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The selection of technology forecasting method using a multi-criteria interval-valued intuitionistic fuzzy group decision making approach

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ABSTRACT

Technological forecasting is a tool for organizations to develop their technology strategies. The quality of forecasting is extremely important for the accuracy of the results and in turn company future. Therefore a proper selection methodology of forecasting technique that considers the characteristics of technology and resources needed such as cost, time is essential. On the other hand, although many forecasting techniques are available, there is a high uncertainty in choosing the most appropriate technique among a set of available techniques. In this paper interval valued intuitionistic fuzzy technique for order preference by similarity to ideal solution (TOPSIS) method is proposed for the solution of technological forecasting technique selection problem. The proposed method includes seven selection criteria and twelve forecasting technique alternatives. The methodology is applied for 3D TV technology. The results revealed that Fisher Pry method is found as the most appropriate method for forecasting since it has the highest closeness coefficient.

1. Introduction

Technology forecasting is the systematic process of describing the emergence, performance, features or impacts of a technology at a time in the future (Technology Futures Analysis Methods Working Group., 2004). It is a tool used for responding the emerging needs of private and public sector organizations in the competitive global environment. The purpose of any type of forecasting and foremost role of the forecaster is to support the decision-makers in making business plans. A primary recommendation in strategy literature is; managers should abandon a maturing technology and embrace a new one to stay competitive (Christensen, 1997). A central, practical problem that managers face is; when to shift investments from the current to the future technology. In other words, deciding between 'the optimization of existing technologies' or 'the development of a new core technology' is one of the most challenging problem of research and development staff of an organization (Slocum & Lundberg, 2001). Seeking answers to these problems make technological forecasting is an important tool for organizations. Although many decision techniques are available, there is a high uncertainty in choosing the most appropriate technique. Beside, all decision making techniques cannot be applied to all forecasting cases. Some of the technological forecasting techniques cannot incorporate the organizational and political scenarios that will influence future technologies. In addition while some techniques consider only expert opinions while some others just consider historical data. The main objective of this study is offering a multi attribute decision making tool to help the decision makers to select the most appropriate technological forecasting technique among a set of available techniques.

Selection of appropriate technological forecasting technique have two main problems. One is; a multi criteria decision making (MCDM) problem where many criteria should be considered in decision-making. And the other one is; a problem containing subjectivity, uncertainty and ambiguity in assessment process (Dağdeviren, Yavuz, & Kılınc, 2009). Therefore this study utilizes interval-valued intuitionistic fuzzy numbers to obtain the performance ratings of the feasible alternatives and proposes a TOPSIS method with interval-valued intuitionistic fuzzy numbers to solve technological forecasting technique selection problem.

2. Literature review

2.1. Technology forecasting techniques

The following table presents a variety of techniques that are commonly used in technology forecasting (Table 1)

Technology trend analysis: If there is a steady stream of technological change and improvement, trend is determined with

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Table 1
Technology forecasting techniques and relevant citations.

Forecasting techniques	Relevant citations
Trend analysis	Coates et al. (2001), Eto (2003), Firat A. K. and Madnick S. (2008), Levary and Han (1995), Meredith and Mantel (1995), Miller and Swinehart (2010) and Mishra et al. (2002)
Growth curve analysis	Bengisu and Nekhili (2006), Chen et al. (2011), Coates et al. (2001), Daim et al. (2006), Kucharavy and De Guio (2011b). Levary and Han (1995), Martino (2003), Meredith and Mantel (1995) and Vanston (2003)
Fisher Pry analysis	Daim et al. (2006), Kucharavy and De Guio (2011b), Tseng et al. (2009), Vanston (2003)
Analogy	Firat et al. (2008), Vanston (2003) and Watts and Porter (1997)
Morphological matrices	Martino (2003), Meredith and Mantel (1995), Vanston (2003) and Watts and Porter (1997)
Patent analysis	Chen et al. (2011), Dubaric et al. (2011), Vanston (2003), Watts and Porter (1997) and Daim et al. (2006)
Scanning, monitoring, tracking	Firat et al. (2008), Martino (2003), Meredith and Mantel (1995), Vanston (2003) and Watts and Porter (1997)
Scenarios	Coates et al. (2001), Daim et al. (2006), Firat et al. (2008), Levary and Han (1995), Martino (2003), Miller and Swinehart (2010), Meredith and Mantel (1995), Tseng et al. (2009), Vanston (2003) and Watts and Porter (1997)
Monte Carlo models	Vanston (2003) and Watts and Porter (1997)
Delphi survey	Coates et al. (2001), Eto (2003), Firat et al. (2008), Levary and Han (1995), Martino (2003), Meredith and Mantel (1995), Miller and Swinehart (2010), Mishra et al. (2010), Tseng et al. (2009), Vanston (2003) and Watts and Porter (1997)
Relevance trees	Levary and Han (1995), Meredith and Mantel (1995) and Miller and Swinehart (2010)
Cross impact analysis	Firat et al. (2008), Levary and Han (1995), Meredith and Mantel (1995) and Miller and Swinehart (2010)

historical data and future is inferred from this trend by extending this pattern (Vanston, 2003).

Growth curves: The growth curve forecasting method is based on the parameter estimation of a technology's life cycle curve (Levary & Han, 1995). It is also helpful in predicting when the technology will reach a particular life cycle stage.

Fisher-Pry analysis: This technique uses logistic curve formulations to project the pattern and rate of adoption of a superior new technology (Vanston, 2003).

Analogy analysis: This technique uses one or more analogous situations project future trends or events (Vanston, 2003) by utilizing similarities between events.

Morphological matrices: It allows envisioning new products and services by defining essential functions involved in current products and services and then postulating alternate ways for accomplishing each of these functions and new ways of combining them (Vanston, 2003).

Patent analysis: In this technique numbers, types and patterns of patents are analyzed to derive information about a particular industry or technology.

Scanning, monitoring and tracking: Scanning seeks to identify any trend or event that might impact the organization. Monitoring is designed to follow general trends in specified areas. Tracking is designed to follow developments in a limited area carefully.

Scenarios: Scenario analysis provides a structured method for integrating a number of individual forecasts into a series of comprehensive, feasible narratives about how the future might develop.

Monte Carlo models: In this technique, all steps involved in the development of a new technology are identified, and their interrelationships specified in a mathematical model. Probability values are assigned to each event and then computer model is run numerous times to determine the overall probabilities.

Delphi survey: It is a qualitative approach that a panel of experts used as the source of information to forecast the likelihood and timing of future event (Levary & Han, 1995).

Relevance trees: It is a normative approach to identify the hierarchical structure of the technological development. The goals and objectives of a proposed technology are broken down into lower level goals and objectives in a tree like format (Levary & Han, 1995).

Cross-impact analysis: This method is an extension of Delphi method and designed to identify cases involving several interrelated future events that may affect the likelihood of a given technology being developed (Levary & Han, 1995). The purpose of this method is to investigate the mutual influence of events.

Technology forecasting techniques are widely studied by various authors. Growth curves are applied to industries by many researchers (Chen, Chen, & Lee, 2011; Moona & Jeon, 2009; Ryu & Byeon, 2011). The most commonly used models on growth curves are *S*-curves and Pearl and Gompertz curves. Franses (1994) developed a model which identified the differences between these two curves and defined the specific application areas for them. Later, Bengisu & Nekhili (2006) used the same model for forecasting. Kucharavy and De Guio (2011a, 2011b) also made detailed research on *S* curves. Daim, Rueda, Martin, and Pisek (2006) suggested using bibliometrics and patent analysis in technology forecasting when sufficient historical data is not available. They provided data from patent and bibliometric analysis and used scenario planning, growth curves and analogies for technology forecasting. Dubaric, Giaznnocarro, Bengtsson, and Ackermann (2011) also used patent data for forecasting wind power technology. Bengisu and Nekhili (2006) used both bibliometric and patent data to form *S*-curves and investigated the correlation between them. Morris, DeYong, Wu, Salman, and Yemenu (2002) used a computer program that helps to perform bibliometric analysis of collections of scientific literature and patents for technology forecasting. Kim et al. (2010) used dual AHP to select the best electrical device technology in Korea.

