criteria, Ou-Yang et al. (2009) proposed a VIKOR variation which measured the closeness of each alternative to the ideal solution by an aspired level and a tolerable level on each criterion. Jing et al. (2019) applied this approach to select tools for lean management. However, the method proposed by Ou-Yang et al. (2009) has limitations: 1) it did not consider uncertain evaluation information, which limits its application in practice given that most decisions are made in uncertain environments (Hajiagha et al., 2014); 2) it did not consider the weights of criteria when measuring individual regrets of alternatives, which may amplify the effect of the values under unimportant criteria on final results; 3) it did not take into account the differences in dimensionality between the group values and individual regrets of alternatives when aggregating the values of them.

Since language is the closest expression of human cognition, evaluators tend to use words such as "important", "high" and "good" to express their opinions in decision-making processes. Linguistic approach (Zadeh, 1975) expresses evaluation information in linguistic terms, enhancing the feasibility, flexibility and credibility of the evaluation process (Wang et al., 2018). To deal with linguistic evaluation information in MCDM problems, a number of extended VIKOR methods associated with different linguistic representation models have been proposed, such as the interval-valued neutrosophic set-based VIKOR (Bausys & Zavadskas, 2015), triangular fuzzy number-based VIKOR (Awasthi et al., 2018), triangular neutrosophic number-based VIKOR (Abdel-Baset et al., 2019), intuitionistic fuzzy set-based VIKOR (Çalı & Balaman, 2019), and picture fuzzy number-based VIKOR (Peng et al., 2020). However, these methods portray the values of linguistic variables using single linguistic terms, and thus have weakness in representing uncertain evaluation information, including the hesitancy and incomplete confidence of individual evaluators, and the inconsistency and incompleteness of group opinions. Although the hesitant fuzzy linguistic VIKOR (Liao et al., 2015) can deal with hesitant fuzzy linguistic information in individual evaluations through multiple linguistic terms, it is difficult to portray the belief of individual evaluators and the distribution of group opinions. Such uncertain information can be modeled with PLTSs, and thus the combination of the PLTS and VIKOR is conducive to MCDM problems in qualitative settings.

1.2. Probabilistic linguistic term set

For MCDM problems with qualitative criteria, subjective evaluations by experts or decision-makers are required. A linguistic term set used for evaluation can be defined as $S=\{s_{-\tau},\cdots,s_0,\cdots,s_\tau\}$, in which s_α, $\alpha=-\tau,\cdots,0,\cdots,\tau$, are linguistic terms used to describe the possible qualitative values of alternatives, satisfying $s_\alpha \succ s_\beta$ if $\alpha>\beta$, $\forall\alpha,\beta\in\{-\tau,\cdots,0,\cdots,\tau\}$. Especially, $s_{-\tau}$, s_0 and s_τ indicate the worst, neutral and best performance values, respectively. A PLTS can be defined as (Pang et al., 2016):

$$P=\{s_\alpha(p_\alpha)\,|\,\alpha=-\tau,\cdots,\tau,\sum\nolimits_{\alpha=-\tau}^{\tau}p_\alpha\le 1\}, \tag{6}$$

where p_α represents the subjective probability that the performance of a linguistic variable is s_α. $p_\alpha=0$ (or $p_\alpha=1$) means that the variable's performance cannot (or can only) be described in s_α. Linguistic terms with a probability of zero may not be listed in the PLTS.

Since a PLTS can be regarded as a probability distribution over a linguistic term set, its expected value can be defined as (Wu & Liao, 2019):

$$E(P)=\sum\nolimits_{\alpha=-\tau}^{\tau}u(s_\alpha)\times\left(p_\alpha\Big/\sum\nolimits_{\alpha=-\tau}^{\tau}p_\alpha\right), \tag{7}$$

where $u(\cdot):S\to[0,1]$ represents a linguistic scale function used to describe the numerical meaning of linguistic terms. If $s_\alpha\succ s_\beta$, then $u(s_\alpha)>u(s_\beta)$. Here we set $u(s_\alpha)=(\alpha+\tau)/2\tau$. Let P_1 and P_2 be two PLTSs. The preference relation between them can be determined by their expected values, that is, if $E(P_1)>E(P_2)$, then $P_1\succ P_2$, and if $E(P_1)=E(P_2)$, then $P_1\sim P_2$.

Probabilistic linguistic distance measure can be used to measure the difference between the information represented by two PLTSs. Before describing the difference, it is necessary to split the probability of linguistic terms in two PLTSs so that the number of their linguistic terms are the same and the corresponding probability of each linguistic term is consistent. For example, two PLTSs $P_1=\{s_\alpha(p_\alpha^1)\,|\,\alpha=-\tau,\cdots,\tau\}$ and $P_2=\{s_\alpha(p_\alpha^2)\,|\,\alpha=-\tau,\cdots,\tau\}$ can be adjusted to $P_1'=\{s_\alpha^{1(k)}(p^{(k)})\,|\,k=1,2,\cdots,K\}$ and $P_2'=\{s_\alpha^{2(k)}(p^{(k)})\,|\,k=1,2,\cdots,K\}$, respectively, such that they all have K linguistic terms and the probability of their kth linguistic term is $p^{(k)}$ $(k\in\{1,2,\cdots,K\})$[3]. There may be duplication of linguistic terms in an adjusted PLTS, but the total probability of each linguistic term remains unchanged. The distance measure between $P_1=\{s_\alpha(p_\alpha^1)\,|\,\alpha=-\tau,\cdots,\tau\}$ and $P_2=\{s_\alpha(p_\alpha^2)\,|\,\alpha=-\tau,\cdots,\tau\}$ can be defined as (Wu et al., 2018):

$$d\left(P_1,P_2\right)=\sum\nolimits_{k=1}^{K}p^{(k)}\left|s_\alpha^{1(k)}-s_\alpha^{2(k)}\right|\Big/2\tau, \tag{8}$$

where $d\left(P_1,P_2\right)\in[0,1]$. If and only if $P_1=P_2$, $d\left(P_1,P_2\right)=0$.

[3] For the convenience of calculation, each linguistic term s_α can be divided into $10p_\alpha$ terms, and each term corresponds to a unit probability "0.1" (here the probability preserves a decimal point) (Liao et al., 2019). If there are missing probabilities in a PLTS, then we normalize the probability of each linguistic term such that the sum of the probabilities is 1.

Example 1. Let $S=\{s_{-1},s_0,s_1\}$ be a linguistic term set, and $P_1=\{s_0(0.6),s_1(0.4)\}$ and $P_2=\{s_{-1}(0.3),s_0(0.7)\}$ be two PLTSs. The adjusted forms of these two PLTSs can be expressed as $P_1'=\{s_0(0.3),s_0(0.3),s_1(0.4)\}$ and $P_2'=\{s_{-1}(0.3),s_0(0.3),s_0(0.4)\}$, respectively, and their distance measure can be calculated by $d(P_1,P_2)=(0.3\times|0-(-1)|+0.3\times|0-0|+0.4\times|1-0|)/2=0.35$.

2. The proposed probabilistic linguistic VIKOR method

This section proposes an extension form of the VIKOR method to solve MCDM problems with inconsistent criteria for different alternatives and the evaluation information is expressed in PLTSs.

