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An intuitionistic fuzzy-grey superiority and inferiority ranking method for third-party reverse logistics provider selection

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ABSTRACT

Organisations often outsource reverse logistics (RL) to third-party RL providers (3PRLPs) to focus on their primary business and reduce costs. The existence of multiple criteria available for choosing a 3PRLP, which are sometimes contradictory and yet related to each other, has led decision-makers to consider the development of multi-criteria decision-making models. The purpose of this study is to develop a hybrid model integrating the analytic network process (ANP) and the intuitionistic fuzzy-grey superiority and inferiority ranking (IFG-SIR) process to help an industrial production group select a 3PRLP. The ANP method is used to analyse the relationships among the different selection criteria and to obtain a weight indicating the relative importance of each criterion. The best 3PRLP is chosen using the IFG-SIR process. The classical SIR technique requires a sufficient amount of data while relying on the technique for order preference by similarity to ideal solutions and simple additive weighted methods. We use intuitionistic fuzzy sets to account for the subjectivity inherent to the potentially strategic opinions of the experts and of grey relation analysis to simplify the ranking process. We present a real-world case study to exhibit the applicability and demonstrate the efficacy of the proposed model.

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1. Introduction

Product quality, customer satisfaction, and presence in competitive markets are among the fundamental requirements for any organisation nowadays. Indeed, these characteristics have become organisational standards, leading companies to search for other factors that influence the purchasing decisions of potential customers. For this reason, reverse logistics (RL) has become a key factor contributing to the success of many organisations.

The increasing importance of RL has led many manufacturers to design dismantling and reconstruction methods as a part of their sustainable development initiatives (Grenchus, Johnson, & McDonnell, 2001; Min, Jeung Ko, & Seong Ko, 2006). Moreover, ecologically conscious customers tend to spend more on environmentally friendly products, increasing the income of those companies that use RL to comply with the requirements of such consumers (Meade & Sarkis, 2002). In this regard, Senthil, Srirangacharyulu, and Ramesh (2014) and Zhu, Sarkis, and Lai (2008) emphasised the significance of the relationship between the environment and RL.

After acknowledging the importance of RL, many manufacturers and retailers have outsourced their RL processes. Outsourcing RL services to third-party RL providers (3PRLPs) helps companies entering new markets and reduces their logistics costs considerably (Kannan, Pokharel, & Sasi Kumar, 2009). Therefore, the task of evaluating and selecting a 3PRLP is fundamental, since it determines the overall performance of the company.

It should be emphasised that the implementation of RL processes has important consequences that extend beyond the domain of a given company. As illustrated in Table 1, this is particularly the case for developing countries designing sustainable environmentally friendly policies while facing considerable internal barriers to the adoption of RL processes. Brazil (Bouzon, Govindan, Taboada Rodriguez, & Campos, 2016; Guarnieri, Sobreiro, Nagano, & Serrano, 2015) and India (Prakash & Barua, 2015, 2016) constitute two recent examples of developing countries whose RL adoption constraints have been analysed in the literature. In this case, strategic considerations regarding the reports and opinions received

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Table 1. Importance of RL processes for environmental and development policies.

Authors	Case study
Vahabzadeh and Yusuff (2015)	Elicitation of expert judgments regarding environmental sound practices in RLs
Guarnieri et al. (2015)	Brazilian National Policy of Solid Waste obliging companies to implement RLs
Bouzon et al. (2016)	Barriers to RL adoption in the Brazilian electrical-electronic industry sector
Prakash and Barua (2015)	Barriers to RL adoption in the Indian electronics industry
Prakash and Barua (2016)	Analysis of the Indian electronics industry

from the experts when evaluating potential RLPs should be included in the corresponding selection process.

The selection process of a 3PRLP generally encompasses several decision criteria, various forms of uncertainty and different combined/integrated decision-making models.