Some articles are about choosing the best forecasting techniques. Eto (2003) studied logical fundamentals of extrapolation and Delphi techniques. Levary and Han (1995) identified main factors affecting forecasting and studied 11 technological forecasting techniques. Then, they prioritized them according to five criteria to find the best method. Similarly, Cheng, Chen, and Chen (2008) used fuzzy AHP for choosing the most appropriate technique considering 8 criteria and found that Delphi technique was the best forecasting method for new materials development. Mishra, Deshmukh, and Vrat (2002) used a decision making technique to find the best method by using 31 forecasting techniques. They found that normative techniques gave better result for defense systems whereas Delphi technique was better for IT. Meade and Islam (1998) surveyed a wide range of possible models on technological forecasting in literature. They suggested three group of curves namely symmetric, nonsymmetric and flexible curves according to data sets they used and applied discriminant analysis for classification purpose.

Some researchers used combinations of multiple techniques. Yoo and Moon (2006) claimed that using multiple techniques gave better results and decreased errors. Tseng, Cheng, and Peng (2009) used a combination of scenario analysis, Delphi method and technological substitution model to analyze the development of a new

Table 2
Criteria for forecasting technique selection and relevant citations.

Criteria	Relevant citations
Data availability	Cheng et al. (2008), Firat et al. (2008), Levary and Han (1995), Mishra et al. (2002), Porter et al. (1991)
Data validity	Cheng et al. (2008), Firat et al. (2008), Levary and Han (1995), Mishra et al. (2002), Porter et al. (1991)
Technology development predictability	Cheng et al. (2008)
Technology similarity (similarity of proposed and existing technology)	Cheng et al. (2008), Firat et al. (2008), Levary and Han (1995), Mishra et al. (2002), Porter et al. (1991)
Method adaptability	Cheng et al. (2008)
Ease of operation	Cheng et al. (2008)
Implementation cost (money available for development of technology)	Cheng et al. (2008), Levary and Han (1995), Firat et al. (2008)

technology. Shen, Chang, Lin, and Yu (2010) integrated fuzzy Delphi method, analytic hierarchy process (AHP), and patent co-citation approach (PCA) for technology selection.

2.2. Criteria for forecasting method selection

The forecasting techniques are selected according to criteria based on the characteristics of technology. In Table 2 there is a list of criteria that are widely used in literature.

Data availability refers to the range of data available for performing the technology forecasting method.

Data validity reflects the degree of validity of the required data for the specific technology forecasting method (Cheng et al., 2008).

Technology development predictability describes how well the development of the new technology is predicted by forecasting method.

Technology similarity refers to the degree of similarity between new and existing technologies (Cheng et al., 2008).

Method adaptability describes forecasting method's dependency to experts' opinions.

Ease of operation reflects the degree of easiness to use the technology forecasting method.

Implementation cost describes the amount of money used for implementation of the technology forecasting method (Cheng et al., 2008).

3. The basic concept of interval-valued intuitionistic fuzzy sets

In fuzzy sets theory membership of an element is a single value between zero and one. However, in reality the non-membership degree of an element in a fuzzy set is not certainly equal to 1 minus the degree of membership (Ye, 2010). The intuitionistic fuzzy set (IFS) can deal with fuzzy information considering both the membership and non-membership of information. After Atanassov (1986) extended Zadeh's fuzzy sets to intuitionistic fuzzy sets, which is a generalization of the concept of fuzzy sets, IFS theory has been developed rapidly. The theory of intuitionistic fuzzy sets is characterized by a membership degree, a non-membership degree, and a hesitation degree. Later, Atanassov and Gargov (1989) also introduced the concept of interval-valued intuitionistic fuzzy sets (IVIFS) as a further generalization of the IFS theory. Zhao, Xu, Liu, and Wang (2012) also used interval-valued intuitionistic fuzzy sets for investigating graph theory-based clustering techniques.

3.1. Basic definitions

Let X be a non-empty and finite set with $Card\,(X) = n$. Let $D[0,1]$ be the set of all closed subintervals of the unit interval $[0,1]$. An IVIFS have a form as (Atanassov & Gargov, 1989):

$$A = \{x, \mu_A(x), v_A(x) : x \in X\} \tag{1}$$

where $\mu_A:X \to D[0,1], v_A:X \to D[0,1]$ with the condition sup $sup\mu_A(x) + supv_A(x) \leqslant 1$ for any $x \in X$ (Atanassov & Gargov, 1989).

The interval $\mu_A(x)$ states the degree of belongingness and $v_A(x)$ denote the degree of non-belongingness of the element x to A.

The operations which will be used in this paper, as follows:

Let $\tilde{a}_1 = \langle[a_1,b_1],[c_1,d_1]\rangle$, $\tilde{a}_2 = \langle[a_2,b_2],[c_2,d_2]\rangle$ and $\tilde{a} = \langle[a,b],[c,d]\rangle$ be three IVIFNs; then

(1) $\tilde{a}_1 \otimes \tilde{a}_2 = \langle[a_1a_2, b_1b_2],\ [c_1 + c_2 - c_1c_2, d_1 + d_2 - d_1d_2]\rangle$;
(2) $\tilde{a}^\lambda = \langle[a^\lambda, b^\lambda],\ [1-(1-c)^\lambda, 1-(1-d)^\lambda]\rangle,\ \lambda > 0$;
(3) $\lambda\tilde{a} = \langle[1-(1-a)^\lambda,\ 1-(1-b)^\lambda],\ [c^\lambda, d^\lambda]\rangle,\ \lambda > 0$;

which can ensure the operational results are also IVIFNs (Park, Park, Kwun, & Tan, 2011). Score fuctions are defined by Xu (2007) as follows:

$$s(\tilde{a}) = \frac{1}{2}(a - c + b - d) \tag{2}$$

where $s(\tilde{a}) \in [-1,1]$. $s(\tilde{a})$ indicates the measure of a IVIFN. The larger the value of $s(\tilde{a})$, the higher the IVIFN $\tilde{a}$. If $s(\tilde{a}) = 1$ then $\tilde{a} = \langle[0,0],\ [1,1]\rangle$ is the largest IVIFN; if $s(\tilde{a}) = 1$, then $\tilde{a} = \langle[1,1],\ [0,0]\rangle$ is the smallest IVIFN.

Accuracy degree of a IVIFN $\tilde{a}$ is calculated from accuracy function h, as follows (Wei & Wang, 2007):

$$h(\tilde{a}) = \frac{1}{2}(a + c + b + d) \tag{3}$$

where $h(\tilde{a}) \in [0,1]$. The larger the value of $h(\tilde{a})$, the higher the accuracy degree of the IVIFN $\tilde{a}$.

Definition 1. Let $\tilde{a}_1 = \langle[a_1,b_1],\ [c_1,d_1]\rangle$ and $\tilde{a}_2 = \langle[a_2,b_2],\ [c_2,d_2]\rangle$ be two IVIFNs, $s(\tilde{a}_1) = \frac{1}{2}(a_1 - c_1 + b_1 - d_1)$ and $s(\tilde{a}_2) = \frac{1}{2}(a_2 - c_2 + b_2 - d_2)$ be the score of $\tilde{a}_1$ and $\tilde{a}_2$, respectively, and $h(\tilde{a}_1) = \frac{1}{2}(a_1 + c_1 + b_1 + d_1)$ and $h(\tilde{a}_2) = \frac{1}{2}(a_2 + c_2 + b_2 + d_2)$ be the accuracy degree of $\tilde{a}_1$ and $\tilde{a}_2$, then

If $s(\tilde{a}) < s(\tilde{a})$, then $(\tilde{a}_1)$ is smaller than $(\tilde{a}_2)$, denoted by $(\tilde{a}_1) < (\tilde{a}_2)$

If $s(\tilde{a}_1) = s(\tilde{a}_2)$, then

(1) if $h(\tilde{a}_1) = h(\tilde{a}_2)$, then $\tilde{a}_1$ represents the same information as $\tilde{a}_2$, i.e., $a_1 = a_2,\ b_1 = b_2,\ c_1 = c_2,\ d_1, d_2$.
(2) if $h(\tilde{a}_1) < h(\tilde{a}_2)$, then $\tilde{a}_1$ is smaller than $\tilde{a}_2$, denoted by $\tilde{a}_1 < \tilde{a}_2$ (Park et al., 2011).