Suppose that there are m alternatives, $A=\{a_1,a_2,\cdots,a_m\}$, and m sets of criteria, $\{c_{11},c_{12},\cdots,c_{1n_1}\}$, $\{c_{21},c_{22},\cdots,c_{2n_2}\},\cdots,\{c_{m1},c_{m2},\cdots,c_{mn_m}\}$, in which n_i is the number of criteria for measuring the performance of a_i and c_{ij} represents the jth criterion of alternative a_i, $i\in\{1,2,\cdots,m\}$, $j\in\{1,2,\cdots,n_i\}$. The weight vector of each set of criteria is denoted as $(w_{11},w_{12},\cdots,w_{1n_1})^{\mathrm{T}}$, $(w_{21},w_{22},\cdots,w_{2n_2})^{\mathrm{T}},\cdots$, $(w_{m1},w_{m2},\cdots,w_{mn_m})^{\mathrm{T}}$, respectively, in which w_{ij} represents the weight of the jth criterion of alternative a_i, satisfying $\sum_{j=1}^{n_i} w_{ij}=1$. The performance of alternative a_i with respect to criterion c_{ij} is described by a PLTS $P_{ij}=\{s_\alpha(p_\alpha^{ij})\,|\,\alpha=-\tau,\cdots,\tau\}$. The decision information of alternative a_i can be represented as a set

$$H(a_i)=\{P_{i1},P_{i2},\cdots,P_{in_i}\}. \tag{9}$$

The probabilistic linguistic VIKOR method proposed in this study has the following steps.

Step 1. Determine the aspired value P_{ij}^+ and tolerable value P_{ij}^- of each criterion c_{ij}, $j\in\{1,2,\cdots,n_i\}$, $i\in\{1,2,\cdots,m\}$. These values are determined by decision-makers based on their expectations and tolerance degrees to alternatives regarding different criteria. When all alternatives are evaluated by the same set of criteria, the aspired and tolerable values of each criterion can be objectively determined by the method used in the traditional VIKOR method. That is, if the criterion is in the benefit form, then $P_{ij}^+=\max_i P_{ij}$ and $P_{ij}^-=\min_i P_{ij}$, and if the criterion is in the cost form, then $P_{ij}^+=\min_i P_{ij}$ and $P_{ij}^-=\max_i P_{ij}$.

Step 2. Calculate the degree of closeness $N(a_{ij})$ between the value P_{ij} of alternative a_i under criterion c_{ij} in a criteria set $\{c_{i1},c_{i2},\cdots,c_{in_i}\}$ and the aspired value P_{ij}^+ of criterion c_{ij}. If c_{ij} is in the benefit form, then

$$N(a_{ij})=\begin{cases}0, & \text{if } P_{ij}\le P_{ij}^- \\ 1-\dfrac{d\left(P_{ij},P_{ij}^+\right)}{d\left(P_{ij}^-,P_{ij}^+\right)}, & \text{if } P_{ij}^-<P_{ij}<P_{ij}^+ \\ 1, & \text{if } P_{ij}\ge P_{ij}^+\end{cases}. \tag{10}$$

If c_{ij} is in the cost form, then

$$N(a_{ij})=\begin{cases}0, & \text{if } P_{ij}\ge P_{ij}^- \\ 1-\dfrac{d\left(P_{ij},P_{ij}^+\right)}{d\left(P_{ij}^-,P_{ij}^+\right)}, & \text{if } P_{ij}^+<P_{ij}<P_{ij}^- \\ 1, & \text{if } P_{ij}\le P_{ij}^+\end{cases}, \tag{11}$$

where $d\left(P_{ij},P_{ij}^{+}\right)$ is the probabilistic linguistic distance measure (see Eq. (8)) between the value P_{ij} of alternative a_i under its jth criterion and the aspired value P_{ij}^{+} of this criterion. $d\left(P_{ij}^{-},P_{ij}^{+}\right)$ is the probabilistic linguistic distance measure between the aspired value P_{ij}^{+} and the tolerable value P_{ij}^{-} of the jth criterion of alternative a_i. The preference relations between the PLTSs P_{ij}, P_{ij}^{+} and P_{ij}^{-} are determined by their expected values (see Eq. (7)). If $P_{ij}^{-}<P_{ij}<P_{ij}^{+}$, then $d\left(P_{ij},P_{ij}^{+}\right)\le d\left(P_{ij}^{-},P_{ij}^{+}\right)$. Thus, $N(a_{ij})\in[0,1]$. The larger the value of $N(a_{ij})$ is, the better the performance of alternative a_i under its jth criterion is.

Step 3. Compute the group value $\tilde{G}_i$ and individual regret $\tilde{R}_i$ of each alternative by Eqs. (12) and (13), respectively.

$$\tilde{G}(a_i)=\sum_{j=1}^{n_i} w_{ij}N(a_{ij}),\ i=1,2,\ldots,m; \tag{12}$$

$$\tilde{R}(a_i)=\max_j\left[w_{ij}(1-N(a_{ij}))\right],\ i=1,2,\ldots,m. \tag{13}$$

In order to define the compromise degrees of alternatives by integrating their group values and individual regrets, the traditional VIKOR method uses a linear normalization method to convert group values and individual regrets into the same scale such that the smallest group value and the smallest individual regret are 0, and the largest group value and the largest individual regret are 1. When the group values and individual regrets of alternatives are not equally distributed, the results obtained by the linear normalization may reduce the reliability of their aggregation. For example, if the group values of most alternatives do not differ much but their individual regrets do, then the linear normalization will exaggerate the differences between the group values of alternatives. To solve this problem, we use the vector normalization which normalizes the maximum value to 1 to preserve the differences between the values of alternatives.

Normalize the group values $\tilde{G}_i$, $i = 1, 2, \ldots, m$, by a vector normalization method[4]:

$$\tilde{G}^N(a_i)=\frac{\tilde{G}(a_i)}{\max_i \tilde{G}(a_i)}. \tag{14}$$

The individual regrets of alternatives defined by the maximization aggregation operator (see Eq. (13)) have different scales and thus cannot be compared directly, especially when the number of criteria for different alternatives differs. The smaller the number of criteria in a criterion set is, the greater the average weight of each criterion is, and therefore the greater the individual regrets of corresponding alternatives are. In this regard, we need to normalize individual regrets to the same scale according to the number of criteria. The individual regrets of different alternatives are first adjusted to the same scale by the factor $n_i\Big/\prod_{i=1,2,\cdots,m} n_i$, and then normalized by a vector normalization method. That is

$$\tilde{R}^N(a_i)=\frac{\tilde{R}(a_i)\times n_i\Big/\prod_{i=1,2,\cdots,m} n_i}{\max_i\left(\tilde{R}(a_i)\times n_i\Big/\prod_{i=1,2,\cdots,m} n_i\right)}=\frac{\tilde{R}(a_i)\times n_i}{\max_i\left(\tilde{R}(a_i)\times n_i\right)}. \tag{15}$$

[4] The group value is defined as the average value of an alternative under different criteria. Thus, the group values of different alternatives have the same scale.

