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METHODOLOGIES AND APPLICATION

A novel extension to VIKOR method under intuitionistic fuzzy context for solving personnel selection problem

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Abstract

Personnel selection is a challenging problem for any organization. The success of a project is determined by the human resources that handle the project. To make better personnel selections, researchers have adopted multi-criteria decision-making (MCDM) approaches. Among these, fuzzy-based MCDM methods are most frequently used, as they handle vagueness and imprecision better. Intuitionistic fuzzy set (IFS) is a popular MCDM context which provides degree of membership and non-membership for preference elicitation. In this work, we propose a novel decision-making framework that consists of two stages. In the first stage, a new extension to the popular VIKOR method is presented under IFS context. The positive and negative ideal solutions are determined, and VIKOR parameters are calculated using transformation procedure. The proposed method combines the strength of both interval-valued fuzzy set and IFS that is more effective in handling vagueness with a simple formulation setup. In the second stage, a personnel selection problem is used to validate the proposed framework. Finally, the superiority and weakness of the proposed framework are discussed by comparison with other methods.

Keywords Personnel selection problem · Intuitionistic fuzzy set · Interval numbers · Multi-criteria decision making · VIKOR method

Abbreviations

IF	Intuitionistic fuzzy
IFS	Intuitionistic fuzzy set
IFV	Intuitionistic fuzzy value
IFPR	Intuitionistic fuzzy preference relation
IVFS	Interval-valued fuzzy set
MCPSP	Multi-criteria team selection problem
AHP	Analytical hierarchical process
PROMETHEE	Preference ranking organization method for enrichment evaluation
TOPSIS	Technique for order of preference by similarity to ideal solution
IVTOPSIS	Interval-valued TOPSIS
IFTOPSIS	Intuitionistic fuzzy TOPSIS
VIKOR	VlseKriterijumska Optimizacija I Kompromisno Resenje
IVVIKOR	Interval-valued VIKOR
WASPAS	Weighted aggregated sum product assessment
EXPROM2	Extended PROMETHEE II
COPRASG	Complex proportional assessment of alternatives with gray relations
MMOORA	Multi-multi-objective optimization on the basis of ratio analysis
IMMOORA	Interval MMOORA

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1 Introduction

Multi-criteria decision making (MCDM) is an inevitable problem in organizations (Triantaphyllou and Shu 1998) as it involves implicit uncertainty and vagueness. Personnel selection problem (PSP) is a complex organizational problem that prioritizes candidates and selects a suitable personnel for the project. Many scholars addressed the PSP from two perspectives, viz., (a) criteria-oriented perspective and (b) method-oriented perspective.

(a) Criteria-oriented perspective:

In the attribute-oriented approach, personnel selection is advocated using a framework. Early research on team member selection adopted this mechanism for finding suitable attributes for effective personnel selection (Adair 2004). Blue et al. (2013) proposed a model for investigating the role of skill and experience as an effective attribute for teaming. Hamlyn-Harris and Hurst (2006) proposed a model for understanding the impact of familiarity on teamwork. Thorndike (1949) investigated different attributes, measures, and test metrics for team formation and found that these factors influence project performance. Robertson and Smith (2001) addressed several predictors for personnel selection such as the validity of the resume, references, personality, and problem-solving. Schmit and Ryan (1993) analyzed the big five trait (BFT) model for dealing with personality aspects in personnel selection.

(b) Method-oriented perspective:

In this section, we discuss PSP by using different methods and the applicability of IFS-based VIKOR on different MCDM problems.

- *PSP by using different method(s)*

Motivated by the idea of Wolpert and Macready (1997), several researchers developed methodical solutions for personnel selection. Researchers have witnessed personnel selection from the viewpoint of the MCDM problem. Safari et al. (2014) defined human resource management (HRM) as the process of finding, evaluating, selecting, hiring, training, and developing human resource for achieving a certain task. Delaney and Huselid (1996) argued that personnel selection could be viewed as a strategic decision-making problem which involves formal decision-making methods. Kabak et al. (2012) stated that personnel selection is a process of choosing an optimal candidate from a given set of candidate employees for solving a given problem. The early idea of using a decision-making method for personnel selections was proposed by Munsterberg (specifically for selecting personnel for a training project). Later, this idea was incorporated into military applications for selecting generals. In the past few decades, researchers have proposed many sophisticated methods for MCDM problems. Some of these methods are also applied to team member selection.

The analytical hierarchy process (AHP) developed by Saaty was a classical decision-making method that was used in military applications (Saaty 1977, 1980, 2013). Tavana et al. (Tavana et al. 1996) used AHP along with the Delphi method for selecting nurses. Islam and Rasad (2006) incorporated the AHP method for evaluating employees. Gibney and Shang (2007) provided a solution based on AHP and order ranking methods for the dean selection problem. Dağdeviren and Yüksel (2007) used ANP for personnel selection. Boran and Yavuz (2008) further extended ANP to a real-time personnel selection problem. Liao and Xu (2015a) proposed a fusing operator for the IFAHP method and used it for choosing suppliers. Xu and Liao (2015) extended AHP under IFS context for supplier selection.

- *IFS-VIKOR for different MCDM problems*

A summary of the survey of IFS-based VIKOR is presented in Table 1. The table covers the use of the IFS-VIKOR method in different applications with a brief discussion on different proposed methods. We focused on recent literature for analysis purposes.

Some challenges encountered from the literature analysis are:

1. Previous studies on VIKOR ranking either provide new formulation with distance measure or apply the existing formulation with information loss. These ideas create computational overhead and unreasonable ranking of objects.
2. PSP is a complicated MCDM problem in which candidates must be prioritized in a rational manner and a suitable personnel must be selected for the project.

Motivated by these challenges and to circumvent the same, some contributions are made in this paper as:

1. The VIKOR method is formulated by combining the power of both IVFS and IFS, and this reduces computational complexity by focusing on basic transformation procedures rather than newer formulation of VIKOR parameters. Also, information loss is mitigated by preserving IFS information throughout the formulation.
2. The proposed framework is applied to PSP for effective selection of personnel for the project. Further, correlation measure is applied to understand the consistency of the proposed method.

The remainder of the paper is constructed as follows. In Sect. 2, some basic concepts are reviewed. Section 3 presents traditional VIKOR ranking procedure which is taken as the genesis for the new extension to VIKOR method under IFS context. In Sect. 4, proposed methodology is presented where a new extension to VIKOR is put forward by using transformation measures under IFS context. Section 5 demonstrates the PSP to validate the practicality of the proposed framework, and Sect. 6 focuses on results and

Table 1 Literature review for IFS-based VIKOR

References	Method(s) (VIKOR)	Aggregator	Weight estimates	Application(s)	Comparison with others	Discussion
Gupta et al. (2016)	Triangular IFS (Trn(FS))	No	Yes	Plant location	Yes	Linguistic data are used, which are converted to its corresponding TrnIFN. Weights of criteria are estimated using Shannon entropy. DMs weights are estimated using Evidence and Bayesian theory
Yang et al. (2016)	Linguistic hesitant IFS	No	Yes	Metro project risk assessment	Yes	Linguistic data are used, which are converted to its corresponding HIFN. Criteria weights are estimated using linear programming
Mousavi et al. (2016)	IFS	Yes	No	Portfolio selection	Yes	Linguistic data are used, which are converted into IFN for analysis. IFWA aggregation operator is used
Dammak et al. (2015)	IFS	No	No	Human capital indicator	Yes	A new formulation for IF-VIKOR is proposed using exponent concept and distance measure
Peng et al. (2015)	IFS	No	No	Plasma chemical vapor deposition and surface mount technology selection	Yes	A novel Taguchi method is used for solving quality problems. IF-VIKOR is proposed for selecting a compromise technology for the study
Rostamzadeh et al. (2015)	TrnIFS	No	No	Green supplier selection	Yes	Linguistic data are used, which are converted into TrIFN for evaluation. An evaluation model was proposed and validated using a case study of laptop manufacturer
Xu et al. (2014)	Interval value IFS (IVIFS)	Yes	Yes	Global supplier selection	No	IVIF-Hybrid averaging operator was used for fusing matrices. Criteria weights are estimated using an optimization model
Tan and Chen (2013)	IVIFS	Yes	Yes	Investor selection	Yes	Choquet integral is used for aggregation of judgments. Criteria weights are calculated using Shapley value
Wan et al. (2013)	TrnIFS	Yes	Yes	Personnel selection	No	Triangular IF weighted averaging operator is used for fusing matrices. Criteria weights are estimated using Shannon entropy, and DMs weights are calculated using Evidence and Bayesian theory
Jiang and Yao (2013)	IVIFS	No	Yes	Supplier selection	No	Fuzzy AHP is used for estimating criteria weights
Chatterjee et al. (2013)	IFS	Yes	No	Supplier selection	Yes	Linguistic terms are used that are converted into IFN for judgment. The IFWA operator is used for aggregation. The Euclidian measure is used for estimating S, R, and Q parameters of VIKOR
Park et al. (2013)	Dynamic IFS&IVIFS	Yes	No	Personnel selection	No	Dynamic and uncertain dynamic IFWG operators are used for fusing judgments
Roostaee et al. (2012)	IFS	Yes	No	Supplier selection	No	Aggregation of judgments is done using IFWA operator. Linguistic ratings are converted into IFN for processing. Delphi method is also integrated with IF-VIKOR. Normalized Hamming distance is used for formulation purpose

Table 1 (continued)

References	Method(s) (VIKOR)	Aggregator	Weight estimates	Application(s)	Comparison with others	Discussion
Devi (2011)	TrnIFS	No	No	Robot selection	No	Linguistic preferences are converted into TrnIFNs for processing
Ying-Yu and De-Jian (2011)	IFS	No	Yes	Air conditioner selection	Yes	Entropy measure is used for aggregation of judgment matrices. Nonlinear normalization model was proposed to formulate VIKOR method
Park et al. (2011)	IVIFS	Yes	Yes	Strategy selection	No	The IVIF-hybrid geometric operator is used for fusing the judgments. Optimization model based on score estimate is used for criteria weights
Miao et al. (2010)	IFS	Yes	Yes	Readiness of C^3I system	No	Linear programming model is used for assigning criteria weights and for aggregation. New formulation for VIKOR is proposed

discussion. Finally, Sect. 7 presents the concluding remarks.