4. Interval-valued intuitionistic fuzzy TOPSIS

A systematic approach to TOPSIS method for multi attribute decision making problems under fuzzy environment is proposed in this section. The weights of criteria and methods are provided by decision-makers as interval-valued intuitionistic fuzzy numbers.

For MAGDM problem, let $A = \{A_1, A_2, \ldots, A_n\}$ be the set of n alternatives, $D = \{D_1, D_2, \ldots, D_l\}$ be the set of decision-makers and $C = \{c_1, c_2, \ldots, c_m\}$ be the set of m attributes.

Table 3
Interval-valued intuitionistic fuzzy decision matrix $R^{(k)}$.

	A_1	A_2	...	A_n
c_1	$\tilde{r}_{11}^{(k)}$	$\tilde{r}_{12}^{(k)}$	...	$\tilde{r}_{1n}^{(k)}$
c_2	$\tilde{r}_{21}^{(k)}$	$\tilde{r}_{22}^{(k)}$	...	$\tilde{r}_{2n}^{(k)}$
:	:	:	:	:
c_m	$\tilde{r}_{m1}^{(k)}$	$\tilde{r}_{m2}^{(k)}$	...	$\tilde{r}_{mn}^{(k)}$

Step 1: Form a committee of decision makers
Step 2: Performance ratings are given to attributes with respect to criteria by decision-makers. In general we have an interval-valued intuitionistic fuzzy decision matrix, provided by decision makers as $R^{(k)} = \left(\tilde{r}_{ij}^{(k)}\right)_{mxn}$, $k = 1, 2, \ldots, l$ (Table 3).
where $\tilde{r}_{ij}^{(k)} = \left\langle \left[a_{ij}^{(k)}, b_{ij}^{(k)}\right], \left[c_{ij}^{(k)}, d_{ij}^{(k)}\right] \right\rangle$ is an IVIFN which represents rating of alternatives with respect to attributes. Also define weights of criteria $w = (w_1, w_2, \ldots, w_m)^T$.
Step 3: Pool the decision-makers opinions to get the aggregated fuzzy ratings. Interval-valued inttuitionistic fuzzy hybrid geometric (IIFGH) operator will be applied to aggregate fuzzy decision matrices into the collective interval-valued intuitionistic fuzzy decision matrix. This operator helps for normalizing decision maker's ratings. Because some individuals may assign distemperately high or low preference values to their preferred or repugnant objects (Xu, 2005). In such a case, "false" or "biased" opinions are assigned low weights. IIFGH operator helps to correct these mistakes.

Let $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_l)$ be weight vector of IIFHG operator, $\alpha_k > 0 \quad k = 1, 2, \ldots, l$ and $\sum_{k=1}^{l} \alpha_k = 1$. μ_l is the mean operator of the collection $1, 2, \ldots, l$ and σ_l is the standard deviation of the collection $1, 2, \ldots, l$ and they are obtained by the following formulas (Xu, 2005).

$$\mu_l = \frac{1}{l}\frac{l(1+l)}{2} = \frac{1+l}{2} \tag{4}$$

$$\sigma_l = \sqrt{\frac{1}{l}\sum_{i=1}^{l}(i-\mu_l)^2} \tag{5}$$

Then weight vector of IIFHG operator $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_l)$ is defined as the following:

$$\alpha_i = \frac{\frac{1}{\sqrt{2\pi}\sigma_l} e^{-[(i-\mu_l)^2/2\sigma_l^2]}}{\sum_{j=1}^{l}\frac{1}{\sqrt{2\pi}\sigma_l} e^{-[(j-\mu_l)^2/2\sigma_l^2]}} = \frac{e^{-[(i-\mu_l)^2/2\sigma_l^2]}}{\sum_{j=1}^{l} e^{-[(j-\mu_l)^2/2\sigma_l^2]}}, \quad i = 1, 2, \ldots, l \tag{6}$$

Consider that $\alpha_j \in [0, 1]$ and $\sum_{j=1}^{l} \alpha_i = 1$.
Because the mean of collection $1, 2, \ldots, l$ is $(1 + l)/2$, then the equation above can be rewritten as

$$\alpha_i = \frac{e^{-[(i-(1+l)/2)^2/2\sigma_l^2]}}{\sum_{j=1}^{l} e^{-[(j-(1+l)/2)^2/2\sigma_l^2]}}, \quad i = 1, 2, \ldots, l \tag{7}$$

Let the second parameter vector of IIFGH operator be $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_l)^T$, $\lambda_k \geqslant 0$, $k = 1, 2, \ldots, l$ and $\sum_{k=1}^{l} \lambda_k = 1$. Weight vector of decision-makers will be applied to $\tilde{r}_{ij}^{(k)}$ to get the weighted IVIFNs $\dot{\tilde{r}}_{ij}^{(k)} = (\tilde{r}_{ij}^{(k)})^{l\lambda_k}$, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$.
If $\dot{\tilde{r}}_{ij}^{\sigma(k)} = \left\langle \left[\dot{a}_{ij}^{\sigma(k)}, \dot{b}_{ij}^{\sigma(k)}\right], \left[\dot{c}_{ij}^{\sigma(k)}, \dot{d}_{ij}^{\sigma(k)}\right] \right\rangle$ indicates the kth largest of the weighted IVIFNs then elements of the collective interval-valued intuitionistic fuzzy decision matrix are obtained by Eq. (8).

$$\begin{aligned}\tilde{r}_{ij} &= IIFGH_{\alpha,\lambda}\left(r_{ij}^{(1)}, r_{ij}^{(2)}, \ldots, r_{ij}^{(l)}\right) = \left(\dot{\tilde{r}}_{ij}^{\sigma(1)}\right)^{\alpha_1} \otimes \left(\dot{\tilde{r}}_{ij}^{\sigma(2)}\right)^{\alpha_2} \otimes \ldots \otimes \left(\dot{\tilde{r}}_{ij}^{\sigma(l)}\right)^{\alpha_l} \\ &= \left\langle \left[\prod_{k=1}^{l}\left(\dot{a}_{ij}^{\sigma(k)}\right)^{\alpha_k}, \prod_{k=1}^{l}\left(\dot{b}_{ij}^{\sigma(k)}\right)^{\alpha_k}\right] \right\rangle, \left\langle \left[1-\prod_{k=1}^{l}\left(1-\dot{c}_{ij}^{\sigma(k)}\right)^{\alpha_k}, 1-\prod_{k=1}^{l}\left(1-\dot{d}_{ij}^{\sigma(k)}\right)^{\alpha_k}\right] \right\rangle\end{aligned} \tag{8}$$

Step 4: Apply attribute weights $w = (w_1, w_2, \ldots, w_m)^T$ on previous matrix to get the weighted collective interval-valued intuitionistic fuzzy decision matrix which is shown $R^* = \left(\tilde{r}_{ij}^*\right)_{mxn}$ where $\sum_{i=1}^{m} w_i = 1$ and $w_i > 0$

$$\tilde{r}_{ij}^* = \left\langle \left[1-(1-a_{ij})^{w_i}, 1-(1-b_{ij})^{w_i}\right], \left[c_{ij}^{w_i}, d_{ij}^{w_i}\right] \right\rangle \tag{9}$$

Now new weighted matrix is developed (Table 4).