After normalization, the group values and individual regrets of alternatives have the same scale, that is, both the maximum group value and individual regret are 1. Then, we rank alternatives by the values of $\tilde{G}^N(a_i)$, $i=1,2,\cdots,m$, in decreasing order. The results are the first subordinate ranking list, denoted as $r_1=\{r_1(a_1),r_1(a_2),\cdots,r_1(a_m)\}$. In addition, we rank the alternatives by the values $\tilde{R}(a_i)$, i = 1, 2, …, m, in ascending order. The results are the second subordinate ranking list, denoted as $r_2=\{r_2(a_1),r_2(a_2),\cdots,r_2(a_m)\}$. When there is no solution that satisfies $\tilde{G}(a_i)=\max_{t=1,2,\cdots,m}\tilde{G}(a_t)$ and $\tilde{R}(a_i)=\min_{t=1,2,\cdots,m}\tilde{R}(a_t)$, we cannot determine the best alternative directly. In this case, we need to make trade-offs between the group values and individual regrets.

Step 4. As one of the most famous group voting rules, Borda rule calculates the Borda number of an object based on the ranking of m objects and uses it as the score of that object (Panja et al., 2020). The Borda number of the ith ranked object is $m - i + 1$. The Borda numbers can visualize the preference relations between alternatives. The values of alternatives can reflect the specific differences between alternatives. The extended Borda rule (Wu et al., 2018) integrates the rank and value information of alternatives to determine the global Borda numbers of alternatives. In this way, the aggregation results are not only robust but also can reflect the specific differences between alternatives. Based on the idea of the extended Borda rule, we define the compromise degree $Q'(a_i)$ of alternative a_i as

$$Q'(a_i)=\eta\times\sqrt{\varphi\left(\tilde{G}^N(a_i)\right)^2+(1-\varphi)\left(\frac{m-r_1(a_i)+1}{m}\right)^2}-$$

$$(1-\eta)\times\sqrt{\varphi\left(\tilde{R}^N(a_i)\right)^2+(1-\varphi)\left(\frac{r_2(a_i)}{m}\right)^2}, \tag{16}$$

where φ and $1-\varphi$ are the weights of "values" and "ranks" used for ranking, and $\varphi\in[0,1]$. The majority rule and opponent rule, which measure the comprehensive performance of alternatives, can be considered as two evaluators defined in the Borda rule. $\tilde{G}^N(a_i)$ and $r_1(a_i)$, $i=1,2,\cdots,m$, are the values and ranks of alternatives determined by the majority rule, and $\tilde{R}^N(a_i)$ and $r_2(a_i)$, i = 1, 2, …, m, are the values and ranks of alternatives determined by the opponent rule. Because the values of $\tilde{R}^N(a_i)$, i = 1, 2, …, m, are in the cost form, the Borda number determined by the opponent rule is the negative value of $\sqrt{\varphi\left(\tilde{R}^N(a_i)\right)^2+(1-\varphi)\left(\frac{r_2(a_i)}{m}\right)^2}$.

We rank alternatives by the values $Q'(a_i)$, i = 1, 2, …, m, in decreasing order. The results are a compromise ranking list, denoted as $r=\{r(a_1),r(a_2),\cdots,r(a_m)\}$. The compromise solution is $a^*=\{a_i \mid \max_{1\le i\le m} Q'(a_i)\}$.

3. A case study: personnel evaluation for different talents

This section elaborates a case study of personnel evaluation to demonstrate the applicability of the proposed method.

3.1. Case description

Personnel evaluation is important for governments and enterprises to identify outstanding talents, and it is a typical MCDM problem that requires comprehensive consideration of knowledge, skills, social roles and other factors. Golec and Kahya (2007) developed a systematic hierarchy for personnel evaluation and selection based on a fuzzy analytic hierarchy process to facilitate the decision-making process through a consistent evaluation standard. To deal with both quantitative and qualitative information in personnel selection, Durson and Karsak (2010) presented an integrated MCDM approach by combining the fuzzy information, 2-tuple linguistic representation model and TOPSIS method. Lin (2010) combined a network analysis method with data envelopment analysis for personnel selection. Dağdeviren (2010) proposed a combination of the network analysis method with TOPSIS method to deal with personnel selection problems in which the network analysis method was used to determine the weights of criteria and the TOPSIS method was used to rank candidates. However, these MCDM methods for personnel evaluation used the same set of criteria for different candidates.

According to research fields, scientific and technological talents can be divided into three categories, including basic research talents, engineering technology talents and innovation and entrepreneurship talents. Basic research talents are in basic research and applications. They mainly study the laws of material movement in nature, reveal the inner connection and objective laws of natural phenomena in scientific and technological activities, and apply the obtained results to practical research. Engineering technology talents focus on technology research and development and application of science and technology, aiming to carry out research on new systems, new products, new structures, new processes and new materials based on applied basic research and application research results. Innovation and entrepreneurship talents are committed to applying scientific research results to practice and transforming existing scientific research results into productivity. Obviously, the evaluation criteria for scientific and technological talents in different fields should be different. The proposed probabilistic linguistic VIKOR method allows assessing different types of scientific and technical talents within the same framework. The following is a case study to illustrate the steps of the proposed method in detail.

A university plans to carry out personnel evaluation and award four prizes: one each for the first, second and third prizes, and one for the ordinary prize. Seven alternatives have passed the preliminary screening and have been recommended for this award. Among these seven candidates, three (a_1, a_2, a_3) belong to basic research talents, two (a_4, a_5) belong to engineering technology talents, and two (a_6, a_7) belong to innovation and entrepreneurship talents. The evaluation criteria for each of the three categories of scientific and technological talents are set as follows:

1) Basic research talents: H index (a comprehensive indicator reflecting the number of posts and citations) (c_{11}), ownership of intellectual property rights (c_{12}), degree of recognition in academia (c_{13}), learning ability (c_{14}), and scientific research interest (c_{15});
2) Engineering technology talents: ownership and application of intellectual property rights (c_{21}), degree of recognition by industry peers (c_{22}), industry/market analysis

capabilities (c_{23}), influence in industrial field (c_{24}), and engineering planning and decision-making capabilities (c_{25});

3) Innovation and entrepreneurship talents: ownership and application of intellectual property rights (c_{31}), degree of recognition by industry peers (c_{32}), intellectual property influence (c_{33}), and marketing and management capabilities (c_{34}).

The three categories of scientific and technological talents have two common criteria: intellectual property rights (c_{12}, c_{21}, c_{31}) and peer recognition (c_{13}, c_{22}, c_{32}), but they differ slightly in content. Basic research talents place emphasis on the ownership of intellectual property rights, while the other two types place emphasis on both the ownership and use. For basic research talents, we mainly examine their peer recognition in academia. For the other two types of talents, we need to examine their peer recognition in enterprises and industries. The innovative knowledge and achievements of basic research talents can be quantitatively evaluated by the number of publications and citations, while engineering technology talents and innovation and entrepreneurship talents have no quantitative requirement on the number of publications and citations due to the characteristics of their research directions, but pay more attention to their industrial capabilities and the influence of intellectual property.