- Multi-criteria decision-making (MCDM) methods, such as the analytic hierarchy process (AHP) and the analytic network process (ANP), are frequently used to model the complex relationships between the different decision-making elements and criteria (Liao, 1998).
- Due to the imprecisions inherent in real-world information, people usually face some uncertainty when assigning their preference evaluations to the choice objects being considered. In order to provide a more comprehensive model of human perception and cognition of uncertainty, Antanassov (1986) extended Zadeh's concept of fuzzy sets to that of intuitionistic fuzzy sets (IFS). An IFS is characterised by a membership function, a non-membership function, and a hesitancy function, providing a more suitable framework to express the uncertainty inherent in the evaluations of experts (Wei, Wang, Lin, & Zhao, 2011; Xu & Liao, 2014).
- Since the selection of a 3PRLP involves both ambiguity and strategic uncertainty, we will combine the ANP and the intuitionistic fuzzy-grey superiority and inferiority (IFG-SIR) models in order to minimise their effect on the final decision. That is, we propose a hybrid conceptual model that combines the ANP and the IFG-SIR methods to evaluate and select 3PRLPs.

The contribution of the current paper is determined in part by the chosen combination of the decision-making models used to evaluate the set of 3PRLPs. Its main feature consists of the intuitionistic fuzzy structure defined to account for the subjective and strategically biased evaluations of the experts when rating the different 3PRLPs based on the selected decision criteria. The main steps defining the decision theoretical structure introduced in the current paper are

(1) Determine the main decision criteria (attributes) on which the selection process of the 3PRLPs will be based. The opinions of different experts will be acquired in this stage. However, a crisp approach will be followed to differentiate these experts from those providing direct evaluations of the RLPs in the following stage.
(2) Given the decision criteria determined in the initial stage, the set of RLPs is evaluated using the ambiguous and strategically uncertain reports of a second group of experts. In order to account for ambiguous and potentially strategic reports, the evaluation process will be divided in a series of steps defined to smooth any opinion biases exhibited within this second group of experts. These steps include
    (a) Implementing an intuitionistic fuzzy aggregation technique to average the evaluations received based on the subjective importance or credibility assigned to each expert.
    (b) The definition of superiority and inferiority performance matrices that will be used to generate two different rankings so as to account for potential biases inherent to the opinions of the experts.
    (c) Applying grey relation analysis (GRA) to the entries of both matrices in order to obtain a relative evaluation of each attribute for every RLP.
(3) Combine the weights assigned to each decision criterion through ANP with the evaluations obtained via IFG-SIR for each potential RLP into a hybrid decision-making model that delivers both a superiority and an inferiority ranking.
(4) Weight the superiority and inferiority rankings in order to obtain a unique final ranking of the different RLPs.

The validity and applicability of the hybrid ANP-IFG-SIR model will be assessed systematically using a real-world example.

The remainder of the paper is organised as follows. The next section provides a review of the literature on the selection of 3PRLPs. In Section 3, we describe the solution

methodology and review some basic notions regarding IFSs as well as the ANP, SIR, and GRA methods. The conceptual model is developed in Section 4. Section 5 contains a real-world study illustrating the performance of the proposed methodology. Section 6 analyses the results obtained and provides managerial insights. Conclusions and directions for future research are given in Section 7.

2. Literature review

RL constitutes a vital business opportunity for companies as well as a useful means of protecting the environment. As a result, an increasing number of researchers have focused on this subject and more academics and experts have been motivated to actualise the analysis of RL, bridge the gaps across studies, and identify research limits. These efforts have led to the development of diverse qualitative and quantitative models.

The initial studies on this topic focused on quantitative models, while qualitative or non-mathematical models were used to describe systems focusing on communication plans and the existing relationships between internal and external factors. Examples of these models were proposed in studies performed on the application of information and communication technology and decision support systems to RL (Daugherty, Richey, Genchev, & Chen, 2005; Dhanda & Hill, 2005; Wu & Liu, 2008).

Since the outsourcing of RL is an important challenge to organisations, it has drawn a considerable amount of research attention. Companies outsource non-core activities in relation to their ability to gain competitive advantage and the complexity of particular activities. Due to the complexity of RL, this process is generally outsourced to a third party called the 3PRLP. In this regard, cost reduction and strategic decisions are considered to be the most important factors leading to the outsourcing of RL services to 3PRLPs (Sahay & Mohan, 2006).

2.1. Initial developments and evolution of the literature

The 3PLP industry has grown faster than the demand of companies for logistic services. Hence, as the market for logistic services evolves, 3PLPs have become the subject of an increasingly significant field of research, where qualitative and MCDM techniques, such as AHP, ANP, data envelopment analysis (DEA), risk matrices, and the fuzzy comprehensive evaluation model, have been consistently applied to model the provision of RL services. For instance, Bian and Yu (2006) applied the AHP to measure the capacity of various Asian countries to implement RL services for international manufacturers of electrical equipment, while Feng (2008) used the AHP and DEA techniques to study the selection process of a 3PRLP.