2 Preliminaries

Some basic concepts are reviewed in this section.

Definition 1 (Atanassov 1986) Consider a crisp set X such that $A \subset X$ with A being a fixed set. Atanassov's IFS $\tilde{A}$ defined on a set X is given by Eq. (1):

$$\tilde{A} = \left(a, \mu_{\tilde{A}}(a), v_{\tilde{A}}(a), \pi_{\tilde{A}}(a)\right) \tag{1}$$

where $\mu_{\tilde{A}}(a)$ is the degree of membership, $v_{\tilde{A}}(a)$ is degree of non-membership, and $\pi_{\tilde{A}}(a)$ is the indeterminacy or hesitation. All $\mu_{\tilde{A}}(a), v_{\tilde{A}}(a), \pi_{\tilde{A}}(a) \in [0,1]$, $\mu_{\tilde{A}}(a) + v_{\tilde{A}}(a) \leq 1$ and $\pi = 1 – \mu – v$.

Remark 1 (Xu 2007a) stated that $\left(\mu_{\tilde{A}}(a), v_{\tilde{A}}(a), \pi_{\tilde{A}}(a)\right)$ is the IFV of the IFS $\tilde{A}$. In this work, we concentrate mainly on the membership and non-membership part and, for brevity, ignore the hesitancy part which is a derivative of these two. Therefore, IFV of the following form is used throughout this work: $\left(\mu_{\tilde{A}}(a), v_{\tilde{A}}(a)\right)$.

Definition 2 (Dudziak and Pekala 2011; Xu 2007b) The intuitionistic fuzzy preference relation (IFPR) $\mathcal{R}$ on a set A is a matrix of order $(n \times n)$, where each instance $r_{ij} = \left(\mu_{ij}, v_{ij}\right)$, where μ_{ij} is the membership value with alternative i preferable over alternative j and v_{ij} is the non-membership value with alternative i not preferable to alternative j. Mathematically, IFPR is represented as shown in Eq. (2):

$$\mathcal{R} = \begin{cases} (0.5, 0.5) & \text{at diagonal} \\ \mu_{ij} + v_{ij} \leq 1 & \forall \mu, v \in [0,1] \\ \mu_{ij} = v_{ji} \text{ and } v_{ij} = \mu_{ji} \\ \pi_{ij} = 1 - \mu_{ij} - v_{ij} \end{cases} \tag{2}$$

where μ_{ii} = $_{ii}$ = diagonal = 0.5

Definition 3 (Xu 2007b) Any IFPR $\mathcal{R} = (r_{kl})_{n \times n}$ will obey the following operation rules, as shown in Eqs. (3–6).

$$r_{ab} \oplus r_{cd} = \left(\mu_{ab} + \mu_{cd} - \mu_{ab}\mu_{cd}, v_{ab}v_{cd}\right) \tag{3}$$

$$r_{ab} \otimes r_{cd} = \left(\mu_{ab}\mu_{cd}, v_{ab} + v_{cd} - v_{ab}v_{cd}\right) \tag{4}$$

$$\lambda r_{ab} = \left(1 - (1 - \mu_{ab})^{\lambda}, v_{ab}^{\lambda}\right) \tag{5}$$

$$r_{ab}^{\lambda} = \left(\mu_{ab}^{\lambda}, 1 - (1 - v_{ab})^{\lambda}\right) \tag{6}$$

Definition 4 (Liao and Xu 2015b): Ranking IFVs is an important phase of the MCDM problem that yields a preference sequence from which a compromise solution is selected. The following schemes are used for ranking. Consider two IFVs ρ_1 and ρ_2 which can be ranked using: *Scheme 1:*

If $S(\rho_1) < S(\rho_2)$ then $\rho_1 < \rho_2$. This mean ρ_2 is larger than ρ_1 (7)

If $S(\rho_1)$ = $S(\rho_2)$ then:

If $H(\rho_1) < H(\rho_2)$ then $\rho_1 < \rho_2$ (8)

If $H(\rho_1) = H(\rho_2)$ then $\rho_1 = \rho_2$ (9)

where S is the score given by $\mu_\rho - v_\rho$ and H is the accuracy given by $\mu_\rho + v_\rho$.

Scheme 2:

If $\tau(\rho_1) < \tau(\rho_2)$ then $\rho_1 > \rho_2$ (10)

where

$$\tau(\rho) = 0.5(1 + \pi_\rho)(1 - \mu_\rho) \quad (11)$$

Scheme 3:

If $L(\rho_1) > L(\rho_2)$ then $\rho_1 > \rho_2$ (12)

If $L(\rho_1) = L(\rho_2)$ then:

If $H(\rho_1) < H(\rho_2)$ then $\rho_1 < \rho_2$ (13)

If $H(\rho_1) = H(\rho_2)$ then $\rho_1 = \rho_2$ (14)

where

$$L(\rho) = {(1 - v_\rho)}/{(1 + \pi_\rho)} \quad (15)$$

3 Traditional VIKOR method

VIKOR is an MCDM ranking method that produces compromise solution (Opricovic 2009). This method finds the preference sequence by ordering alternatives from best to worst based on the set of conflicting criteria. The criteria are classified as benefit and cost factors that serve as ordering alternatives for VIKOR ranking. The goal of VIKOR is to maximize the benefit attribute and minimize the cost attribute. In general, any organization prefers improvement of benefit factors and minimization of cost factors. For instance, factors such as quality, scope, and profit are to be maximized and hence are categorized as benefit factors. In contrast, factors such as risk, cost, and time are to be minimized and therefore are classified into the cost category.

VIKOR ranking is based on the L_p metric. The method is used for identifying a suitable alternative from a set of alternatives based on specific criteria. Researchers generally formalize a decision matrix that consists of four components, which are: criteria—this includes both cost and benefit attributes pertaining to the set of alternatives under study, alternatives—the subject of concern that are preferentially ordered to obtain an optimal compromise solution, fitness values—values corresponding to an alternative pertaining to each criterion, and weight of criteria—infers the strength and impact of the criteria with respect to a specific domain. Table 2 shows a generalized decision matrix that considers both the cost and benefit criteria for k different alternatives. The fitness values of each of the alternative are represented by $\psi_{\alpha\beta}$, where α and β are the row and column values.

The VIKOR method estimates a compromise solution. In general, we calculate $\Delta f^1 = f_1^* - f_1^c$ and $\Delta f^2 = f_2^* - f_2^c$ (Gul et al. 2016) and perform aggregation using the L_p metric, which is given by Eq. (16).

Table 2 Judgment matrix

Decision matrix	Cost and benefit criteria							
	C_1	C_2	…	C_n	B_1	B_2	…	B_m
λ_1	ψ_{11}	…	…	ψ_{1n}	…	…	…	ψ_{1m}
λ_2	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
…	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
λ_k	ψ_{k1}	…	…	ψ_{kn}	…	…	…	ψ_{km}

Weight of criteria (W) = (ω_1, ω_2, …, ω_t)

$$L_p = \left(\sum_{k=1}^{n} \left({(\psi_k^{\max} - \psi_{ik})}/{(\psi_k^{\max} - \psi_k^{\min})} \right)^p \right)^{1/p} \quad (16)$$

where $\psi_k^{\max}$ is the maximum fitness value, $\psi_k^{\min}$ is the minimum fitness value, and $1 \leq p \leq \infty$.

The algorithm for the classical VIKOR method is given below:

Step 1 Calculate the positive and negative ideal solution (PIS and NIS, respectively) using Eq. (17). The PIS measures the ideal state of any MCDM problem, which involves boosting benefit and cutting cost. NIS is the opposite of PIS.

$$E = \begin{cases} P^+ = \vee_i(\psi_{ij}); N^- = \wedge_i(\psi_{ij}) \text{if criteria} = \text{benefit} \\ P^+ = \wedge_i(\psi_{ij}); N^- = \vee_i(\psi_{ij}) \text{if criteria} = \text{cost} \end{cases} \quad (17)$$

where P^+ is PIS, N^- is NIS, $\vee$ is the maximization operator, $\wedge$ is the minimization operator, and E is the estimate of ideal solutions.

Step 2 Determine the utility function of the group and the regret of individuals. Utility acts as a catalyst for decision making, while regret delimits the process, as shown in Eqs. (18, 19).

$$S = \sum_j \omega \left(\frac{P^+ - \psi_{ij}}{P^+ - N^-} \right) \quad (18)$$

$$R = \vee_j \omega \left(\frac{N^- - \psi_{ij}}{P^+ - N^-} \right) \quad (19)$$

where S is the utility of the group, R is the individual regret, and ω is criteria weight.