Step 5: Determine interval-valued intuitionistic fuzzy positive ideal solution (IVIFPIS) and interval-valued intuitionistic fuzzy negative ideal solution (IVIFNIS).
IVIFPIS denoted by O^* and IVIFNIS denoted by O^-. Let B and C are the set of benefit criteria and cost criteria, respectively, and

$$\begin{aligned}O^* &= \left\{\langle e_i, (max_j, \tilde{r}_{ij}^* \middle| i \in B), \ (min_j, \tilde{r}_{ij}^* \middle| i \in C)\rangle \middle| i = 1, 2, \ldots, m\right\}^T \\ &= \{\tilde{r}_1^+, \tilde{r}_2^+, \ldots, \tilde{r}_m^+\}\end{aligned} \tag{10}$$

$$\begin{aligned}O^- &= \left\{\langle e_i, (min_j, \tilde{r}_{ij}^* \middle| i \in B), (max_j, \tilde{r}_{ij}^* \middle| i \in C)\rangle \middle| i = 1, 2, \ldots, m\right\}^T \\ &= \{\tilde{r}_1^-, \tilde{r}_2^-, \ldots, \tilde{r}_m^-\}\end{aligned} \tag{11}$$

where $\tilde{r}_i^+ = \langle [a_i^+, b_i^+], [c_i^+, d_i^+] \rangle$ and $\tilde{r}_i^- = \langle [a_i^-, b_i^-], [c_i^-, d_i^-] \rangle$, $i = 1, 2, \ldots, m$.
Step 6: Calculate the separation means.

The distance of each alternative from O^* and O^- and which is known as separation means, can be calculated from extension of Grzegorzewski's method as (Grzegorzewski, 2004);

$$S_j^* = \frac{1}{2n}\sum_{i=1}^{m}\left[max\left(\left|a_{ij}^* - a_i^+\right|, \left|b_{ij}^* - b_i^+\right|\right) + max\left(\left|c_{ij}^* - c_i^+\right|, \left|d_{ij}^* - d_i^+\right|\right)\right] \tag{12}$$

$$S_j^* = \frac{1}{2n}\sum_{i=1}^{m}\left[max\left(\left|a_{ij}^* - a_i^-\right|, \left|b_{ij}^* - b_i^-\right|\right) + max\left(\left|c_{ij}^* - c_i^-\right|, \left|d_{ij}^* - d_i^-\right|\right)\right] \tag{13}$$

Step 7: Calculate the closeness coefficient.
The closeness coefficient determines the ranking order of each alternatives and calculated as

$$C_j = \frac{S_j^-}{S_j^* + S_j^-} \tag{14}$$

Step 8: According to closeness coefficient, ranking order of each alternative can be determined.
An alternative is closer to IVIFPIS and farther from IVFINIS as closeness coefficient C_j approaches to 1. The value of C_j varies between 0 and 1. Therefore, the ranking order can be determined according the C_j. The bigger closeness coefficient, the better the alternative A_j will be.

Table 4
Weighted collective interval-valued intuitionistic fuzzy decision matrix R^*.

	A_1	A_2	...	A_n
c_1	$\tilde{r}_{11}^*$	$\tilde{r}_{12}^*$	...	$\tilde{r}_{1n}^*$
c_2	$\tilde{r}_{21}^*$	$\tilde{r}_{22}^*$	...	$\tilde{r}_{2n}^*$
:	:	:	:	:
c_m	$\tilde{r}_{m1}^*$	$\tilde{r}_{m2}^*$	...	$\tilde{r}_{mn}^*$

5. Survey design

3D TV technology was selected for the forecasting problem. The alternative forecasting techniques used are the ones that are discussed in literature section namely trend analysis, growth curve analysis, Fisher Pry analysis, analogy, morphological matrices, patent analysis, scanning/monitoring/tracking, scenarios, Monte Carlo models, Delphi survey, relevance trees, cross impact analysis. These alternatives will be evaluated with respect to seven criteria c_j ($j = 1, 2, \ldots, 7$) which are data availability (c_1), data validity (c_2), technology development predictability (c_3), technology similarity (c_4), method adaptability (c_5), ease of operation (c_6), implementation cost (c_7). Benefit attributes are c_1, c_2, c_3, c_4, c_6 and cost attributes are c_5 and c_7.

5.1. Knowledge acquisition

Knowledge acquisition, also known as knowledge elicitation, involves extracting problem-solving expertise from knowledge sources, which are usually domain experts Hoffman (1987). Firstly, because group productivity is both quantitatively and qualitatively better to that of an average individual (Liou, 1999) a group of experts is preferred for knowledge acquisition process of this study.

Secondly, the knowledge acquisition process involved one facilitator who has a competency on both interval-valued intuitionistic fuzzy group decision making process and forecasting techniques also interacting with two domain experts, each of which brings a certain set of attributes to this interaction. The facilitator presented the questions to the group and then monitored the responses from the experts. The group interaction is allowed the expression of diverse opinions about the alternatives with respect to each criterion. A domain expert is defined as an articulate, knowledgeable person with a reputation for producing good solutions to problems in a particular field (Waterman, 1985). On the other hand multiple domain experts can provide the mix of knowledge that is required in a complex structure and provide coverage for the many problems and solutions (Money & Harrald, 1995). In this study the experts' domain covered to a certain extent the areas of technology forecasting, technology management, strategic management and television technology.

A decision maker cannot be expected to have sufficient expertise to comment on all aspects of the problem but on a part of the problem for which he/she is competent (Weiss & Rao, 1987). Therefore determining the weights of every decision maker is also an important problem in decision making. Although it is difficult to assess each decision maker in terms of the level of their expertise on the main problem area as well as in sub areas, there are some trials to solve this problem with methods like application of eigenvector based method by Ramanathan and Ganesh (1994), TOPSIS model by Yue (2012), AHP model by Van den Honert (2001) and please refer to Yue (2012) for some other related research methods. In this paper for the sake of practicality weights are determined by group members by weighing each other according to the level of their expertise on technology forecasting and sub areas such as technology management and TV technologies.

5.2. Application

The steps of the methodology proposed are as follows:

Step 1: three decision makers who are the experts on the problem area were selected as

$$D = \{D_1, D_2, D_3\}$$

Step 2: Weights of criteria were given by each expert as crisp numbers on 1–10 scale. These three criteria ratings were combined by calculating arithmetic means and then linear normalization was made for final weights. Table 5 shows the priorities of the evaluation criteria.

According to Table 5 technology development similarity has the highest weight of 0.23, followed by the criterion data availability 0.19. Technology similarity and ease of operation have the weights of 0.05 and 0.09 are comparatively unimportant.

Experts were required to give performance ratings to all technological forecasting methods with respect to criteria. Thus interval-valued intuitionistic fuzzy decision matrices $R^{(k)} = \left(\tilde{r}_{ij}^{(k)}\right)_{12x7}$ were created as Tables 6–8.

Step 3: The decision-makers opinions pooled to get the aggregated fuzzy ratings by utilizing IIFGH operator and collective interval-valued intuitionistic fuzzy decision matrix was formed as Table 9. Weight vector of decision makers was found as $\lambda = (0.45, 0.35, 0.2)^T$ according to their expertise level. These weights were applied to each decision matrix as $\tilde{r}_{ij}^{(\dot{k})} = \left(\tilde{r}_{ij}^{(k)}\right)^{l\lambda_k}$.
The weight vector of IIFHG operator was calculated from Eqs. (4), (5), (7). Then collective interval-valued intuitionistic fuzzy decision matrix was calculated from Eq. (8).
Also IIFGH operator weights were found as $\alpha = (0.243, 0.514, 0.243)^T$.
Step 4: The weight of criteria was aggregated using Eq. (9) to get the weighted collective interval-valued intuitionistic fuzzy decision matrix. Results are shown was in Table 10.
Step 5: Interval-valued intuitionistic fuzzy positive ideal solution (IVIFPIS) and interval-valued intuitionistic fuzzy negative ideal solution (IVIFNIS) were determined using Eqs. (10) and (11) and given in Table 11.
Step 6: Calculate S_j^{ast} and S_j^{-} separation means as Eqs. (12) and (13).
Step 7: Calculate the closeness coefficient. The results are given in Table 12.
Step 8: According to closeness coefficient, ranking order of each alternative could be determined. Ranking order is seen in Table 13.