Researchers gradually realised that it is highly important to determine the relationships existing among the criteria involved in the selection of a 3PLP. As a result, the interpretive structural modelling (ISM) technique started gaining increasing popularity in this field. For example, Kannan, Haq, Sasikumar, and Arunachalam (2008) used a hybrid AHP/ISM model to identify and analyse mutual effects among the criteria defined to select third-party providers based on environmental conditions. Govindan, Palaniappan, Zhu, and Kannan (2012) conducted a similar research to analyse inter-criteria relationships when selecting 3PRLPs.

In addition, due to the uncertainties inherent to the input data, researchers inevitably incorporated fuzzy sets into their analyses. For instance, Haq and Kannan (2006a) suggested the use of the AHP technique and a fuzzy algorithm to select a third-party provider, while Haq and Kannan (2006b) combined the ISM method together with fuzzy AHP in order to evaluate different alternatives. Similarly, Kannan et al. (2009) employed the ISM technique along with fuzzy technique for order preference by similarity to ideal solutions (TOPSIS) to select and evaluate 3PRLPs. Recently, Senthil et al. (2014) evaluated and selected 3PRLPs using AHP, TOPSIS, and fuzzy sets.

Although the AHP and ISM models have been used extensively in this field of research, they are subject to important limitations. For instance, the ISM technique increases the ability of decision-makers to analyse the interactions between the criteria involved in the evaluation of 3PRLPs, but lacks statistical validity (Govindan et al., 2012). In addition, the simplicity of the hierarchical structure defining the AHP may deemphasise the interdependencies existing among criteria (Roper-Lowe & Sharp, 1990). As a result, network models have been introduced to deal with such deficiencies.

Network models structure the interactions and the analyses of interdependences in a logical and unique way (Saaty & Ozdemir, 2005). For instance, Tengda and Xiangyang (2008) and Ravi, Shankar, and Tiwari (2005) used the ANP to study outsourcing and decision-making in the application of RLs. These authors asserted that, since the ANP considers various dimensions of analytic information, it is capable of identifying the critical and necessary criteria required for every strategic decision. However, given the difficulty of determining exact parameter values within a complex evaluation system, such systems must be divided into several subsections in order to simplify the corresponding evaluation process (Liou, Tzeng, & Chang, 2007; Zareinejad, Javanmard, & Arak, 2013). We analyse the main consequences derived from the structural complexity of the evaluation system in the next section.

Table 2. Current developments and trends in the literature and paper contribution.

Authors	Attribute ranking	Fuzzy ranking	3PLP selection	Fuzzy selection	Expert evaluation	Fuzzy evaluation
Efendigil et al. (2008)	Fuzzy AHP	√	Artificial neural network			
Kannan (2009)	Fuzzy AHP	√				
Govindan and Murugesan (2011)	Fuzzy extent analysis	√				
Guarnieri et al. (2015)	Systematic literature review		Conceptual methodological framework			
Sharma and Kumar (2015)	Quality function deployment		Taguchi loss function			
Vahabzadeh and Yusuff (2015)	Fuzzy VIKOR	√				
Bouzon et al. (2016)	Fuzzy Delphi AHP	√				
Govindan et al. (2016)	Grey DEMATEL	√				
Sahu et al. (2015)			Interval-valued fuzzy numbers	√		
Khodaverdi and Hashemi (2015)	AHP		Grey relational analysis	√		
Alkhatib et al. (2015)	Fuzzy DEMATEL	√	Fuzzy TOPSIS	√		
Prakash and Barua (2015)	Fuzzy AHP	√	Fuzzy TOPSIS	√		
Prakash and Barua (2016)	Fuzzy AHP	√	Fuzzy TOPSIS	√		
Current paper	ANP		SIR-GRA	√	IFS	√

2.2. Current developments and trends in the literature

In the latter years, the literature on RLs has experienced a substantial incremental attention given, among others, the positive environmental effects derived from the implementation of RL services. Three recent surveys on the selection of RLPs are provided by Agrawal, Singh, and Murtaza (2015), Govindan, Soleimani, and Kannan (2015), and Vahabzadeh and Yusuff (2015).