Step 3 Estimate the rank coefficient $\mathbb{Q}$ that will prioritize the alternatives, as shown in Eq. (20).

$$\mathbb{Q} = v^{(S - S_\wedge)}/_{(S_\vee - S_\wedge)} + (1 - v)^{(R - R_\wedge)}/_{(R_\vee - R_\wedge)} \quad (20)$$

where v is the weight estimate of the strategy (between [0,1]), $S_\wedge$ is the minimum of group utility, $S_\vee$ is the maximum of group utility, $R_\wedge$ is the minimum of individual regret, and $R_\vee$ is the maximum of individual regret.

Step 4 The final preference order for the given set of alternatives is framed using the rank coefficient value from Step 3. The smallest $\mathbb{Q}$ value indicates better preference in which the lowest $\mathbb{Q}$ value is ranked 1 and we proceed to the next iteration by identifying the next lower $\mathbb{Q}$ value and so forth. Two conditions are developed for ranking

Acceptable Advantage:

The acceptable advantage is the difference between the first and second positioned alternatives, given by Eq. (21).

$$\mathbb{Q}(\lambda^1) - \mathbb{Q}(\lambda^2) \geq 1/_{(m-1)} \quad (21)$$

where λ^1 is the alternative in the first position, λ^2 is the alternative in the second position, and m is the total number of alternatives.

Acceptable Stability:

Optimal ranking of the alternatives is performed using g^u and I^r functions. Stable preference orders are obtained based on the decision process used by DMs.

When acceptable advantage fails, a set of alternatives would be chosen as compromise solution. When acceptable stability fails, we use λ^1 and λ^2 as compromise solutions.

4 Proposed methodology

This section addresses the FIFV method that is proposed as an extension of the VIKOR method to handle IFVs, a metric used by DMs for representing preference values. As discussed above, DMs are often reluctant to reveal their preference choices due to several implicit and explicit factors. These factors force DMs to be uncertain of their choices; thus, a single value cannot be used as a valid metric for preference information. Therefore, researchers have found different mechanisms for expressing preference for the alternatives under study. Of these fuzzy sets, two are most widely used: IFS and interval-valued fuzzy sets (IVFS). Recently, researchers also used hesitant fuzzy sets (HFSs) for indicating preference for selecting the alternatives (Torra and Narukawa 2009). However, HFS-based preference information is complex to handle and increases the computational time and dimension of processing (Liao and Xu 2013). To keep the process of decision making computationally effective, we used IFS in our research. However, IFS is not as effective as HFS in representing fuzziness but is a viable candidate for representing fuzziness. To better represent uncertainty, we integrated IFS and IVFS; additionally, researchers have demonstrated that IFS and IVFS are similar.

The following represents a comparative investigation of IFS and IVFS to better understand the decision-making process.

1. IVFS is a type of fuzzy set that is used to represent values in terms of lower and upper limits that range between [0,1].
2. IFSs are a generalization of classical fuzzy sets that use a triplet for every IFV. This triplet consists of a membership function, a non-membership function, and a hesitancy part that is derived from membership and non-membership values. Most often, cognitive thinking by DMs brings the hesitation or indeterminacy values that are neglected in traditional fuzzy sets. Moreover, DMs make decisions based on hesitancy aspects. Definition 1 clarifies the semantics of IFS.
3. In this work, we used a novel type of transformation to transform IFS into IVFS and vice versa (Xu and Liao 2015). Based on this transformation, we propose the FIFV method for MCDM problems. The reason for using this transformation is that it simplifies the formulation of FIFV and saves time in terms of modeling. The basic idea of the proposed FIFV scheme is borrowed from interval-valued VIKOR. However, the setup of the scheme is formulated for an IFS environment. The detailed working procedure is described below:

The DM rates the alternatives in the form of IFVs; he/she is also weighed using IFVs. The weight of the criteria is represented by a crisp set as well as by IFS. Based on Sect. 4, we propose the following procedure for the FIFV ranking method. Initially, the IFS is transformed to IVFS, then proceeds with the steps given below.

Step 1 Calculate the PIS and NIS, as shown in Eqs. (22, 23).

$$P^+ = \wedge_{\text{cost}(i)}\left(\psi_{ij}^l\right) \text{ or } \vee_{\text{Benefit}(i)}\left(\psi_{ij}^u\right) \quad (22)$$

$$N^- = \vee_{\text{cost}(i)}\left(\psi_{ij}^l\right) \text{ or } \wedge_{\text{Benefit}(i)}\left(\psi_{ij}^u\right) \quad (23)$$

Step 2 Calculate the group utility (g) and individual regret (I) function:

$$\mathrm{g}^{l} = \sum_{\text{Benefit}} \omega\gamma + \sum_{\text{Cost}} \omega\delta \quad (24)$$

$$\mathrm{g}^{u} = \sum_{\text{Benefit}} \omega\alpha + \sum_{\text{Cost}} \omega\beta \quad (25)$$

$$\mathrm{I}^{l} = \vee_{\text{Benefit,Cost}}(\omega\gamma, \omega\delta) \quad (26)$$

$$\mathrm{I}^{u} = \vee_{\text{Benefit,Cost}}(\omega\alpha, \omega\beta) \quad (27)$$

where $\gamma = \left(\frac{P^{+}-\psi_{ij}^{u}}{P^{+}-N^{-}}\right)$; $\delta = \left(\frac{\psi_{ij}^{l}-P^{+}}{N^{-}-P^{+}}\right)$; $\alpha = \left(\frac{P^{+}-\psi_{ij}^{l}}{P^{+}-N^{-}}\right)$; $\beta = \left(\frac{\psi_{ij}^{u}-P^{+}}{N^{-}-P^{+}}\right)$

Step 3 Determine the rank coefficient $\mathbb{Q}$ to estimate the preference sequence for the set of alternatives:

$$\mathbb{Q}^{l} = \varphi\left(\frac{\mathrm{g}^{\mathrm{l}} - \mathrm{g}^{\wedge}}{\mathrm{g}^{\vee} - \mathrm{g}^{\wedge}}\right) + (1-\varphi)\left(\frac{\mathrm{I}^{l} - \mathrm{I}^{\wedge}}{\mathrm{I}^{\vee} - \mathrm{I}^{\wedge}}\right) \quad (28)$$

$$\mathbb{Q}^{u} = \varphi\left(\frac{\mathrm{g}^{\mathrm{u}} - \mathrm{g}^{\wedge}}{\mathrm{g}^{\vee} - \mathrm{g}^{\wedge}}\right) + (1-\varphi)\left(\frac{\mathrm{I}^{u} - \mathrm{I}^{\wedge}}{\mathrm{I}^{\vee} - \mathrm{I}^{\wedge}}\right) \quad (29)$$

where φ is the weight of the strategy defined by DM, $\mathrm{g}^{\wedge}$ is the $\min(\mathrm{g}^{l})$, $\mathrm{g}^{\vee}$ is the maximum (g^{u}), $\mathrm{I}^{\wedge}$ is the minimum (I^{l}), and $\mathrm{I}^{\vee}$ is the maximum (I^{u}).

It should be noted here that (27) contains an IFV weighting factor. There is an IFV weight vector associated with each criterion that can be transformed into IVFS for processing, using the transformation procedure described below.

Step 4 Obtain the value for $\mathbb{Q}$ to estimate the final preference order and the compromise solution from the set of alternatives. Use (28) to transform IVFS to IFS, then rank the $\mathbb{Q}$ values using Definition 4. For ranking, use Scheme 1, Scheme 2, or Scheme 3. In this work, we made inferences from the results obtained from Scheme 3. Also, we compared the IFS-based preference order with the preference order obtained using IVFS to check the validity of the FIFV method.

The simple transformation procedure used for converting IFS to IVFS and vice versa simplifies the FIFV procedure and makes it effective to formulate; also, it saves a lot of time otherwise needed for proposing new formulations under the IFS domain for VIKOR. Also, FIFV uses both IFS and IVFS to make planned transformations during the implementation process.

5 Personnel selection example

5.1 Background

The PSP is a challenging problem in any organization, since all projects involve teamwork. Managers often find it difficult to choose suitable candidates for the project. Optimal candidate selection is governed by many factors, such as skill, experience, availability, and personnel job satisfaction (Adair 2004). In this work, we assumed that the candidates participating in the MCDM study satisfy these rudimentary criteria. Based on the suggestion given by (Miller 1956), any DM can manage only eight criteria at most. Chan and Kumar (2007) formulated the criteria for selecting the best global suppliers; based on these, we formulated five criteria for the PSP. PSP selection criteria were based on Chan and Kumar (2007). The five key attributes of PSP are given below:

- ξ_1*: Cost* This criterion is categorized under the cost factor. The sub-criteria for cost attributes are: η_{11}—cumulative salaries for teammates, η_{12}—resource utilization cost, and η_{13}—travel expenses.
- ξ_2: *Service Performance* This criterion is categorized under the benefit factor. The sub-criteria of this attribute are: η_{21}—responsiveness, η_{22}—delivery time, η_{23}—ease of communication, and η_{24}—research and development and technical support.
- ξ_3*: Product/Project Quality* This criterion is classified as a benefit parameter. There are four sub-criteria: η_{31}—project/product rejection rate, η_{32}—solution to quality problem, η_{33}—assessment of quality, and η_{34}—improved lead time.
- ξ_4*: Risk* This attribute is categorized under the cost parameter. There are four sub-criteria: η_{41}—economic risk, η_{42}—organizational/political risk, η_{43}—location risk, and η_{44}—cultural/social risk.
- ξ_5: *Team Personnel Profile* This attribute comes under the benefit category. There are four sub-criteria governing this attribute: η_{51}—financial status, η_{52}—previous success story, η_{53}—relationship with colleagues and customers, and η_{54}—area of specialization.