Three kinds of linguistic term sets are used for evaluation, including $S_1 = \{s_{-3}$ = very low, s_{-2} = low, s_{-1} = a litle low, s_0 = medium, s_1 = a litle high, s_2 = high, s_3 = very high$\}$; $S_2 = \{s_{-3}$ = very bad, s_{-2} = bad, s_{-1} = a litle bad, s_0 = medium, s_1 = a litle good, s_2 = good, s_3 = very good$\}$; $S_3 = \{s_{-3}$ = very small, s_{-2} = small, s_{-1} = a litle small, s_0 = medium, s_1 = a litle big, s_2 = big, s_3 = very big$\}$. S_1 applies to the evaluation of the criteria c_{11}, c_{13}, c_{14}, c_{15}, c_{22}, c_{23}, c_{25}, c_{32} and c_{34}, S_2 applies to the evaluation of the criteria c_{12}, c_{21} and c_{31}, and S_3 applies to the evaluation of the criteria c_{24} and c_{33}. All criteria are benefit forms. The weight vectors of the three sets of criteria $C_1 = \{c_{11},\cdots,c_{15}\}$, $C_2 = \{c_{21},\cdots,c_{25}\}$ and $C_3 = \{c_{31},\cdots,c_{34}\}$ used for measuring the performances of basic research talents, engineering technology talents and innovation and entrepreneurship talents are $W_1 = (0.5,0.1,0.2,\ 0.1,0.1)^{\mathrm{T}}$, $W_2 = (0.25,0.25,0.2,0.2,0.1)^{\mathrm{T}}$ and $W_3 = (0.3,0.2,0.3,0.2)^{\mathrm{T}}$, respectively. Experts' evaluation information of the seven candidates is expressed in PLTSs, as shown in Tables 1–3.

Table 1. The evaluation information of basic research talents

	c_{11}	c_{12}	c_{13}	c_{14}	c_{15}
a_1	$\{s_{-1}(0.6), s_0(0.4)\}$	$\{s_{-1}(0.4), s_0(0.6)\}$	$\{s_2(1)\}$	$\{s_1(0.2), s_2(0.8)\}$	$\{s_{-1}(1)\}$
a_2	$\{s_2(0.5), s_3(0.5)\}$	$\{s_1(1)\}$	$\{s_2(0.5), s_3(0.5)\}$	$\{s_2(1)\}$	$\{s_1(0.2), s_2(0.8)\}$
a_3	$\{s_0(0.2), s_1(0.8)\}$	$\{s_0(1)\}$	$\{s_1(0.6), s_2(0.4)\}$	$\{s_1(0.5), s_2(0.5)\}$	$\{s_1(1)\}$
$h_S^{j*}(p)$	$\{s_3(1)\}$	$\{s_3(1)\}$	$\{s_3(1)\}$	$\{s_3(1)\}$	$\{s_3(1)\}$
$h_S^{j\circ}(p)$	$\{s_{-1}(1)\}$	$\{s_{-1}(1)\}$	$\{s_{-1}(1)\}$	$\{s_{-1}(1)\}$	$\{s_{-1}(1)\}$

Table 2. The evaluation information of engineering technology talents

	c_{21}	c_{22}	c_{23}	c_{24}	c_{25}
a_4	$\{s_2(0.5), s_3(0.5)\}$	$\{s_1(0.4), s_2(0.6)\}$	$\{s_2(1)\}$	$\{s_1(1)\}$	$\{s_2(1)\}$
a_5	$\{s_1(1)\}$	$\{s_0(0.3), s_1(0.7)\}$	$\{s_1(0.5), s_2(0.5)\}$	$\{s_0(0.8), s_1(0.2)\}$	$\{s_1(1)\}$
$h_S^{j*}(p)$	$\{s_3(1)\}$	$\{s_3(1)\}$	$\{s_3(1)\}$	$\{s_3(1)\}$	$\{s_3(1)\}$
$h_S^{j\circ}(p)$	$\{s_{-1}(1)\}$	$\{s_{-1}(1)\}$	$\{s_{-1}(1)\}$	$\{s_{-1}(1)\}$	$\{s_{-1}(1)\}$

Table 3. The evaluation information of innovation and entrepreneurship talents

	c_{31}	c_{32}	c_{33}	c_{34}
a_6	$\{s_2(0.6), s_3(0.4)\}$	$\{s_1(0.2), s_2(0.8)\}$	$\{s_1(0.6), s_2(0.2), s_3(0.2)\}$	$\{s_1(1)\}$
a_7	$\{s_{-1}(0.8), s_0(0.2)\}$	$\{s_0(0.8), s_1(0.2)\}$	$\{s_2(0.6), s_3(0.4)\}$	$\{s_{-1}(0.6), s_0(0.3), s_1(0.1)\}$
$h_S^{j*}(p)$	$\{s_3(1)\}$	$\{s_3(1)\}$	$\{s_3(1)\}$	$\{s_3(1)\}$
$h_S^{j\circ}(p)$	$\{s_{-1}(1)\}$	$\{s_{-1}(1)\}$	$\{s_{-1}(1)\}$	$\{s_{-1}(1)\}$

3.2. Resolving process to the case

The calculation steps are as follows:

Step 1. The aspired and tolerable values of each criterion are set as $\{s_3(1)\}$ and $\{s_{-1}(1)\}$, respectively.

Step 2. Using Eq. (10), we obtain the degrees of closeness between the values of alternatives and the aspired values of criteria, as shown in Table 4.

Table 4. The degrees of closeness between the values of alternatives and the aspired values of criteria

Basic research talents	c_{11}	c_{12}	c_{13}	c_{14}	c_{15}
a_1	0.100	0.150	0.750	0.700	0
a_2	0.875	0.500	0.875	0.750	0.700
a_3	0.450	0.250	0.600	0.625	0.500
Engineering technology talents	c_{21}	c_{22}	c_{23}	c_{24}	c_{25}
a_4	0.875	0.650	0.750	0.500	0.750
a_5	0.500	0.425	0.625	0.300	0.500
Innovation and entrepreneurship talents	c_{31}	c_{32}	c_{33}	c_{34}	
a_6	0.850	0.700	0.650	0.500	
a_7	0.050	0.300	0.850	0.125	

Step 3. Calculate the group values and individual regrets of alternatives by Eqs (12) and (13), respectively, and then normalize them by Eqs (14) and (15), respectively. The results are shown in Table 5. The first subordinate ranking list of the seven alternatives is $r_1 = \{7,1,4,2,5,3,6\}$, that is $a_2 \succ a_4 \succ a_6 \succ a_3 \succ a_5 \succ a_7 \succ a_1$. The second subordinate ranking list is $r_2 = \{7,1,6,3,4,2,5\}$, that is $a_2 \succ a_6 \succ a_4 \succ a_5 \succ a_7 \succ a_3 \succ a_1$.