5.3. Sensitivity analysis

TOPSIS is a decision-making method to find the best alternative among a set of feasible alternatives or to rank the alternatives considering several criteria. To give a correct decision, the order obtained from the method should be reliable. But TOPSIS method can produce "rank reversal" outcomes when an alternative is added or removed (García-Cascales & Lamata, 2012; Wang & Luo, 2009).

Fisher-Pry, growth curves, technical trend analysis, patent analysis, Monte Carlo method and analogy analysis are top six methods with closeness coefficient greater than 0.5. As the

Table 5
Criteria weights.

Criteria	Weights
Data availability	0.19
Data validity	0.17
Tech. development predictability	0.23
Tech. similarity	0.05
Method adaptability	0.14
Ease of operation	0.09
Implementation cost	0.13

Table 6
Interval-valued intuitionistic fuzzy decision matrix $R^{(1)}$.

Methods	Data availability	Data validity	Tech. development predictability	Tech. similarity	Method adaptability	Ease of operation	Implementation cost
Decision maker 1							
Tech. trend analysis	([0.6; 0.8]; [0.1; 0.2])	([0.6; 0.75]; [0.05; 0.15])	([0.6; 0.85]; [0.05; 0.15])	([0.1; 0.2]; [0.7; 0.8])	([0.3; 0.5]; [0.4; 0.5])	([0.6; 0.8]; [0.1; 0.2])	([0.2; 0.4]; [0.5; 0.6])
Growth curves	([0.5; 0.7]; [0.2; 0.3])	([0.6; 0.8]; [0.1; 0.2])	([0.7; 0.9]; [0.05; 0.1])	([0.15; 0.3]; [0.6; 0.7])	([0.2; 0.4]; [0.5; 0.6])	([0.7; 0.85]; [0.1; 0.15])	([0.1; 0.3]; [0.5; 0.7])
Fisher-Pry	([0.65; 0.75]; [0.15; 0.2])	([0.7; 0.85]; [0.1; 0.15])	([0.8; 0.9]; [0.05; 0.1])	([0.65; 0.85]; [0.1; 0.15])	([0.25; 0.5]; [0.3; 0.45])	([0.55; 0.7]; [0.15; 0.25])	([0.15; 0.4]; [0.5; 0.6])
Analogy analysis	([0.2; 0.35]; [0.5; 0.65])	([0.2; 0.3]; [0.6; 0.7])	([0.25; 0.5]; [0.3; 0.5])	([0.8; 0.95]; [0.0; 0.05])	([0.4; 0.8]; [0.1; 0.2])	([0.65; 0.8]; [0.1; 0.2])	([0.25; 0.6]; [0.3; 0.4])
Morphological matrices	([0.3; 0.6]; [0.2; 0.4])	([0.3; 0.5]; [0.2; 0.5])	([0.4; 0.65]; [0.1; 0.35])	([0.45; 0.7]; [0.2; 0.3])	([0.5; 0.85]; [0.05; 0.15])	([0.15; 0.6]; [0.2; 0.4])	([0.5; 0.8]; [0.1; 0.2])
Patent analysis	([0.4; 0.65]; [0.2; 0.35])	([0.5; 0.7]; [0.1; 0.3])	([0.35; 0.7]; [0.2; 0.3])	([0.05; 0.1]; [0.6; 0.8])	([0.2; 0.4]; [0.3; 0.6])	([0.75; 0.9]; [0.05; 0.10])	([0.1; 0.2]; [0.6; 0.8])
Scanning, monitoring, tracking	([0.6; 0.8]; [0.1; 0.2])	([0.3; 0.6]; [0.2; 0.35])	([0.2; 0.6]; [0.2; 0.3])	([0.6; 0.8]; [0.05; 0.15])	([0.7; 0.95]; [0.0; 0.05])	([0.1; 0.4]; [0.4; 0.6])	([0.65; 0.85]; [0.1; 0.15])
Scenario writing	([0.2; 0.4]; [0.5; 0.6])	([0.4; 0.6]; [0.2; 0.35])	([0.2; 0.4]; [0.5; 0.6])	([0.6; 0.8]; [0.1; 0.2])	([0.6; 0.85]; [0.1; 0.15])	([0.1; 0.3]; [0.5; 0.65])	([0.75; 0.85]; [0.1; 0.15])
Monte Carlo models	([0.5; 0.8]; [0.1; 0.2])	([0.5; 0.7]; [0.1; 0.25])	([0.75; 0.9]; [0.0; 0.05])	([0.25; 0.35]; [0.4; 0.6])	([0.4; 0.6]; [0.3; 0.4])	([0.6; 0.8]; [0.1; 0.2])	([0.5; 0.8]; [0.1; 0.2])
Delphi	([0.1; 0.3]; [0.5; 0.7])	([0.4; 0.5]; [0.3; 0.5])	([0.3; 0.7]; [0.1; 0.3])	([0.7; 0.85]; [0.05; 0.15])	([0.6; 0.75]; [0.1; 0.2])	([0.2; 0.4]; [0.5; 0.6])	([0.7; 0.85]; [0.0; 0.1])
Relevance trees	([0.3; 0.6]; [0.3; 0.4])	([0.5; 0.6]; [0.2; 0.4])	([0.3; 0.4]; [0.3; 0.5])	([0.6; 0.8]; [0.1; 0.2])	([0.7; 0.85]; [0.1; 0.15])	([0.3; 0.5]; [0.2; 0.4])	([0.75; 0.9]; [0.05; 0.1])
Cross-impact analysis	([0.3; 0.5]; [0.2; 0.4])	([0.5; 0.7]; [0.1; 0.2])	([0.6; 0.75]; [0.1; 0.2])	([0.7; 0.9]; [0.0; 0.1])	([0.7; 0.85]; [0.05; 0.1])	([0.3; 0.5]; [0.4; 0.5])	([0.8; 0.9]; [0.0; 0.1])

Table 7
Interval-valued intuitionistic fuzzy decision matrix $R^{(2)}$.