Based on the advice given by human resources officials, we arrive at a conclusion regarding the weight assignments for each of the criterion. According to their advice, team personnel profile (ξ_5) is the most essential attribute because it is directly related to members of the team, which is given more weight in the benefit category. Next, quality of project/product (ξ_3) and service performance (ξ_2), which also belong to the benefit category, are given equal weights. There are two attributes in the cost category (cost and risk, ξ_1 and ξ_4, respectively), which are related to the organization and are given equal weights. Since ξ_1 and ξ_4 belong to the cost category, they are to be kept to a minimum. We next set the biased weight as $W_b = (0.1, 0.2, 0.2, 0.1, 0.4)^{\mathrm{T}}$, which closely resembles the choice selected by the experts.

Figure 1 depicts the hierarchical arrangement of the PSP for solving the problem using MCDM methods. Figure 2 depicts the FIFV ranking method procedure. This flowchart demonstrates the step-by-step operation involved in the proposed FIFV method. Next, we propose an algorithm for solving the multi-criteria PSP (MCPSP) that involves five competing criteria of which two are cost and three are benefit. The objective of this MCPSP problem is to choose an optimal candidate for the project. The algorithm for MCPSP is as follows:

Step 1: Define the problem We identify a proper MCDM problem for investigation and then choose a set of alternatives and the corresponding criteria for estimation. Also, DMs rate the alternatives with respect to each criterion.

Step 2: Construct the Decision Matrix A decision matrix is next formulated. The rating of alternatives is done using IFVs. Different DMs give different opinions for each alternative of each respective criterion. Each criterion has its own importance with respect to a particular domain.

Criteria weights are allocated to the criteria using two schemes:

Scheme 1: Biased Weight (b)—According to this scheme, criteria are given weights based on importance, influence, and effect on a specific domain. The weight values are assigned directly by DMs or calculated methodically.

Scheme 2: Unbiased Weight (ub)—This is another scheme for allocating weight to the criteria. In Scheme 2, $1/_n$ is assigned as a weight value where n is the total number of criteria. For example, if there are two cost factors and three benefit factors, the unbiased weights would be $W_{ub} = \left(\frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5}\right)^{\mathrm{T}}$.

In this paper, intuitionistic fuzzy weight (IFW) is used. The weights of each criterion are in the form of IFV. There are two methods for setting IFWs, as shown in (30), which check for the satisfaction of weights based on the constraint depicted; if weight values are mismatched, the weights are obtained again.

$$\text{DMs' choice} = \begin{cases} \omega_b = \text{Methodical or DMs' direct value with } \sum w = 1 \\ \omega_{ub} = 1/_n \text{ with } \sum w = 1 \\ \omega_{ahp} = \text{IFAHP or DMs' random IFVs} \end{cases} \tag{30}$$

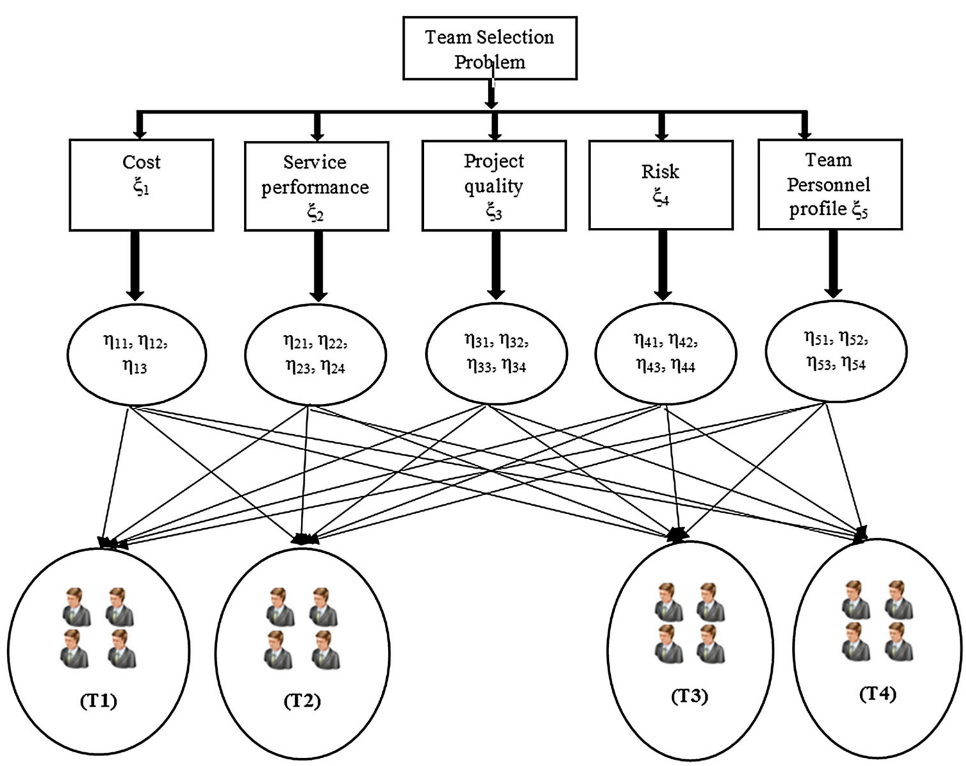

Fig. 1 Hierarchical structure of PSP

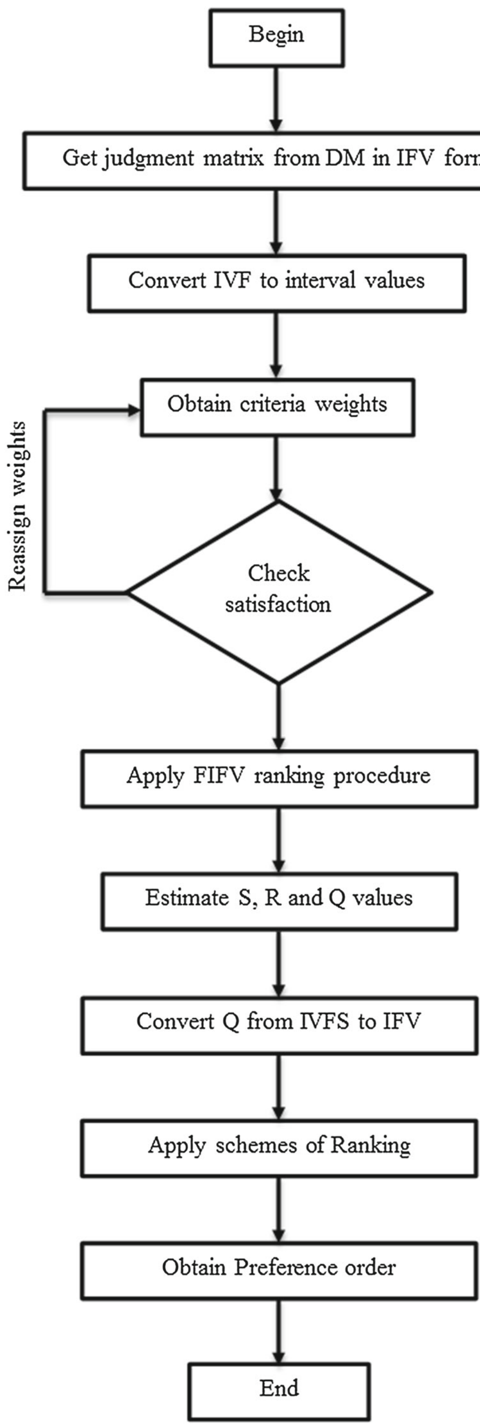

Fig. 2 Working procedure of FIFV

Intuitionistic fuzzy AHP (IFAHP) was used to calculate weight values for criteria, and they are given by, ((0.2172, 0.6039),(0.0977,0.7418),(0.1785,0.6585),(0.1367,0.7151), (0.06, 0.8317)). These values are adapted from Xu and Liao (2015) for complete details on ω_{ahp}.

Step 3: Apply MCDM ranking methods Several researchers have proposed different ranking methods. As discussed in Sect. 2, all these methods use a judgment matrix to produce a preference sequence from which an optimal solution is obtained. In this work, we propose a FIFV-based method for ranking alternatives that makes use of IFS and VIKOR ranking properties. Xu and Liao (2015) proposed a new normalized rank summation approach based on interval numbers and their operational laws. According to this method:

$$(\mu_i, v_i) \to [\mu_i, 1 - v_i] \tag{31}$$

Eq. (31) represents the conversion procedure used for converting IFVs to interval values. Using (31), Xu and Liao (2015) proposed a method for estimating criteria weights, as shown in (32).

$$\omega_a = \left[\frac{\sum_{b-1}^{n} \mu_{ab}}{\sum_{a=1}^{n} \sum_{b=1}^{n} (1 - v_{ab})}, \frac{\sum_{b-1}^{n} (1 - v_{ab})}{\sum_{a=1}^{n} \sum_{b=1}^{n} \mu_{ab}} \right] \tag{32}$$

Eq. (33) is used to convert the interval values to IFVs. This equation is applied in the ending phase of FIFV ranking to obtain an optimal preference sequence.

$$[\mu_i, 1 - v_i] = (\mu_i, 1 - x) = (\mu_i, v_i) \tag{33}$$

where $x = 1 - v_i$.