Table 5. The group values and individual regrets of alternatives obtained by the proposed method

Alternative	Group value		Individual regret		Compromise degree	
	Value	Rank	Value	Rank	Value (η = 0.5, φ = 0.5)	Rank
a_1	0.353	7	1.000	7	–0.459	7
a_2	1.000	1	0.139	1	0.496	1
a_3	0.598	4	0.611	6	–0.008	5
a_4	0.875	2	0.222	3	0.349	2
a_5	0.577	5	0.319	4	0.101	4
a_6	0.854	3	0.187	2	0.334	3
a_7	0.440	6	0.507	5	–0.028	6

Step 4. 11 values of the parameter η are considered, including 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1. In determining the compromise degrees of alternatives, $\eta < 0.5$ means that the majority rule is important than the opponent rule, $\eta > 0.5$ means that the opponent rule is important than the majority rule, and $\eta = 0.5$ means that the two rules are the same important. In this case, let $\varphi = 0.5$, that is, the ranks and values are equally important in aggregation. Using Eq. (16), we calculate the compromise degrees of alternatives based on the 11 values of η, respectively. The ranks are shown in Figure 1. To test the robustness of the results, we calculate the deviation D (see Eq. (17)) between the rankings obtained by different values of the parameter, and get $D = 0.906$.

$$D = 1 - \frac{1}{M}\sum_{i=1}^{m}\frac{1}{L}\left(\sum_{l=1}^{L}\left| r^l(a_i) - \frac{1}{L}\sum_{l=1}^{L} r^l(a_i)\right|\right), \tag{17}$$

where L is the number of the values of the parameter considered in sentiment analysis. $r^l(a_i)$ is the rank of a_i obtained based on the lth value of the parameter. M indicates the maximum difference in ranks between the two rankings. If m is even, then $M = m^2/2$, and if it is odd, then $M = (m^2 - 1)/2$.

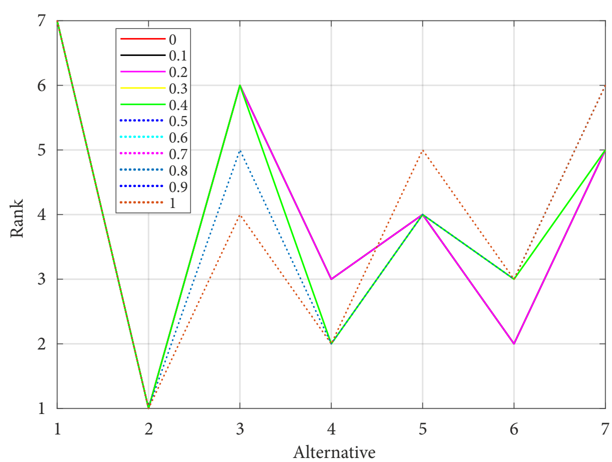

Figure 1. Rankings of alternatives obtained based on different values of η

When $\eta \in \{0, 0.1, 0.2\}$, the ranking list is $a_2 \succ a_6 \succ a_4 \succ a_5 \succ a_7 \succ a_3 \succ a_1$; when $\eta \in \{0.3, 0.4, \cdots, 0.8\}$, the ranking list is $a_2 \succ a_4 \succ a_6 \succ a_5 \succ a_7 \succ a_3 \succ a_1$ or $a_2 \succ a_4 \succ a_6 \succ a_5 \succ a_3 \succ a_7 \succ a_1$; when $\eta \in \{0.9, 1\}$, the ranking list is $a_2 \succ a_4 \succ a_6 \succ a_3 \succ a_5 \succ a_7 \succ a_1$. Overall, alternative a_2 always ranks first, while alternative a_1 ranks last. In the case that the parameter η takes different values, alternative a_3 has the biggest change in ranking, because it performs not outstanding under criterion c_{11}, but performs good on the other criteria. The award can be determined based on the following three scenarios:

1) If decision-makers value the opponent rule rather than the majority rule (risk averse attitude), then it should give talents a_2, a_6 and a_4 first, second and third prize, respectively, and give talent a_5 ordinary prize.
2) If decision-makers value both the opponent rule and the majority rule (risk neutral attitude), then it should give talents a_2, a_4 and a_6 first, second and third prize, respectively, and give talent a_5 ordinary prize.
3) If decision-makers value the majority rule rather than the opponent rule (risk preference attitude), then it should give talents a_2, a_4 and a_6 first, second and third prize, respectively, and give talent a_3 ordinary prize.

In order to analyze the impact of the parameter φ on ranking results, 11 values of φ are considered, including 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1. In this case, let $\eta = 0.5$. The ranking lists of alternatives obtained based on the 11 values of φ are shown in Figure 2. The deviation between the rankings is 0.961. Overall, only the preference relation between alternatives a_3 and a_7 changes. If $\varphi \in \{0, 0.1, 0.2, 0.3\}$, the ranking list is $a_2 \succ a_4 \succ a_6 \succ a_5 \succ a_7 \succ a_3 \succ a_1$; otherwise, the ranking list is $a_2 \succ a_4 \succ a_6 \succ a_5 \succ a_3 \succ a_7 \succ a_1$. Therefore, the decision results obtained in this case study are robust.

3.3. Comparative analysis

To illustrate the effectiveness of the proposed method, this section uses the probabilistic linguistic VIKOR method proposed by M. Lin et al. (2021a) to solve the case. This method is a direct extension of the original VIKOR method. More specifically, to address the MCDM

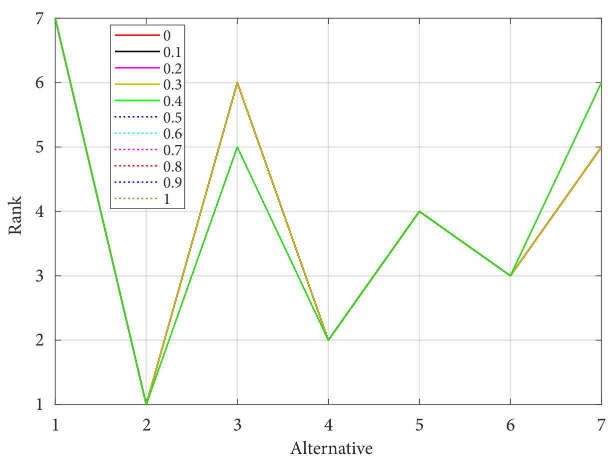

Figure 2. Rankings of alternatives obtained based on different values of φ

problems with PLTSs, this method used the probabilistic linguistic distance measure to calculate the distance between the values of alternatives and the best values of all criteria. The other steps of this method are the same as the original VIKOR method. The best and the worst values of each criterion are obtained by comparing the values between alternatives. Using Eq. (10), we obtain the normalization values of alternatives under different criteria, as shown in Table 6.

Table 6. The normalization values of alternatives under different criteria

Basic research talents	c_{11}	c_{12}	c_{13}	c_{14}	c_{15}
a_1	0.000	0.000	0.375	0.200	0.000
a_2	0.861	0.412	0.688	0.333	0.700
a_3	0.389	0.118	0.000	0.000	0.500
Engineering technology talents	c_{21}	c_{22}	c_{23}	c_{24}	c_{25}
a_4	0.750	0.391	0.333	0.286	0.500
a_5	0.000	0.000	0.000	0.000	0.000
Innovation and entrepreneurship talents	c_{31}	c_{32}	c_{33}	c_{34}	
a_6	0.842	0.571	0.000	0.429	
a_7	0.000	0.000	0.571	0.000	

Using Eqs (3) and (4), we obtain the group values and individual regrets of alternatives, and then rank the alternatives by these two kinds of values, respectively. The results are shown in Table 7. When calculating the compromise degrees by Eq. (5), we consider 11 values of the parameter η, including 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1. Figure 3 shows the ranks of alternatives determined by the compromise degrees of alternatives. The deviation between the rankings is 0.886. If η = 0.5 and φ = 0.5, the ranking list is $a_2 \succ a_4 \succ a_6 \succ a_3 \succ a_7 \succ a_5 \succ a_1$, which is different from the result obtained by the proposed method. The WS coefficient of similarity (Sałabun & Urbaniak, 2020) between the ranking obtained by the proposed method and that by the method proposed by M. Lin et al. (2021a) is 0.965.