Methods	Data availability	Data validity	Tech. development predictability	Tech. similarity	Method adaptability	Ease of operation	Implementation cost
Decision maker 2							
Tech. trend analysis	([0.65; 0.75]; [0.1; 0.2])	([0.8; 0.9]; [0.07; 0.1])	([0.5; 0.7]; [0.2; 0.3])	([0.1; 0.3]; [0.5; 0.7])	([0.2; 0.5]; [0.4; 0.5])	([0.4; 0.7]; [0.2; 0.3])	([0.3; 0.6]; [0.25; 0.35])
Growth curves	([0.6; 0.7]; [0.1; 0.2])	([0.8; 0.9]; [0.07; 0.1])	([0.7; 0.9]; [0.05; 0.1])	([0.1; 0.4]; [0.5; 0.6])	([0.2; 0.4]; [0.3; 0.6])	([0.4; 0.7]; [0.2; 0.3])	([0.2; 0.6]; [0.3; 0.4])
Fisher-Pry	([0.6; 0.8]; [0.05; 0.2])	([0.7; 0.9]; [0.01; 0.05])	([0.6; 0.8]; [0.1; 0.2])	([0.6; 0.9]; [0.0; 0.1])	([0.4; 0.6]; [0.2; 0.4])	([0.4; 0.6]; [0.2; 0.4])	([0.2; 0.65]; [0.3; 0.35])
Analogy analysis	([0.2; 0.5]; [0.3; 0.5])	([0.1; 0.5]; [0.4; 0.5])	([0.4; 0.6]; [0.3; 0.4])	([0.9; 1.0]; [0.0; 0.0])	([0.5; 0.7]; [0.2; 0.3])	([0.5; 0.8]; [0.1; 0.2])	([0.4; 0.75]; [0.1; 0.25])
Morphological matrices	([0.3; 0.6]; [0.2; 0.4])	([0.2; 0.5]; [0.2; 0.5])	([0.5; 0.7]; [0.1; 0.3])	([0.4; 0.7]; [0.1; 0.3])	([0.6; 0.9]; [0.01; 0.1])	([0.2; 0.5]; [0.2; 0.4])	([0.6; 0.85]; [0.05; 0.15])
Patent analysis	([0.4; 0.7]; [0.1; 0.2])	([0.4; 0.7]; [0.1; 0.3])	([0.45; 0.7]; [0.2; 0.3])	([0.1; 0.4]; [0.4; 0.6])	([0.1; 0.2]; [0.5; 0.8])	([0.8; 0.95]; [0.0; 0.05])	([0.3; 0.4]; [0.5; 0.6])
Scanning, monitoring, tracking	([0.5; 0.7]; [0.2; 0.3])	([0.5; 0.6]; [0.3; 0.4])	([0.35; 0.55]; [0.3; 0.4])	([0.4; 0.6]; [0.2; 0.3])	([0.6; 0.8]; [0.1; 0.2])	([0.2; 0.5]; [0.3; 0.4])	([0.5; 0.8]; [0.1; 0.2])
Scenario writing	([0.2; 0.3]; [0.5; 0.6])	([0.4; 0.5]; [0.3; 0.5])	([0.3; 0.4]; [0.4; 0.6])	([0.5; 0.7]; [0.2; 0.3])	([0.8; 0.95]; [0.0; 0.05])	([0.3; 0.5]; [0.4; 0.5])	([0.7; 0.8]; [0.1; 0.2])
Monte Carlo models	([0.5; 0.7]; [0.2; 0.3])	([0.6; 0.7]; [0.1; 0.2])	([0.7; 0.8]; [0.1; 0.2])	([0.4; 0.5]; [0.2; 0.3])	([0.5; 0.7]; [0.1; 0.2])	([0.7; 0.85]; [0.1; 0.15])	([0.7; 0.8]; [0.1; 0.2])
Delphi	([0.1; 0.3];([0.5; 0.7])	([0.2; 0.4]; [0.4; 0.6])	([0.7; 0.8]; [0.1; 0.2])	([0.7; 0.8]; [0.1; 0.2])	([0.7; 0.9]; [0.0; 0.1])	([0.5; 0.7]; [0.1; 0.2])	([0.7; 0.9]; [0.0; 0.1])
Relevance trees	([0.2; 0.3]; [0.5; 0.6])	([0.5; 0.6]; [0.2; 0.3])	([0.5; 0.6]; [0.2; 0.3])	([0.5; 0.6]; [0.2; 0.3])	([0.8; 0.95]; [0.0; 0.05])	([0.5; 0.6]; [0.1; 0.4])	([0.7; 0.85]; [0.1; 0.15])
Cross-impact analysis	([0.4; 0.5]; [0.4; 0.5])	([0.3; 0.5]; [0.3; 0.4])	([0.7; 0.9]; [0.0; 0.1])	([0.6; 0.8]; [0.1; 0.2])	([0.8; 0.9]; [0.0; 0.1])	([0.6; 0.8]; [0.05; 0.15])	([0.6; 0.8]; [0.1; 0.2])

remained six methods have closeness coefficients which are less than 0.3, they cannot be selected for forecasting 3D television technology. The best two alternatives, Fisher-Pry and growth curve have very similar coefficients. Due to the rank reversal problem arising in TOPSIS, extracting low valued alternatives may affect closeness coefficients of the top six alternatives and especially the ranking of the best two alternatives. To consider the rank reversal problem, we reapplied proposed TOPSIS method for six methods which have closeness coefficient higher than 0.5. In Table 14, second column represents the coefficients of top six alternatives when low valued alternatives are kept out. The ranking is the same with Table 13.

García-Cascales and Lamata (2012) proposed a method to solve the rank reversal problem by introducing fictitious alternatives into problem. These alternatives correspond with the best possible alternative and the worst possible one. In TOPSIS based on interval-valued intuitionistic fuzzy numbers, the weights of the best fictitious alternative and the worst alternative are defined as below, for benefit criteria and cost criteria, respectively:

- $\tilde{r}_{best} = \langle [1,1],\ [0,0] \rangle$ for benefit criteria
- $\tilde{r}_{best} = \langle [0,0],\ [1,1] \rangle$ for cost criteria
- $\tilde{r}_{worst} = \langle [0,0],\ [1,1] \rangle$ for benefit criteria
- $\tilde{r}_{worst} = \langle [1,1],\ [0,0] \rangle$ for cost criteria

Table 8
Interval-valued intuitionistic fuzzy decision matrix $R^{(3)}$.

Methods	Data availability	Data validity	Tech. development predictability	Tech. similarity	Method adaptability	Ease of operation	Implementation cost
Decision maker 3							
Tech. trend analysis	([0.7; 0.9]; [0.0; 0.1])	([0.6; 0.7]; [0.2; 0.3])	([0.5; 0.6]; [0.2; 0.3])	([0.1; 0.2]; [0.6; 0.7])	([0.05; 0.10]; [0.8; 0.9])	([0.3; 0.7]; [0.1; 0.25])	([0.2; 0.5]; [0.4; 0.5])
Growth curves	([0.5; 0.8]; [0.1; 0.2])	([0.55; 0.7]; [0.15; 0.25])	([0.7; 0.9]; [0.05; 0.1])	([0.1; 0.3]; [0.5; 0.7])	([0.2; 0.4]; [0.4; 0.6])	([0.4; 0.6]; [0.2; 0.3])	([0.3; 0.6]; [0.3; 0.4])
Fisher-Pry	([0.7; 0.8]; [0.05; 0.15])	([0.6; 0.8]; [0.1; 0.2])	([0.6; 0.8]; [0.1; 0.2])	([0.7; 0.9]; [0.05; 0.1])	([0.3; 0.6]; [0.3; 0.4])	([0.3; 0.5]; [0.3; 0.4])	([0.4; 0.7]; [0.2; 0.3])
Analogy analysis	([0.3; 0.4]; [0.4; 0.55])	([0.2; 0.4]; [0.5; 0.6])	([0.25; 0.35]; [0.4; 0.6])	([0.85; 0.95]; [0.0; 0.05])	([0.6; 0.8]; [0.1; 0.2])	([0.4; 0.6]; [0.2; 0.35])	([0.5; 0.7]; [0.1; 0.2])
Morphological matrices	([0.2; 0.3]; [0.5; 0.7])	([0.1; 0.3]; [0.6; 0.7])	([0.5; 0.7]; [0.1; 0.2])	([0.5; 0.6]; [0.2; 0.4])	([0.6; 0.9]; [0.05; 0.1])	([0.2; 0.4]; [0.4; 0.5])	([0.5; 0.8]; [0.1; 0.2])
Patent analysis	([0.35; 0.6]; [0.2; 0.35])	([0.4; 0.6]; [0.3; 0.35])	([0.3; 0.5]; [0.3; 0.4])	([0.1; 0.15]; [0.7; 0.85])	([0.0; 0.05]; [0.8; 0.95])	([0.7; 0.9]; [0.0; 0.10])	([0.2; 0.4]; [0.4; 0.55])
Scanning, monitoring, tracking	([0.6; 0.7]; [0.1; 0.25])	([0.3; 0.6]; [0.2; 0.3])	([0.2; 0.4]; [0.4; 0.5])	([0.7; 0.9]; [0.0; 0.1])	([0.7; 0.85]; [0.05; 0.15])	([0.1; 0.3]; [0.5; 0.7])	([0.6; 0.8]; [0.1; 0.2])
Scenario writing	([0.3; 0.5]; [0.4; 0.5])	([0.25; 0.5]; [0.4; 0.5])	([0.3; 0.4]; [0.4; 0.6])	([0.7; 0.8]; [0.1; 0.2])	([0.7; 0.85]; [0.05; 0.10])	([0.2; 0.3]; [0.6; 0.8])	([0.5; 0.7]; [0.1; 0.3])
Monte Carlo models	([0.5; 0.6]; [0.2; 0.3])	([0.5; 0.7]; [0.1; 0.2])	([0.75; 0.85]; [0.1; 0.15])	([0.2; 0.35]; [0.5; 0.65])	([0.3; 0.4]; [0.4; 0.6])	([0.5; 0.7]; [0.2; 0.3])	([0.4; 0.5]; [0.4; 0.5])
Delphi	([0.3; 0.45]; [0.4; 0.55])	([0.1; 0.3]; [0.4; 0.6])	([0.6; 0.8]; [0.1; 0.2])	([0.7; 0.8]; [0.1; 0.2])	([0.65; 0.75]; [0.1; 0.2])	([0.2; 0.3]; [0.5; 0.6])	([0.7; 0.8]; [0.1; 0.2])
Relevance trees	([0.2; 0.4]; [0.4; 0.55])	([0.2; 0.3]; [0.5; 0.7])	([0.2; 0.3]; [0.5; 0.6])	([0.6; 0.75]; [0.1; 0.25])	([0.6; 0.7]; [0.2; 0.3])	([0.1; 0.2]; [0.6; 0.7])	([0.4; 0.6]; [0.2; 0.35])
Cross-impact analysis	([0.4; 0.5]; [0.3; 0.5])	([0.2; 0.4]; [0.5; 0.6])	([0.6; 0.75]; [0.15; 0.20])	([0.7; 0.8]; [0.1; 0.2])	([0.7; 0.8]; [0.1; 0.2])	([0.1; 0.3]; [0.5; 0.7])	([0.7; 0.85]; [0.1; 0.15])