Step 4: Obtain the compromise solution Step 4 generates a preference order, which ranks the alternatives based on the set of competing criteria. From the preference order, an optimal compromise solution is chosen. For example, if the preference order of three items is $I_2 \succ I_1 \succ I_3$, then the compromise solution sequence is (with two conditions satisfied): I_2 preferred over I_1 which in turn is preferable to I_3. Thus, an optimal compromise solution is I_2.

Step 5: Validate the Consistency of the FIFV method In this step, the proposed FIFV method is compared to state-of-the-art methods to ensure consistency. We apply the concept of majority wins to check how well the inference of our proposed method coincides with the inferences produced by the state-of-the-art methods. If most of the state-of-the-art methods correlate with the proposed FIFV method, then the inference is consistent. We also test the consistency of our proposed method using the Spearman correlation method.

5.2 Empirical study

The following empirical study is presented to show how the proposed FIFV method works. The problem of MCPSP is widely studied by software companies. In this empirical study, a start-up company is investigated that needs a suitable programmer for a project. Initially, 18 candidates applied for the job. After screening all the candidates, eight members were shortlisted. These eight members were further evaluated and a final set of four candidates was chosen. All candidates satisfied the rudimentary criteria needed for the study. The main objective of the empirical study is to choose an optimal candidate (out of four) for the project. The decision matrix from three DMs was obtained; all three DMs were encouraged to give their ratings in the form of IFVs. Thus, three judgment matrices of order (4×5) with four alternatives and five criteria were obtained. Table 2 represents the skeleton view of a judgment matrix.

Algorithm:

1. A judgment matrix is constructed for each DM and associated preferences regarding alternatives with respect to each criterion. These values are IFVs, as depicted in Tables 3.
2. Convert the aggregated decision matrix from IFVs to interval values using Eq. (31). Next, calculate the weight for each criterion using (32). Weight values are presented in range format and are shown in Table 4.
3. Apply the proposed FIFV method for ranking alternatives. The details of the FIFV method are shown in Eqs. (22–29). The estimate is shown in Tables 5, 6, and 7.
4. Next, obtain g^u, I^r, and $\mathbb{Q}$ values as interval numbers. Convert the interval-based $\mathbb{Q}$ value to IFVs using (33), as shown in Table 8.
5. Rank the alternatives using the procedure given in Sect. 5, which generates a preference order that is used to select the optimal team for the project. This is depicted in Table 9.
6. Validate the consistency of the proposed method by comparing it to different state-of-the-art ranking methods. Use majority wins and Spearman correlation methods to test consistency, as described earlier.

6 Results and discussion

The MCPSP is an interesting type of MCDM problem that is NP-hard in nature (Dorn et al. 2011). Generally, there is not a fixed approach or optimal method for solving NP-hard problems, which is a motivating factor for conducting research in this field. Many different ranking schemes have been proposed for MCDM problems, as discussed in Sect. 2. In this section, we validated the consistency of the FIFV method by comparing it with state-of-the-art methods. This comparison allowed us to identify the optimal preference order and a suitable compromise solution. As previously mentioned, we applied the majority wins concept to decide on a suitable preference order from which we selected an optimal compromise solution. We also validated the consistency of the proposed FIFV method by using the Spearman correlation method. We applied this method to different ranking schemes to determine whether the FIFV method is consistent with existing methods.

Table 10 shows the tournament comparison of different ranking methods. These results suggest that there is a high-level of competition between each alternative, which indicates that all teams adequate for the project. We proposed a novel FIFV method that selects λ_4 as the compromise solution. We used different strategy thresholds including 0.3, 0.5, 0.7, and 0.9 to estimate the preference order. These strategy thresholds are widely used in the literature for investigations. We also used a different weighting mechanism for the investigation. Criteria were weighted using the biased method, unbiased method, and AHP method. The AHP weights were IFVs that were obtained from Xu and Liao (2015). FIFV uses IFV as an input for the process, which is a better choice for representing uncertainty and imprecision. Other methods convert IFVs either to IVFSs or a single-valued term by taking the mean of the ranges, which limits the information, and therefore, uncertainty, is handled less effectively as compared to other methods. Boran et al. (2011) proposed the IFTOPSIS method that also uses IFVs as input. The IFTOPSIS method is therefore compared with FIFV. The problem with the TOPSIS method is that it does not

Table 3 IFS-based preference information

Personnel	Criteria under study				
	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5
λ_1	(0.35, 0.27)	(0.33, 0.38)	(0.68, 0.17)	(0.12, 0.34)	(0.67, 0.20)
λ_2	(0.18, 0.45)	(0.16, 0.50)	(0.66, 0.14)	(0.22, 0.46)	(0.62, 0.28)
λ_3	(0.13, 0.51)	(0.20, 0.43)	(0.62, 0.17)	(0.18, 0.32)	(0.64, 0.17)
λ_4	(0.18, 0.42)	(0.21, 0.57)	(0.66, 0.20)	(0.14, 0.45)	(0.62, 0.29)

Table 4 Interval-valued rating

Interval-valued preferences	Criteria under study				
	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5
λ_1	[0.35, 0.73]	[0.33, 0.62]	[0.68, 0.83]	[0.12, 0.66]	[0.67, 0.80]
λ_2	[0.18, 0.55]	[0.16, 0.50]	[0.66, 0.85]	[0.22, 0.54]	[0.62, 0.72]
λ_3	[0.13, 0.49]	[0.20, 0.56]	[0.62, 0.83]	[0.18, 0.68]	[0.64, 0.83]
λ_4	[0.18, 0.58]	[0.21, 0.43]	[0.66, 0.80]	[0.14, 0.55]	[0.62, 0.71]

Table 5 Positive and negative ideal solution

Ideal solution	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5
P^+	0.13	0.62	0.85	0.12	0.83
N^-	0.73	0.16	0.62	0.68	0.62

Table 6 Estimate of PIS and NIS for group utility and individual regret

Weight criteria	Ideal solution	g^u	I^r
ω_{ub}	P^+	0.065	0.03
	N^-	0.88	0.2
ω_b	P^+	0.054	0.03
	N^-	0.91	0.4
ω_{ahp}	P^+	0.046	0.023
	N^-	3.2	0.83

categorize criteria and therefore less appropriate for MCDM problems that involve benefit and cost criteria. The PSP method uses typical cost and benefit criteria, and therefore, TOPSIS may not be the best choice for analysis. Ranking methods such as WASPAS, MMOORA, COPRASG, and EXPROM2 use mean values as their input for evaluation that masks imprecision and uncertainty, and therefore, these methods are not effective. Xu and Liao (2015) made a claim that IFVs can better represent fuzziness (by membership and non-membership degrees) as compared to IVFSs. PROMETHEE, which is an outranking method that uses mean value as its input, has recently inspired many researchers to focus on MCDM. Although the alternatives selected by PROMETHEE, COPRASG, EXPROM2, and IMMOORA are similar to the compromise solution selected by the FIFV method, imprecision is better represented by FIFV as compared to these other methods. FIFV and IVVIKOR (Sayadi et al. 2009) are the only methods that use AHP weights, which are IFVs. AHP weighting of criteria is a better choice for representing

Table 7 Estimate of rank coefficient

Estimates		λ_1	λ_2	λ_3	λ_4
ω_{ub}	g^u	[0.12, 0.82]	[0.21, 0.86]	[0.065, 0.88]	[0.26, 0.84]
	I^r	[0.073, 0.2]	[0.10, 0.2]	[0.026, 0.2]	[0.11, 0.2]
$\mathbb{Q}$	$\varphi = 0.3$	[0.21, 0.98]	[0.37, 0.99]	[0, 1]	[0.42, 0.98]
	$\varphi = 0.5$	[0.17, 0.96]	[0.31, 0.98]	[0, 1]	[0.37, 0.98]
	$\varphi = 0.7$	[0.13, 0.94]	[0.26, 0.97]	[0, 1]	[0.32, 0.97]
	$\varphi = 0.9$	[0.087, 0.93]	[0.20, 0.97]	[0, 1]	[0.27, 0.96]
ω_b	g^u	[0.11, 0.78]	[0.29, 0.91]	[0.054, 0.9]	[0.36, 0.89]
	I^r	[0.057, 0.30]	[0.21, 0.4]	[0.026, 0.36]	[0.22, 0.40]
$\mathbb{Q}$	$\varphi = 0.3$	[0.078, 0.77]	[0.42, 1]	[0, 0.93]	[0.48, 0.99]
	$\varphi = 0.5$	[0.075, 0.79]	[0.38, 1]	[0, 0.94]	[0.44, 0.99]
	$\varphi = 0.7$	[0.046, 0.78]	[0.34, 1]	[0, 0.97]	[0.42, 0.98]
	$\varphi = 0.9$	[0.068, 0.83]	[0.29, 1]	[0, 0.98]	[0.38, 0.98]
ω_{ahp}	g^u	[0.10, 2.9]	[0.11, 3.06]	[0.046, 3.17]	[0.16, 3.02]
	I^r	[0.079, 0.72]	[0.046, 0.83]	[0.023, 0.75]	[0.072, 0.83]
$\mathbb{Q}$	$\varphi = 0.3$	[0.054, 0.87]	[0.026, 0.99]	[0, 0.93]	[0.054, 0.98]
	$\varphi = 0.5$	[0.043, 0.88]	[0.025, 0.98]	[0, 0.95]	[0.049, 0.98]
	$\varphi = 0.7$	[0.033, 0.89]	[0.023, 0.97]	[0, 0.97]	[0.44, 0.97]
	$\varphi = 0.9$	[0.023, 0.91]	[0.021, 0.97]	[0, 0.99]	[0.039, 0.96]