1. From Table 3, we can find that a_6 performs better than a_7 in all criteria except criterion c_{33}, and a_6 performs at least a little good under criterion c_{33}, but a_7 performs not good under both criteria c_{31} and c_{34}. Therefore, the worst performance of a_6 is better than that of a_7. However, according to the method proposed by M. Lin et al. (2021a), the individual regrets of a_6 and a_7 are the same. If η = 0, then both a_6 and a_7 are equally ranked, which is not consistent with intuitive judgment. According to our proposed method, the individual regret of a_6 is larger than the individual regret of a_7, and the rank of a_6 is always higher than the rank of a_7.
2. From Table 3, we can find that a_5 performs at least moderate under all its criteria, but a_1 performs a little bad under criterion c_{11}, c_{12} and c_{15}. Therefore, a_5 is better than a_1. However, according to the method proposed by M. Lin et al. (2021a), the group value of a_1 is larger than the group value of a_5. If η = 0.9 or 1, a_1 ranks higher than a_5, which is inconsistent with intuitive judgments. According to the proposed method, a_1 always ranks the last.

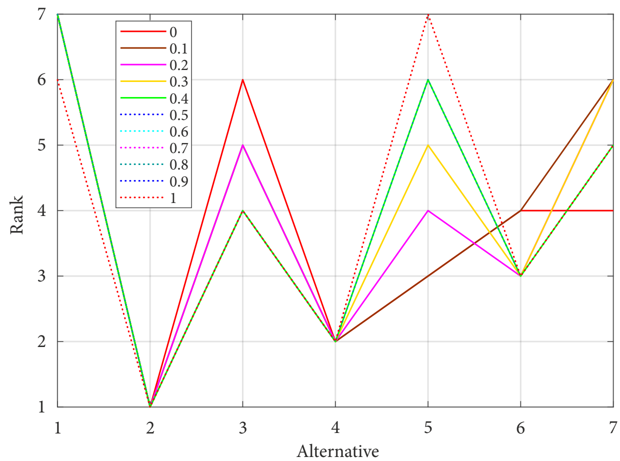

Figure 3. Rankings of alternatives obtained by the method in M. Lin et al. (2021a) based on different values of η

3. The deviation between the rankings obtained in sensitive analysis shows that the ranking results obtained by our proposed method are more stable than the ranking results obtained by the method proposed by M. Lin et al. (2021a). It is proved that the proposed aggregation operator (i.e., Eq. (16)) is more robust than the aggregation operator (i.e., Eq. (5)) used in the original VIKOR method.

Overall, the results obtained by our proposed method are consistent with intuition, which indicates the reliability of the method. This case study also proves that the traditional VIKOR method is not suitable for solving the MCDM problems with inconsistent criteria of different alternatives.

Table 7. The group values and individual regrets of alternatives obtained by the method in M. Lin et al. (2021a)

Alternative	Group value		Individual regret		Index value	
	Value	Rank	Value	Rank	Value (η = 0.5, φ = 0.5)	Rank
a_1	0.095	6	0.500	7	0.933	7
a_2	0.713	1	0.069	1	0.000	1
a_3	0.256	4	0.306	6	0.594	4
a_4	0.459	2	0.152	2	0.274	2
a_5	0.000	7	0.250	3	0.710	6
a_6	0.453	3	0.300	4	0.450	3
a_7	0.171	5	0.300	4	0.647	5

3.4. Discussions

Existing MCDM methods aim to achieve comparability among alternatives which are measured by the same set of criteria. The main advantage of the proposed MCDM method is that the comparability among alternatives can be achieved in the case of inconsistent sets of criteria for different alternatives. For the case study, since the evaluation criteria (even the number of criteria) for the three types of talents are inconsistent, it is not possible to calculate the marginal values for each talent under each criterion using the multiple criterion value theory and obtain the overall values of the talents by an aggregation operator. A common and simple solution is to directly aggregate the evaluations of alternatives under their respective criteria in a weighted average manner to obtain a comprehensive evaluation. This method is easy to understand, but it does not yield reliable results. On the one hand, the performances of an alternative under different criteria have different dimensions, even if they are evaluated with the same linguistic term sets. For example, an acceptable price of a product for a consumer is "not expensive" and an acceptable quality is "at least a little good". In this regard, the overall performance of an alternative cannot be measured by directly combining evaluations under different criteria. On the other hand, the weighted average is a fully compensation operator that allows an alternative's poor performance under some criteria to be fully compensated by its good performance under other criteria. The compromise solutions selected in this way may perform poorly under some criteria. This does not satisfy the value system of risk-averse decision makers. The approach proposed in this paper avoids these two problems. To address the problem of inconsistent dimensions, the closeness of an alternative to the aspired value of each criterion is measured by the distance measure, making the values of an alternative under different criteria comparable (see Table 4). To satisfy the value system of decision makers with different risk attitudes, two aggregation rules including the majority rule and the opponent rule are used to determine compromise solutions. The decision result varies flexibly depending on the decision maker's tolerance attitude toward poor performance under a criterion (see Figure 1).

Another advantage of the proposed method is the improved trade-off mechanism between the majority rule and the opponent rule to define the compromise degrees of alternatives. The integration of both subordinate values and ranks to judge the overall performance of alternatives increases the robustness of decision results (see Figures 1 and 2). Decision-makers can determine the overall ranking of alternatives directly and no longer need to further make trade-offs among the rankings determined by group values, individual regrets and compromise degrees of alternatives. In addition, the case study demonstrates that the proposed approach can effectively handle qualitative decision information. Uncertainty in decision information does not affect uncertainty in decision results. The main purpose of linguistic approaches is to enable evaluators to express their opinions as truly and comprehensively as possible in a customary manner, rather than to increase the difficulty of expressing information. The PLTS provides the flexibility to depict different types of qualitative evaluation information by combining two commonly used tools for expressing uncertain information: linguistic terms and probabilities. Therefore, the findings of this study on combining MCDM methods with PLTSs have implications for uncertainty decision analysis.

Conclusions

In this paper, we considered MCDM problems with different sets of criteria for different alternatives and proposed a probabilistic linguistic VIKOR method to measure the group values and individual regrets of alternatives based on the aspired and tolerable values of criteria. We perceive the introduced method as a novel VIKOR method, because the method to measure the closeness degree of each alternative to the ideal solution, the normalization techniques and the aggregation function were improved. The aggregation function proposed in this paper is robust, since it integrates both the cardinal and ordinal information determined by the group values and individual regrets, respectively. If the risk attitude (i.e., the tolerance to the worst performance of an alternative under a single criterion) of a decision-maker is determined, the compromise solution can be judged and all alternatives can be ranked directly based on the compromise degrees of alternatives obtained by the aggregation operator, instead of judging the compromise solution by considering the group values, individual regrets and compromise degrees of alternatives together according to the compromise-ranking rule used in the traditional VIKOR. The proposed method has a wide range of applications because it can deal with MCDM problems with qualitative criteria whose values are generated by subjective evaluations.