Table 9
Collective interval-valued intuitionistic fuzzy decision matrix R.

Methods	Data availability	Data validity	Tech. development predictability	Tech. similarity	Method adaptability	Ease of operation	Implementation cost
Tech. trend analysis	([0.636; 0.784]; [0.087; 0.189])	([0.682; 0.794]; [0.099; 0.173])	([0.531; 0.757]; [0.118; 0.226])	([0.097; 0.244]; [0.595; 0.742])	([0.186; 0.370]; [0.513; 0.630])	([0.466; 0.742]; [0.135; 0.250])	([0.244; 0.508]; [0.367; 0.470])
Growth curves	([0.547; 0.710]; [0.135; 0.237])	([0.664; 0.811]; [0.098; 0.172])	([0.697; 0.899]; [0.051; 0.101])	([0.111; 0.345]; [0.540; 0.655])	([0.196; 0.395]; [0.390; 0.605])	([0.531; 0.739]; [0.148; 0.225])	([0.165; 0.475]; [0.376; 0.525])
Fisher-Pry	([0.626; 0.781]; [0.085; 0.195])	([0.706; 0.874]; [0.067; 0.126])	([0.698; 0.850]; [0.075; 0.150])	([0.626; 0.882]; [0.041; 0.118])	([0.325; 0.561]; [0.251; 0.421])	([0.439; 0.619]; [0.199; 0.333])	([0.197; 0.557]; [0.364; 0.443])
Analogy analysis	([0.208; 0.427]; [0.390; 0.566])	([0.135; 0.405]; [0.492; 0.595])	([0.316; 0.519]; [0.319; 0.471])	([0.861; 0.968]; [0.000; 0.032])	([0.473; 0.742]; [0.157; 0.258])	([0.548; 0.750]; [0.122; 0.231])	([0.350; 0.687]; [0.172; 0.299])
Morphological matrices	([0.302; 0.512]; [0.291; 0.488])	([0.220; 0.460]; [0.338; 0.540])	([0.460; 0.680]; [0.101; 0.307])	([0.424; 0.681]; [0.150; 0.319])	([0.561; 0.882]; [0.029; 0.118])	([0.178; 0.509]; [0.235; 0.420])	([0.547; 0.824]; [0.075; 0.176])
Patent analysis	([0.387; 0.665]; [0.150; 0.277])	([0.425; 0.681]; [0.134; 0.311])	([0.386; 0.663]; [0.218; 0.319])	([0.102; 0.207]; [0.552; 0.740])	([0.000; 0.201]; [0.516; 0.799])	([0.770; 0.923]; [0.017; 0.077])	([0.194; 0.315]; [0.527; 0.680])
Scanning, monitoring, tracking	([0.546; 0.742]; [0.135; 0.250])	([0.389; 0.596]; [0.258; 0.374])	([0.265; 0.536]; [0.288; 0.390])	([0.527; 0.740]; [0.088; 0.197])	([0.651; 0.890]; [0.034; 0.110])	([0.153; 0.428]; [0.376; 0.552])	([0.577; 0.817]; [0.109; 0.183])
Scenario writing	([0.208; 0.349]; [0.491; 0.592])	([0.342; 0.531]; [0.274; 0.438])	([0.258; 0.395]; [0.439; 0.605])	([0.558; 0.757]; [0.135; 0.243])	([0.716; 0.890]; [0.049; 0.094])	([0.000; 0.000]; [1.000; 1.000])	([0.678; 0.798]; [0.101; 0.202])
Monte Carlo models	([0.468; 0.726]; [0.150; 0.258])	([0.547; 0.697]; [0.101; 0.219])	([0.717; 0.857]; [0.041; 0.110])	([0.306; 0.430]; [0.355; 0.511])	([0.428; 0.582]; [0.260; 0.398])	([0.624; 0.799]; [0.122; 0.201])	([0.494; 0.731]; [0.160; 0.269])
Delphi	([0.114; 0.313]; [0.491; 0.687])	([0.251; 0.411]; [0.364; 0.572])	([0.516; 0.763]; [0.101; 0.237])	([0.697; 0.814]; [0.085; 0.186])	([0.676; 0.811]; [0.065; 0.155])	([0.301; 0.466]; [0.374; 0.473])	([0.697; 0.867]; [0.015; 0.117])
Relevance trees	([0.227; 0.451]; [0.393; 0.506])	([0.410; 0.517]; [0.269; 0.463])	([0.344; 0.448]; [0.321; 0.452])	([0.546; 0.721]; [0.135; 0.250])	([0.718; 0.838]; [0.098; 0.162])	([0.260; 0.429]; [0.270; 0.483])	([0.657; 0.821]; [0.101; 0.169])
Cross-impact analysis	([0.359; 0.495]; [0.330; 0.474])	([0.357; 0.562]; [0.288; 0.385])	([0.660; 0.811]; [0.081; 0.155])	([0.651; 0.850]; [0.041; 0.150])	([0.753; 0.862]; [0.048; 0.122])	([0.291; 0.519]; [0.326; 0.473])	([0.714; 0.857]; [0.041; 0.143])

The results of proposed TOPSIS method, when the best and the worst fictitious alternatives are added to the problem, are given third column of Table 14. No difference is occurred in the ranking of the alternatives indicating that the result is reliable.

6. Results and discussion

Fisher Pry method has the highest closeness coefficient of 0.6198 therefore the most suitable for forecasting 3D TV technology. It is followed by the growth curve method with 0.596. This result is understandable since both techniques depends on the same assumptions and they both are quantitative techniques. In addition the presence of historical data of 3D TV technology makes it possible to apply quantitative techniques.

Table 13 indicates that normative techniques are appropriate for this problem. The results are discussed by experts and they also approved the results and found them understandable. In addition, although Delphi is one of the most commonly used technique, according to the results, it was not found appropriate for forecast-

Table 10
Weighted collective interval-valued intuitionistic fuzzy decision matrix R^*.