Table 8 Conversion of IVFSs to IFVs

Estimate		IVFSs				IFVs			
$\mathbb{Q}$		λ_1	λ_2	λ_3	λ_4	λ_1	λ_2	λ_3	λ_4
Values	$\varphi = 0.3$	$[0.21, 0.98]$	$[0.37, 0.99]$	$[0, 1]$	$[0.42, 0.98]$	$(0.21, 0.02)$	$(0.37, 0.01)$	$(0, 0)$	$(0.42, 0.02)$
	$\varphi = 0.5$	$[0.17, 0.96]$	$[0.31, 0.98]$	$[0, 1]$	$[0.37, 0.98]$	$(0.17, 0.04)$	$(0.21, 0.02)$	$(0, 0)$	$(0.37, 0.02)$
	$\varphi = 0.7$	$[0.13, 0.94]$	$[0.26, 0.97]$	$[0, 1]$	$[0.32, 0.97]$	$(0.13, 0.06)$	$(0.26, 0.03)$	$(0, 0)$	$(0.32, 0.03)$
	$\varphi = 0.9$	$[0.087, 0.93]$	$[0.20, 0.97]$	$[0, 1]$	$[0.27, 0.96]$	$(0.087, 0.07)$	$(0.2, 0.03)$	$(0, 0)$	$(0.27, 0.04)$
Preference order		$\varphi = 0.3$				$\lambda_3 \succ \lambda_1 \succ \lambda_2 \succ \lambda_4$			
		$\varphi = 0.5$				$\lambda_3 \succ \lambda_1 \succ \lambda_2 \succ \lambda_4$			
		$\varphi = 0.7$				$\lambda_3 \succ \lambda_1 \succ \lambda_2 \succ \lambda_4$			
		$\varphi = 0.9$				$\lambda_3 \succ \lambda_1 \succ \lambda_2 \succ \lambda_4$			
$\mathbb{Q}$	$\varphi = 0.3$	$[0.078, 0.77]$	$[0.42, 1]$	$[0, 0.93]$	$[0.48, 0.99]$	$(0.078, 0.23)$	$(0.42, 0)$	$(0, 0.07)$	$(0.48, 0.01)$
Values	$\varphi = 0.5$	$[0.075, 0.79]$	$[0.38, 1]$	$[0, 0.94]$	$[0.44, 0.99]$	$(0.075, 0.21)$	$(0.38, 0)$	$(0, 0.06)$	$(0.44, 0.01)$
	$\varphi = 0.7$	$[0.046, 0.78]$	$[0.34, 1]$	$[0, 0.97]$	$[0.42, 0.98]$	$(0.046, 0.22)$	$(0.34, 0)$	$(0, 0.03)$	$(0.42, 0.02)$
	$\varphi = 0.9$	$[0.068, 0.83]$	$[0.29, 1]$	$[0, 0.98]$	$[0.38, 0.98]$	$(0.068, 0.17)$	$(0.29, 0)$	$(0, 0.02)$	$(0.38, 0.02)$
Preference order		$\varphi = 0.3$				$\lambda_1 \succ \lambda_3 \succ \lambda_2 \succ \lambda_4$			
		$\varphi = 0.5$				$\lambda_1 \succ \lambda_3 \succ \lambda_2 \succ \lambda_4$			
		$\varphi = 0.7$				$\lambda_1 \succ \lambda_3 \succ \lambda_2 \succ \lambda_4$			
		$\varphi = 0.9$				$\lambda_1 \succ \lambda_3 \succ \lambda_2 \succ \lambda_4$			
$\mathbb{Q}$	$\varphi = 0.3$	$[0.054, 0.87]$	$[0.026, 0.99]$	$[0, 0.93]$	$[0.054, 0.98]$	$(0.054, 0.13)$	$(0.026, 0.01)$	$(0, 0.07)$	$(0.054, 0.02)$
Values	$\varphi = 0.5$	$[0.043, 0.88]$	$[0.025, 0.98]$	$[0, 0.95]$	$[0.049, 0.98]$	$(0.043, 0.12)$	$(0.025, 0.02)$	$(0, 0.05)$	$(0.049, 0.02)$
	$\varphi = 0.7$	$[0.033, 0.89]$	$[0.023, 0.97]$	$[0, 0.97]$	$[0.044, 0.97]$	$(0.033, 0.11)$	$(0.023, 0.03)$	$(0, 0.03)$	$(0.044, 0.03)$
	$\varphi = 0.9$	$[0.023, 0.91]$	$[0.021, 0.97]$	$[0, 0.99]$	$[0.039, 0.96]$	$(0.023, 0.09)$	$(0.021, 0.03)$	$(0, 0.01)$	$(0.039, 0.04)$
Preference order		$\varphi = 0.3$				$\lambda_1 \succ \lambda_3 \succ \lambda_4 \succ \lambda_2$			
		$\varphi = 0.5$				$\lambda_1 \succ \lambda_3 \succ \lambda_4 \succ \lambda_2$			
		$\varphi = 0.7$				$\lambda_1 \succ \lambda_3 \succ \lambda_2 \succ \lambda_4$			
		$\varphi = 0.9$				$\lambda_1 \succ \lambda_3 \succ \lambda_2 \succ \lambda_4$			

fuzziness. IFVs also enhance the rate of understanding of the importance of each criterion.

Table 10 indicates that the compromise solution λ_4 is a suitable alternative for the process (based on its closeness to ideal solution). Based on the majority wins concept, we infer that λ_4 is a better alternative for the process. This concept measures the total number of times an alternative is selected as a compromise solution by the ranking methods. In Table 10, the alternative λ_4 is selected 21 times by different ranking schemes, and hence, λ_4 wins the selection. We used the Spearman correlation method (Spearman 1904) to further investigate the consistency of the proposed method. Figures 3 and 4 depict the correlation between the proposed FIFV method and other ranking methods and also demonstrate the consistency of the proposed scheme with other state-of-the-art methods by finding the relationship between the preference orders of each method. The observed variation in correlation values is due to variation in the preference orders. The reason for preference order variation is due to the difference in ranking style used for each method. The styles of normalizing, aggregating, and forming preferences differ by method, and hence, deviations in preference order were identified. Although such variations occur, the selection of compromise solution by different schemes is the same. (λ_4 is selected by the majority of ranking methods.) Our proposed FIFV coincides with this selection, which demonstrates its consistency with state-of-the-art methods (Figs. 4, 5).

7 Conclusion

This paper provides a new extension to VIKOR ranking method under IFS context for solving MCPSP. The method uses the transformation procedure for its implementation which effectively retains the IFS information throughout

Table 9 Ranking schemes of FIFV method

Different ranking schemes	Threshold for DMs' strategy	Ranking of alternatives			
Apply Scheme 3 of (27) (ω_b)		$L\left(\mathbb{Q}^{\lambda_1}\right)$	$L\left(\mathbb{Q}^{\lambda_2}\right)$	$L\left(\mathbb{Q}^{\lambda_3}\right)$	$L\left(\mathbb{Q}^{\lambda_4}\right)$
	$\varphi = 0.3$	0.45	0.63	0.48	0.65
	$\varphi = 0.5$	0.46	0.62	0.48	0.67
	$\varphi = 0.7$	0.45	0.6	0.49	0.63
	$\varphi = 0.9$	0.47	0.58	0.49	0.61
Preference order	$\varphi = 0.3$	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$			
	$\varphi = 0.5$	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$			
	$\varphi = 0.7$	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$			
	$\varphi = 0.9$	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$			
Apply Scheme 3 of (27) (ω_{ub})	$\varphi = 0.3$	0.55	0.61	0.5	0.63
	$\varphi = 0.5$	0.54	0.55	0.5	0.61
	$\varphi = 0.7$	0.52	0.58	0.5	0.59
	$\varphi = 0.9$	0.50	0.55	0.5	0.57
Preference order	$\varphi = 0.3$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
	$\varphi = 0.5$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
	$\varphi = 0.7$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
	$\varphi = 0.9$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
Apply Scheme 3 of (27) (ω_{ahp})	$\varphi = 0.3$	0.48	0.5	0.48	0.51
	$\varphi = 0.5$	0.48	0.5	0.48	0.51
	$\varphi = 0.7$	0.48	0.5	0.49	0.5
	$\varphi = 0.9$	0.48	0.5	0.5	0.5
Preference order	$\varphi = 0.3$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
	$\varphi = 0.5$	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$			
	$\varphi = 0.7$	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$			
	$\varphi = 0.9$	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$			
Apply Scheme 2 of (27) (ω_b)		$\tau\left(\mathbb{Q}^{\lambda_1}\right)$	$\tau\left(\mathbb{Q}^{\lambda_2}\right)$	$\tau\left(\mathbb{Q}^{\lambda_3}\right)$	$\tau\left(\mathbb{Q}^{\lambda_4}\right)$
	$\varphi = 0.3$	0.78	0.46	0.96	0.39
	$\varphi = 0.5$	0.79	0.5	0.97	0.43
	$\varphi = 0.7$	0.82	0.55	0.99	0.45
	$\varphi = 0.9$	0.82	0.61	0.99	0.5
Preference order	$\varphi = 0.3$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
	$\varphi = 0.5$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
	$\varphi = 0.7$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
	$\varphi = 0.9$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
Apply Scheme 2 of (27) (ω_{ub})	$\varphi = 0.3$	0.7	0.51	1	0.45
	$\varphi = 0.5$	0.74	0.7	1	0.51
	$\varphi = 0.7$	0.79	0.63	1	0.56
	$\varphi = 0.9$	0.84	0.71	1	0.62
Preference order	$\varphi = 0.3$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
	$\varphi = 0.5$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
	$\varphi = 0.7$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
	$\varphi = 0.9$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
Apply Scheme 2 of (27) (ω_{ahp})	$\varphi = 0.3$	0.86	0.95	0.96	0.91
	$\varphi = 0.5$	0.88	0.95	0.97	0.92
	$\varphi = 0.7$	0.90	0.95	0.98	0.92
	$\varphi = 0.9$	0.922	0.95	0.99	0.923