Some issues remain for future research. The proposed method did not take into account the interactions between criteria. Future research may consider the introduction of Choquet integral to improve the aggregation operators to model interactions between criteria. In addition, the proposed method for MCDM is based on direct preference elicitation, and decision-makers are required to provide the values of parameters in this method, including the weights of criteria and the tolerance degree to the worst performance under a criterion. This requires a large cognitive effort for decision-makers. In the future, it is interesting to consider preference disaggregation analysis with indirect preference elicitation, which is user-friendly, only requiring decision-makers to make holistic judgments on reference alternatives that they are familiar with (Doumpos & Zopounidis, 2019). The proposed VIKOR method can be used as the underlying preference model in which the parameters are learned through ordered regression techniques to reconstruct decision examples.

Funding

The work was supported by the National Natural Science Foundation of China under Grant 71771156, 71971145, 72171158.

Author contributions

Xingli Wu, Huchang Liao, Edmundas Kazimieras Zavadskas and Jurgita Antuchevičienė proposed the original idea and conceived the study. Xingli Wu, Huchang Liao, Edmundas Kazimieras Zavadskas and Jurgita Antuchevičienė were responsible for developing the method, collecting and analyzing the data. Xingli Wu and Huchang Liao were responsible for data interpretation. Xingli Wu and Huchang Liao wrote the first draft of the article. Edmundas Kazimieras Zavadskas and Jurgita Antuchevičienė revised the paper.

Disclosure statement

The authors have no competing financial, professional, or personal interests from other parties that are related to this paper.

References

Abdel-Baset, M., Chang, V., Gamal, A., & Smarandache, F. (2019). An integrated neutrosophic ANP and VIKOR method for achieving sustainable supplier selection: A case study in importing field. *Computers in Industry*, *106*, 94–110. https://doi.org/10.1016/j.compind.2018.12.017

Antucheviciene, J., Zakarevicius, A., & Zavadskas, E. K. (2011). Measuring congruence of ranking results applying particular MCDM methods. *Informatica*, *22*(3), 319–338. https://doi.org/10.15388/Informatica.2011.329

Antucheviciene, J., Zavadskas, E. K., & Zakarevicius, A. (2012). Ranking redevelopment decisions of derelict buildings and analysis of ranking results. *Economic Computation and Economic Cybernetics Studies and Research*, *46*(2), 37–62.

Anvari, A., Zulkifli, N., & Arghish, O. (2014). Application of a modified VIKOR method for decision-making problems in lean tool selection. *International Journal of Advanced Manufacturing Technology*, *71*, 829–841. https://doi.org/10.1007/s00170-013-5520-x

Awasthi, A., Govindan, K., & Gold, S. (2018). Multi-tier sustainable global supplier selection using a fuzzy AHP-VIKOR based approach. *International Journal of Production Economics*, *195*, 106–117. https://doi.org/10.1016/j.ijpe.2017.10.013

Bausys, R., & Zavadskas, E. K. (2015). Multicriteria decision making approach by VIKOR under interval neutrosophic set environment. *Economic Computation and Economic Cybernetics Studies and Research*, *49*(4), 33–48.

Brans, J. P., & Vincke, P. (1985). A preference ranking organisation method (The PROMETHEE method for multiple criteria decision making). *Management Science*, *31*(6), 647–656. https://doi.org/10.1287/mnsc.31.6.647

Çalı, S., & Balaman, Ş. Y. (2019). A novel outranking based multi criteria group decision making methodology integrating ELECTRE and VIKOR under intuitionistic fuzzy environment. *Expert Systems with Applications*, *119*, 36–50. https://doi.org/10.1016/j.eswa.2018.10.039

Chen, S. J., & Hwang, C. L. (1992). *Fuzzy multiple attribute decision making*. Springer. https://doi.org/10.1007/978-3-642-46768-4

Cinelli, M., Kadziński, M., Gonzalez, M., & Słowiński, R. (2020). How to support the application of multiple criteria decision analysis? Let us start with a comprehensive taxonomy. *Omega*, *96*, 102261. https://doi.org/10.1016/j.omega.2020.102261

Dağdeviren, M. (2010). A hybrid multi-criteria decision-making model for personnel selection in manufacturing systems. *Journal of Intelligent Manufacturing*, *21*(4), 451–460. https://doi.org/10.1007/s10845-008-0200-7

Doumpos, M., & Zopounidis, C. (2019). Preference disaggregation for multicriteria decision aiding: An overview and perspectives. In M. Doumpos, J. Figueira, S. Greco, & C. Zopounidis (Eds.), *New perspectives in multiple criteria decision making* (pp. 115–130). Springer, Cham. https://doi.org/10.1007/978-3-030-11482-4_4

Dursun, M., & Karsak, E. E. (2010). A fuzzy MCDM approach for personnel selection. *Expert Systems with Applications*, *37*(6), 4324–4330. https://doi.org/10.1016/j.eswa.2009.11.067

Dyer, J. S., & Smith, J. E. (2021). Innovations in the science and practice of decision analysis: The role of *management science*. *Management Science*, *67*(9), 5364–5378. https://doi.org/10.1287/mnsc.2020.3652

Golec, A., & Kahya, E. (2007). A fuzzy model for competency-based employee evaluation and selection. *Computers & Industrial Engineering*, *52*(1), 143–161. https://doi.org/10.1016/j.cie.2006.11.004

Gou, X. J., Xu, Z. S., Liao, H. C., & Herrera, F. (2021). Probabilistic double hierarchy linguistic term set and its use in designing an improved VIKOR method: The application in smart healthcare. *Journal of the Operational Research Society*, *72*(12), 2611–2630. https://doi.org/10.1080/01605682.2020.1806741

Greco, S., Matarazzo, B., & Słowiński, R. (2016). Decision rule approach. In S. Greco, M. Ehrgott, & J. R. Figueira (Eds.), *International series in operations research & management science: Vol. 233. Multiple criteria decision analysis: State of the art surveys* (pp. 497–552). Springer-Verlag. https://doi.org/10.1007/978-1-4939-3094-4_13

Hajiagha, S. H. R., Mahdiraji, H. A., Zavadskas, E. K., & Hashemi, S. S. (2014). Fuzzy multi-objective linear programming based on compromise VIKOR method. *International Journal of Information Technology & Decision Making*, *13*(4), 679–698. https://doi.org/10.1142/S0219622014500667

Hashemkhani Zolfani, S. H., Torkayesh, A. E., & Bazrafshan, R. (2021). Vision-based weighting system (ViWeS) in prospective MADM. *Operational Research in Engineering Sciences: Theory and Applications*, *4*(2), 140–150. https://doi.org/10.31181/oresta20402140z

Jing, S., Niu, Z., & Chang, P. C. (2019). The application of VIKOR for the tool selection in lean management. *Journal of Intelligent Manufacturing*, *30*, 2901–2912. https://doi.org/10.1007/s10845-015-1152-3

Keeney, R., & Raiffa, H. (1976). *Decisions with multiple objectives: Preferences and value tradeoffs*. Wiley.