Methods	Data availability	Data validity	Tech. development predictability	Tech. similarity	Method adaptability	Ease of operation	Implementation cost
Tech. trend analysis	([0.175; 0.253]; [0.629; 0.729])	([0.177; 0.236]; [0.675; 0.742])	([0.160; 0.278]; [0.612; 0.710])	([0.005; 0.014]; [0.974; 0.985])	([0.028; 0.063]; [0.911; 0.937])	([0.055; 0.115]; [0.835; 0.883])	([0.036; 0.088]; [0.878; 0.907])
Growth curves	([0.140; 0.210]; [0.684; 0.761])	([0.169; 0.247]; [0.674; 0.741])	([0.240; 0.410]; [0.504; 0.590])	([0.006; 0.021]; [0.970; 0.979])	([0.030; 0.068]; [0.876; 0.932])	([0.066; 0.114]; [0.842; 0.874])	([0.023; 0.080]; [0.881; 0.920])
Fisher-Pry	([0.170; 0.251]; [0.626; 0.733])	([0.188; 0.297]; [0.632; 0.703])	([0.241; 0.354]; [0.551; 0.646])	([0.048; 0.101]; [0.852; 0.899])	([0.054; 0.109]; [0.824; 0.886])	([0.051; 0.083]; [0.865; 0.906])	([0.028; 0.100]; [0.877; 0.900])
Analogy analysis	([0.043; 0.100]; [0.836; 0.898])	([0.024; 0.084]; [0.886; 0.916])	([0.084; 0.155]; [0.769; 0.841])	([0.094; 0.158]; [0.000; 0.842])	([0.086; 0.173]; [0.772; 0.827])	([0.069; 0.117]; [0.828; 0.876])	([0.054; 0.140]; [0.795; 0.855])
Morphological matrices	([0.066; 0.127]; [0.791; 0.873])	([0.041; 0.099]; [0.832; 0.901])	([0.132; 0.231]; [0.590; 0.762])	([0.027; 0.056]; [0.910; 0.944])	([0.109; 0.259]; [0.609; 0.741])	([0.017; 0.062]; [0.878; 0.925])	([0.098; 0.202]; [0.714; 0.798])
Patent analysis	([0.089; 0.188]; [0.697; 0.784])	([0.090; 0.177]; [0.711; 0.820])	([0.106; 0.221]; [0.704; 0.769])	([0.005; 0.012]; [0.971; 0.985])	([0.000; 0.031]; [0.912; 0.969])	([0.124; 0.206]; [0.693; 0.794])	([0.028; 0.048]; [0.920; 0.951])
Scanning, monitoring, tracking	([0.139; 0.227]; [0.684; 0.768])	([0.080; 0.143]; [0.794; 0.846])	([0.068; 0.162]; [0.751; 0.805])	([0.037; 0.065]; [0.886; 0.922])	([0.137; 0.266]; [0.623; 0.734])	([0.015; 0.049]; [0.916; 0.948])	([0.106; 0.198]; [0.750; 0.802])
Scenario writing	([0.043; 0.078]; [0.874; 0.905])	([0.069; 0.121]; [0.802; 0.869])	([0.066; 0.109]; [0.827; 0.891])	([0.040; 0.068]; [0.905; 0.932])	([0.162; 0.266]; [0.656; 0.718])	([0.000; 0.000]; [1.000; 1.000])	([0.137; 0.188]; [0.742; 0.812])
Monte Carlo models	([0.113; 0.218]; [0.697; 0.773])	([0.126; 0.184]; [0.677; 0.772])	([0.252; 0.361]; [0.480; 0.602])	([0.018; 0.028]; [0.950; 0.967])	([0.075; 0.115]; [0.828; 0.879])	([0.084; 0.134]; [0.828; 0.866])	([0.085; 0.157]; [0.788; 0.843])
Delphi	([0.023; 0.069]; [0.874; 0.931])	([0.048; 0.086]; [0.842; 0.909])	([0.154; 0.282]; [0.590; 0.718])	([0.058; 0.081]; [0.884; 0.919])	([0.146; 0.208]; [0.682; 0.770])	([0.032; 0.055]; [0.915; 0.935])	([0.144; 0.231]; [0.579; 0.757])
Relevance trees	([0.048; 0.108]; [0.837; 0.879])	([0.086; 0.116]; [0.800; 0.877])	([0.092; 0.128]; [0.770; 0.833])	([0.039; 0.062]; [0.905; 0.933])	([0.162; 0.225]; [0.722; 0.775])	([0.027; 0.049]; [0.889; 0.937])	([0.130; 0.200]; [0.742; 0.794])
Cross-impact analysis	([0.081; 0.122]; [0.810; 0.868])	([0.072; 0.131]; [0.809; 0.850])	([0.220; 0.318]; [0.561; 0.651])	([0.051; 0.090]; [0.852; 0.910])	([0.178; 0.242]; [0.654; 0.745])	([0.030; 0.064]; [0.904; 0.935])	([0.150; 0.223]; [0.660; 0.777])

Table 11
IVIFPIS and IVIFPNIS.

O^*	O^-
([0.023; 0.069]; [0.874; 0.931])	([0.175; 0.253]; [0.629; 0.729])
([0.024; 0.084]; [0.886; 0.916])	([0.188; 0.297]; [0.632; 0.703])
([0.066; 0.109]; [0.827; 0.891])	([0.240; 0.410]; [0.504; 0.590])
([0.005; 0.014]; [0.974; 0.985])	([0.094; 0.158]; [0.000; 0.842])
([0.162; 0.266]; [0.656; 0.718])	([0.000; 0.031]; [0.912; 0.969])
([0.000; 0.000]; [1.000; 1.000])	([0.124; 0.206]; [0.693; 0.794])
([0.144; 0.231]; [0.579; 0.757])	([0.028; 0.048]; [0.920; 0.951])

Table 12
Separation means and closeness coefficients.

Methods	S_j^- negative ideal solution	S_j^- positive ideal solution	Closeness coefficients
Tech. trend analysis	0.168	0.132	0.559
Growth curves	0.177	0.120	0.596
Fisher-Pry	0.185	0.113	0.619
Analogy analysis	0.149	0.148	0.502
Morphological matrices	0.081	0.233	0.258
Patent analysis	0.166	0.135	0.551
Scanning, monitoring, tracking	0.084	0.221	0.274
Scenario writing	0.036	0.264	0.119
Monte Carlo models	0.156	0.149	0.511
Delphi	0.063	0.240	0.207
Relevance trees	0.064	0.237	0.213
Cross-impact analysis	0.087	0.213	0.290

Table 13
Ranking order of alternatives.

Methods	Closeness coefficient
Fisher-Pry	0.619
Growth curves	0.596
Tech. trend analysis	0.559
Patent analysis	0.551
Monte Carlo models	0.511
Analogy analysis	0.502
Cross-impact analysis	0.290
Scanning, monitoring, tracking	0.274
Morphological matrices	0.258
Relevance trees	0.213
Delphi	0.207
Scenario writing	0.119

ing 3D TV technology. Both Scenario Writing and Delphi technique are qualitative techniques since they partially depend on brain storming.

7. Conclusion

Selection of technological forecasting technique is a difficult problem that includes quantitative and qualitative aspects. In addition, the process is costly and usually time consuming. During the selection process, information of forecasting techniques with respect to criteria are usually uncertain, therefore, decision makers cannot easily express judgments and grade techniques with exact and crisp values. Therefore, the aim of this study is to provide an effective selection tool that overcomes these difficulties and provides accurate results to the decision makers.

IVIFS is a useful tool to deal with fuzziness and uncertainty in MADM problems. In addition to this, to avoid an unreasonably large number of pairwise comparisons, the fuzzy TOPSIS is a better procedure to achieve the ranking results. In this paper interval-valued intuitionistic fuzzy TOPSIS model is employed for selecting technological forecasting technique under fuzzy environment. For each technological forecasting technique, the group decision matrix are characterized by IVIFNs. To the best of our knowledge, this is the first time that IVIFT is applied to the selection of technological forecasting technique. In addition, because TOPSIS method can produce rank reversal outcomes when an alternative is added or removed a sensitivity analysis is also proposed by keeping only the best six alternatives as well as by introducing fictitious alternatives as the best possible alternative and the worst possible one.

On the other hand there is a limitation of the model developed. It will get harder to make the scoring for the decision makers when

Table 14
The results of sensitivity analysis.

Alternatives	Keeping only the best six alternatives	The method of García-Cascales and Lamata (2012)
Fisher-Pry	0.519	0.419
Growth curves	0.489	0.413
Tech. trend analysis	0.443	0.402
Patent analysis	0.435	0.397
Monte Carlo models	0.385	0.393
Analogy analysis	0.373	0.373
Cross-impact analysis		0.335
Scanning, monitoring, tracking		0.328
Morphological matrices		0.323
Delphi		0.314
Relevance trees		0.309
Scenario writing		0.287

the number of alternatives increase. In this case grouping the alternatives under some criteria may be required. For further studies a technique can be developed for this grouping purpose.

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