Table 9 (continued)

Different ranking schemes	Threshold for DMs' strategy	Ranking of alternatives			
Preference order	$\varphi = 0.3$	$\lambda_1 \succ \lambda_4 \succ \lambda_2 \succ \lambda_3$			
	$\varphi = 0.5$	$\lambda_1 \succ \lambda_4 \succ \lambda_2 \succ \lambda_3$			
	$\varphi = 0.7$	$\lambda_1 \succ \lambda_4 \succ \lambda_2 \succ \lambda_3$			
	$\varphi = 0.9$	$\lambda_1 \succ \lambda_4 \succ \lambda_2 \succ \lambda_3$			
Apply Scheme 1 of (27) (ω_b)		$S\left(\mathbb{Q}^{\lambda_1}\right)$	$S\left(\mathbb{Q}^{\lambda_2}\right)$	$S\left(\mathbb{Q}^{\lambda_3}\right)$	$S\left(\mathbb{Q}^{\lambda_4}\right)$
	$\varphi = 0.3$	− 0.15	0.42	− 0.07	0.47
	$\varphi = 0.5$	− 0.13	0.38	− 0.06	0.43
	$\varphi = 0.7$	− 0.17	0.34	− 0.03	0.40
	$\varphi = 0.9$	− 0.1	0.29	− 0.02	0.36
Preference order	$\varphi = 0.3$	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$			
	$\varphi = 0.5$	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$			
	$\varphi = 0.7$	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$			
	$\varphi = 0.9$	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$			
Apply Scheme 1 of (27) (ω_{ub})	$\varphi = 0.3$	0.19	0.36	0	0.4
	$\varphi = 0.5$	0.13	0.19	0	0.35
	$\varphi = 0.7$	0.07	0.23	0	0.29
	$\varphi = 0.9$	0.017	0.17	0	0.23
Preference order	$\varphi = 0.3$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
	$\varphi = 0.5$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
	$\varphi = 0.7$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
	$\varphi = 0.9$	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$			
Apply Scheme 1 of (27) (ω_{ahp})	$\varphi = 0.3$	− 0.076	0.016	− 0.07	0.034
	$\varphi = 0.5$	− 0.077	0.005	− 0.05	0.029
	$\varphi = 0.7$	− 0.077	− 0.007	− 0.03	0.014
	$\varphi = 0.9$	− 0.067	− 0.009	− 0.01	− 0.001
Preference order	$\varphi = 0.3$	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$			
	$\varphi = 0.5$	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$			
	$\varphi = 0.7$	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$			
	$\varphi = 0.9$	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$			

the decision-making process. Sensitivity analysis is performed over strategy values, criteria weight values, and ranking schemes, and from the analysis, we observe that the method is robust and provides rational ranking order under similarity measure. Some advantages of the proposed FIFV method are: (1) IFS information is retained throughout the decision-making process; (2) the FIFV method takes advantage of the fact that IFVs and IVFSs are similar such that only minor modifications are needed in the formulation of the ranking method which mitigates the computational overhead to certain extent; (3) the FIFV method is the first method of its kind that effectively models the uncertainty and performs a detailed investigation on the effects of criteria weights and strategy values; (4) the compromise solution selected by FIFV method is consistent and rational. We verified this using the majority wins concept and the Spearman correlation method. While investigating the benefits of FIFV method, we also identified some limitations, including: (1) the method needs skilled DMs for its implementation and for deriving

Table 10 Tournament investigation of different ranking schemes

Ranking methods	Strategy threshold and weighting		Criteria ranking				Preference order	Compromise solution
			λ_1	λ_2	λ_3	λ_4		
FIFV (proposed)	$\varphi = 0.3$	ω_b	4	2	3	1	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$	λ_4
		ω_{ub}	3	2	4	1	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$	λ_4
		ω_{ahp}	3	2	4	1	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$	λ_4
	$\varphi = 0.5$	ω_b	4	2	3	1	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$	λ_4
		ω_{ub}	3	2	4	1	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$	λ_4
		ω_{ahp}	4	2	3	1	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$	λ_4
	$\varphi = 0.7$	ω_b	4	2	3	1	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$	λ_4
		ω_{ub}	3	2	4	1	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$	λ_4
		ω_{ahp}	4	2	3	1	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$	λ_4
	$\varphi = 0.9$	ω_b	4	2	3	1	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$	λ_4
		ω_{ub}	3	2	4	1	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$	λ_4
		ω_{ahp}	4	2	3	1	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$	λ_4
IVVIKOR (Sayadi et al. 2009)	$\varphi = 0.3$	ω_b	1	3	2	4	$\lambda_1 \succ \lambda_3 \succ \lambda_2 \succ \lambda_4$	λ_1
		ω_{ub}	2	3	1	4	$\lambda_3 \succ \lambda_1 \succ \lambda_2 \succ \lambda_4$	λ_3
		ω_{ahp}	1	4	2	3	$\lambda_1 \succ \lambda_3 \succ \lambda_4 \succ \lambda_2$	λ_1
	$\varphi = 0.5$	ω_b	1	3	2	4	$\lambda_1 \succ \lambda_3 \succ \lambda_2 \succ \lambda_4$	λ_1
		ω_{ub}	2	3	1	4	$\lambda_3 \succ \lambda_1 \succ \lambda_2 \succ \lambda_4$	λ_3
		ω_{ahp}	1	4	2	3	$\lambda_1 \succ \lambda_3 \succ \lambda_4 \succ \lambda_2$	λ_1
	$\varphi = 0.7$	ω_b	1	3	2	4	$\lambda_1 \succ \lambda_3 \succ \lambda_2 \succ \lambda_4$	λ_1
		ω_{ub}	2	3	1	4	$\lambda_3 \succ \lambda_1 \succ \lambda_2 \succ \lambda_4$	λ_3
		ω_{ahp}	1	3	2	4	$\lambda_1 \succ \lambda_3 \succ \lambda_2 \succ \lambda_4$	λ_1
	$\varphi = 0.9$	ω_b	1	3	2	4	$\lambda_1 \succ \lambda_3 \succ \lambda_2 \succ \lambda_4$	λ_1
		ω_b	2	3	1	4	$\lambda_3 \succ \lambda_1 \succ \lambda_2 \succ \lambda_4$	λ_3
		ω_{ahp}	1	3	2	4	$\lambda_1 \succ \lambda_3 \succ \lambda_2 \succ \lambda_4$	λ_1
VIKOR	$\varphi = 0.3$	ω_b	N/A	N/A	N/A	N/A	–	–
		ω_{ub}	4	3	1	2	$\lambda_3 \succ \lambda_4 \succ \lambda_2 \succ \lambda_1$	λ_3
	$\varphi = 0.5$	ω_b	N/A	N/A	N/A	N/A	–	–
		ω_{ub}	4	3	1	2	$\lambda_3 \succ \lambda_4 \succ \lambda_2 \succ \lambda_1$	λ_3
	$\varphi = 0.7$	ω_b	N/A	N/A	N/A	N/A	–	–
		ω_{ub}	4	3	1	2	$\lambda_3 \succ \lambda_4 \succ \lambda_2 \succ \lambda_1$	λ_3
	$\varphi = 0.9$	ω_b	N/A	N/A	N/A	N/A	–	–
		ω_{ub}	4	3	1	2	$\lambda_3 \succ \lambda_4 \succ \lambda_2 \succ \lambda_1$	λ_3
TOPSIS	ω_b		4	3	1	2	$\lambda_3 \succ \lambda_4 \succ \lambda_2 \succ \lambda_1$	λ_3
	ω_{ub}		4	1	2	3	$\lambda_2 \succ \lambda_3 \succ \lambda_4 \succ \lambda_1$	λ_2
IVTOPSIS (Jahanshahloo et al. 2006)	ω_b		4	3	1	2	$\lambda_3 \succ \lambda_4 \succ \lambda_2 \succ \lambda_1$	λ_3
	ω_{ub}		4	1	2	3	$\lambda_2 \succ \lambda_3 \succ \lambda_4 \succ \lambda_1$	λ_2
IFTOPSIS (Boran et al. 2009)	ω_b		4	2	3	1	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$	λ_4
	ω_{ub}		3	2	4	1	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$	λ_4
Multi-MOORA	ω_b		4	3	1	2	$\lambda_3 \succ \lambda_4 \succ \lambda_2 \succ \lambda_1$	λ_3
	ω_{ub}		4	1	2	3	$\lambda_2 \succ \lambda_3 \succ \lambda_4 \succ \lambda_1$	λ_2
IMMOORA (Hafezalkotob et al. 2016)	ω_b		4	2	3	1	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$	λ_4
	ω_{ub}		3	2	4	1	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$	λ_4
PROMETHEE (Chatterjee and Chakraborty 2012)	ω_b		4	2	3	1	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$	λ_4
	ω_{ub}		3	2	4	1	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$	λ_4
COPRASG (Chatterjee and Chakraborty 2012)	ω_b		4	2	3	1	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$	λ_4
	ω_{ub}		3	2	4	1	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$	λ_4