Kilic, H. S., Demirci, A. E., & Delen, D. (2020). An integrated decision analysis methodology based on IF-DEMATEL and IF-ELECTRE for personnel selection. *Decision Support Systems*, *137*, 113360. https://doi.org/10.1016/j.dss.2020.113360

Komazec, N., & Petrović, A. (2019). Application of the AHP-VIKOR hybrid model in media selection for informing of endangered in emergency situations. *Operational Research in Engineering Sciences: Theory and Applications*, *2*(2), 12–23. https://oresta.rabek.org/index.php/oresta/article/view/21

Liao, H. C., & Wu, X. L. (2020). DNMA: A double normalization-based multiple aggregation method for multi-expert multi-criteria decision making. *Omega*, *94*, 102058. https://doi.org/10.1016/j.omega.2019.04.001

Liao, H. C., Jiang, L. S., Lev, B., & Fujita, H. (2019). Novel operations of PLTSs based on the disparity degrees of linguistic terms and their use in designing the probabilistic linguistic ELECTRE III method. *Applied Soft Computing*, *80*, 450–464. https://doi.org/10.1016/j.asoc.2019.04.018

Liao, H. C., Mi, X. M., & Xu, Z. S. (2020). A survey of decision-making methods with probabilistic linguistic information: Bibliometrics, preliminaries, methodologies, applications and future directions. *Fuzzy Optimization and Decision Making*, *19*(1), 81–134. https://doi.org/10.1007/s10700-019-09309-5

Liao, H. C., Xu, Z. S., & Zeng, X. J. (2015). Hesitant fuzzy linguistic VIKOR method and its application in qualitative multiple criteria decision making. *IEEE Transactions on Fuzzy Systems*, *23*(5), 1343–1355. https://doi.org/10.1109/TFUZZ.2014.2360556

Lin, H. T. (2010). Personnel selection using analytic network process and fuzzy data envelopment analysis approaches. *Computers & Industrial Engineering*, *59*(4), 937–944. https://doi.org/10.1016/j.cie.2010.09.004

Lin, M. W., Chen, Z. Y., Xu, Z. S., Gou, X. J., & Herrera, F. (2021a). Score function based on concentration degree for probabilistic linguistic term sets: An application to TOPSIS and VIKOR. *Information Sciences*, *551*, 270–290. https://doi.org/10.1016/j.ins.2020.10.061

Lin, S.-H., Hsu, C.-C., Zhong, T., He, X., Li, J.-H., Tzeng, G.-H., & Hsieh, J.-C. (2021b). Exploring location determinants of Asia's unique beverage shops based on a hybrid MADM model. *International Journal of Strategic Property Management*, *25*(4), 291–315. https://doi.org/10.3846/ijspm.2021.14796

Machina, M. J., & Schmeidler, D. (1992). A more robust definition of subjective probability. *Econometrica*, *60*(4), 745–780. https://doi.org/10.2307/2951565

Mardani, A., Zavadskas, E. K., Govindan, K., Senin, A. A., & Jusoh, A. (2016). VIKOR technique: A systematic review of the state of the art literature on methodologies and applications. *Sustainability*, *8*(1), 37. https://doi.org/10.3390/su8010037

Opricovic, S. (1998). *Multicriteria optimization of civil engineering systems*. Faculty of Civil Engineering, University of Belgrade, Belgrade.

Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European Journal of Operational Research*, *156*(2), 445–455. https://doi.org/10.1016/S0377-2217(03)00020-1

Ou-Yang, Y. P., Shieh, H. M., Leu, J. D., & Tzeng, G. H. (2009). A VIKOR-based multiple criteria decision method for improving information security risk. *International Journal of Information Technology* & *Decision Making*, *8*(2), 267–287. https://doi.org/10.1142/S0219622009003375

Pang, Q., Wang, H., & Xu, Z. S. (2016). Probabilistic linguistic term sets in multi-attribute group decision making. *Information Sciences*, *369*, 128–143. https://doi.org/10.1016/j.ins.2016.06.021

Panja, S., Bag, S., Hao, F., & Roy, B. (2020). A smart contract system for decentralized Borda count voting. *IEEE Transactions on Engineering Management*, *67*(4), 1323–1339. https://doi.org/10.1109/TEM.2020.2986371

Peng, J. J., Tian, C., Zhang, W. Y., Zhang, S., & Wang, J. Q. (2020). An integrated multi-criteria decision-making framework for sustainable supplier selection under picture fuzzy environment. *Technological and Economic Development of Economy*, *26*(3), 573–598. https://doi.org/10.3846/tede.2020.12110

Roozbahani, A., Ebrahimi, E., & Banihabib, M. E. (2018). A framework for ground water management based on Bayesian Network and MCDM techniques. *Water Resources Management*, *32*, 4985–5005. https://doi.org/10.1007/s11269-018-2118-y

Roy, B. (1968). Classement et choix en presence de points de vue multiples (La methode ELECTRE). *Revue Francaise D Informatique de Recherche Operationnelle*, *2*(8), 57–75. https://doi.org/10.1051/ro/196802V100571

Sałabun, W., & Urbaniak, K. (2020). A new coefficient of rankings similarity in decision-making problems. In Krzhizhanovskaya, V. et al. (Eds.), *Lecture Notes in Computer Science: Vol. 12138. Computational science – ICCS 2020* (pp. 632–645). Springer, Cham. https://doi.org/10.1007/978-3-030-50417-5_47

Su, L., Wang, T., Li, H. M., Chao, Y. C., & Wang, L. Y. (2020). Multi-criteria decision making for identification of unbalanced bidding. *Journal of Civil Engineering and Management*, *26*(1), 43–52. https://doi.org/10.3846/jcem.2019.11568

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124

Wang, H., Xu, Z. S., & Jun, X. J. (2018). Modeling complex linguistic expressions in qualitative decision making: An overview. *Knowledge-Based Systems*, *144*, 174–187. https://doi.org/10.1016/j.knosys.2017.12.030

Wu, X. L., & Liao, H. C. (2019). A consensus-based probabilistic linguistic gained and lost dominance score method. *European Journal of Operational Research*, *272*(3), 1017–1027. https://doi.org/10.1016/j.ejor.2018.07.044

Wu, X. L., Liao, H. C., Xu, Z. S., Hafezalkotob, A., & Herrera, F. (2018). Probabilistic linguistic MULTIMOORA: A multi-criteria decision making method based on the probabilistic linguistic expectation function and the improved Borda rule. *IEEE Transactions on Fuzzy Systems*, *26*(6), 3688–3702. https://doi.org/10.1109/TFUZZ.2018.2843330

Zadeh, L. A. (1975). The concept of a linguistic variable and its applications to approximate reasoning – Part I. *Information Sciences*, *8*(3), 199–249. https://doi.org/10.1016/0020-0255(75)90036-5

Zheng, J., & Lienert, J. (2018). Stakeholder interviews with two MAVT preference elicitation philosophies in a Swiss water infrastructure decision: Aggregation using SWING-weighting and disaggregation using UTA GMS. *European Journal of Operational Research*, *267*(1), 273–287. https://doi.org/10.1016/j.ejor.2017.11.018