Table 10 continued

Ranking methods	Strategy threshold and weighting	Criteria ranking				Preference order	Compromise solution
		λ_1	λ_2	λ_3	λ_4		
WASPAS	ω_b	4	3	1	2	$\lambda_3 \succ \lambda_4 \succ \lambda_2 \succ \lambda_1$	λ_3
	ω_{ub}	4	1	2	3	$\lambda_2 \succ \lambda_3 \succ \lambda_4 \succ \lambda_1$	λ_2
EXPROM2 (Chatterjee and Chakraborty 2012)	ω_b	4	2	3	1	$\lambda_4 \succ \lambda_2 \succ \lambda_3 \succ \lambda_1$	λ_4
	ω_{ub}	3	2	4	1	$\lambda_4 \succ \lambda_2 \succ \lambda_1 \succ \lambda_3$	λ_4

N/A: Not applicable, due to the ranking coefficient $(\mathbb{Q}) \rightarrow \infty$

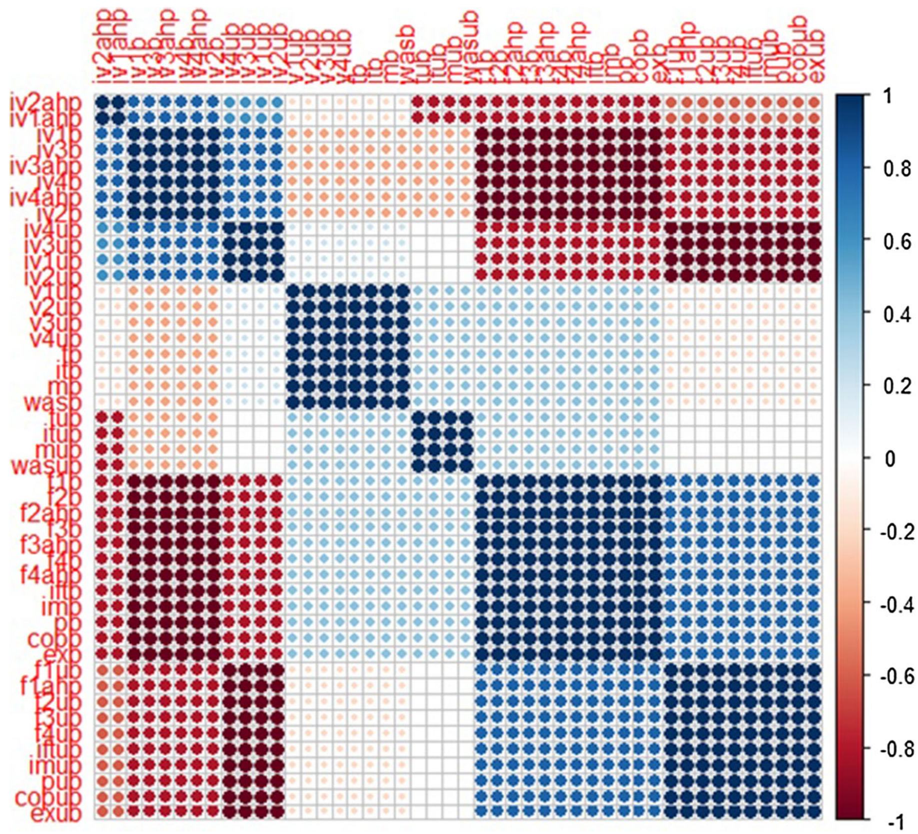

Fig. 3 Spearman correlation estimate

inferences from the process; (2) since the method is formal, it is procedural and methodical; hence, each step must be performed with care, which consumes considerable computation costs.

As future direction, new aggregation operators may be proposed which better depicts the human cognition and interrelationship between criteria. Also, as an interesting variant of IFS, cubic numbers (Amin et al. 2018; Fahmi et al. 2017, 2018a, b; Hosseinzadeh et al. 2014) can be used as preference information and new decision frameworks can be developed for representing fuzzy information more efficiently.

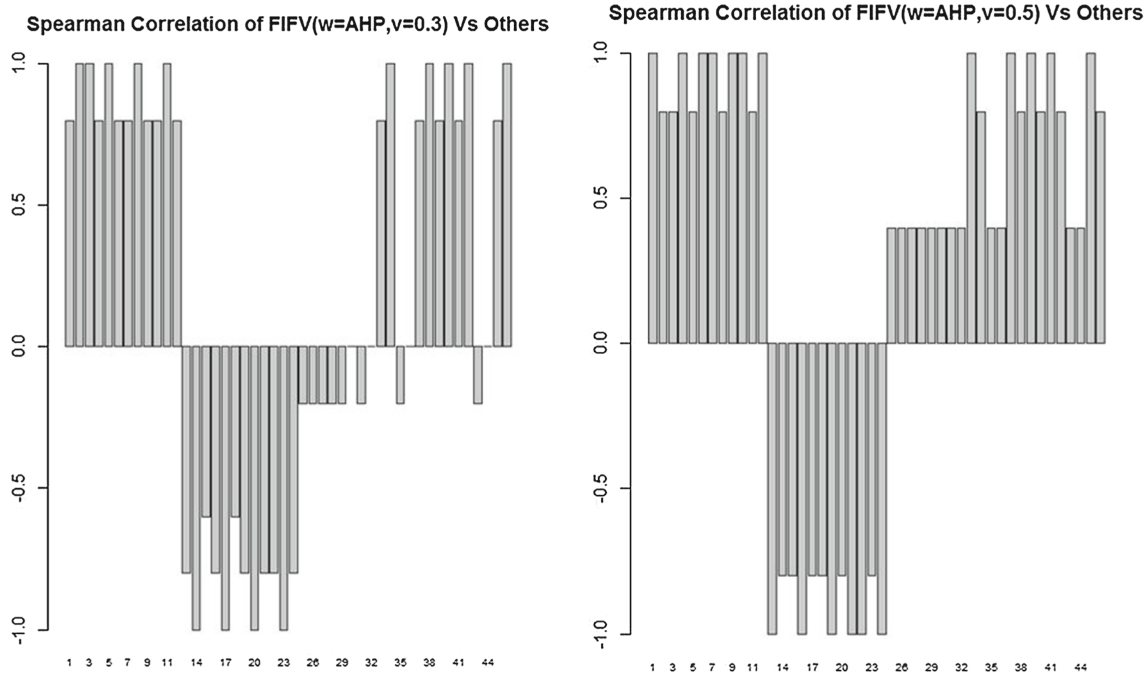

Fig. 4 Spearman correlation for 0.3 and 0.5 strategy values

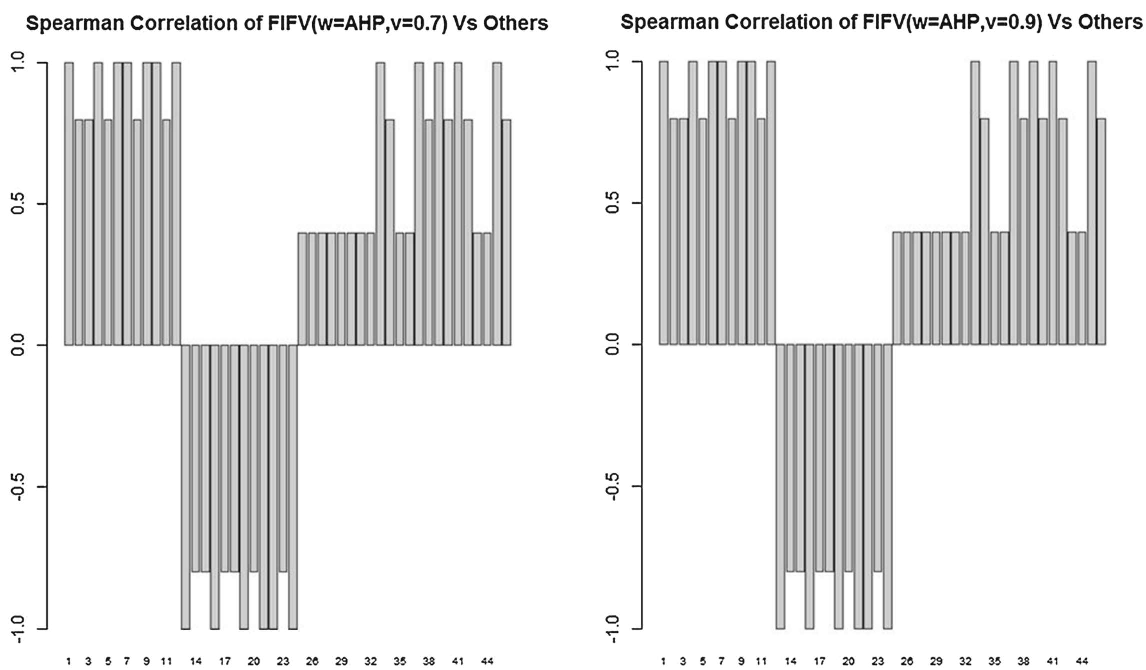

Fig. 5 Spearman correlation for 0.7 and 0.9 strategy values

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Compliance with ethical standards

Conflict of interest All authors of this research paper declare that there is no conflict of interest.

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