A fundamental feature of the RLs literature is the relatively small amount of 3PRLPs models developed following fuzzy approaches within MCDM environments. That is, the classification of the literature performed by Govindan et al. (2015) reveals a marginal amount of research papers dealing with 3PRLP selection problems from a fuzzy-MCDM perspective, a total of three (Efendigil, Önüt, & Kongar, 2008; Govindan & Murugesan, 2011; Kannan, 2009).

We should emphasise the fact that the final choice made is based on the opinions of different groups of experts that must be elicited along the evaluation process. As already stated, the ambiguity and imprecision inherent to the reports provided by different experts have been repeatedly acknowledged in the literature. However, despite this fact, the experts have not been evaluated in terms of either their credibility or the existence of subjective biased interests. In this regard, the main contribution of the current paper has been explicitly highlighted in Table 2, where the defining characteristics of the main models related to the current one have also been summarised.

As emphasised at the end of the previous section, the initial research on the selection of 3PRLPs focused on ranking the main attributes (decision criteria) with which a 3PRLP should be endowed using fuzzy evaluation methods. Efendigil et al. (2008) implemented a two-phase model based on fuzzy AHP to select the most important attributes and an artificial neural network to classify the different 3PRLPs. Kannan (2009) used fuzzy AHP to rank the main attributes determining the selection of 3PRLPs, while Govindan and Murugesan (2011) applied fuzzy extent analysis to perform the same type of task. Similarly to other alternative techniques such as VIKOR, TOPSIS, and ELECTRE, extent analysis requires a substantial amount of numerical calculations, increasing the time required to make a decision.

Absent explicit fuzzy considerations regarding the reports of the experts, Guarnieri et al. (2015) performed a systematic literature review to propose a conceptual methodological framework that helps decision-makers selecting 3PRLPs. Sharma and Kumar (2015) used quality function deployment to relate the attributes to the requirements of the decision-makers, while the performance of the 3PLPs was evaluated through the weighted loss scores computed using a Taguchi loss function. Both these papers acknowledge the two sources of expert information required to evaluate the potential providers. However, they do not consider the strategic incentives of the experts when evaluating the set of 3PRLPs, a particularly important issue in developing countries or in those with a

weak institutional environment such as Brazil (Guarnieri et al., 2015).

The literature has focused on exploiting the properties of the fuzzy attribute ranking techniques, those of the fuzzy 3PLP selection processes, or both of them.

- Within the first group of papers, Vahabzadeh, Asiaei, and Zailani (2015) implemented a fuzzy VIKOR approach to measure and rank the effect that different green environmental factors have on the main recovery options in RLs. More importantly, they also suggested the design of a group decision-making process based on fuzzy multi-attribute decision-making methods when considering the best recovery option.

Bouzon et al. (2016) collected the opinions of different experts in order to identify the main barriers to RL adoption using the fuzzy Delphi method. These barriers were then ranked by other set of experts through the AHP. Govindan, Khodaverdi, and Vafadarnikjoo (2016) used grey decision-making trial and evaluation laboratory (DEMATEL) to determine the interdependent relationships existing among different 3PLP selection criteria, an approach that can be considered as an alternative to the ANP when ranking the set of attributes.

- Within the second group of papers, Sahu, Datta, and Mahapatra (2015) defined a fuzzy environment to account for group decision-making processes where decision-makers issue subjective judgments. Khodaverdi and Hashemi (2015) combined AHP - to rank the selection criteria – and grey relational analysis – to select 3PRLPs – in their hybrid model but did not consider evaluating the experts or their reports.
- The literature has evolved towards scenarios where the uncertainty arising from the opinions of the different groups of experts ranking the attributes and selecting the 3PRLP has been accounted for and integrated within the corresponding decision-making models. Alkhatib, Darlington, Yang, and Nguyen (2015) used fuzzy DEMATEL to determine the weights of logistics resources and fuzzy TOPSIS to rank the alternatives.

Prakash and Barua (2015) combined fuzzy AHP – to weight barriers to the adoption of RL processes – with fuzzy TOPSIS – to deliver a ranking of RLs adoption solutions that can be implemented to overcome the barriers. A similar approach was followed by these authors (Prakash & Barua, 2016) to define the set of criteria considered in the selection 3PRLPs. Note, however, that in all these decision-making models the subjective motivations of the experts providing the reports remain unstudied.

3. The solution methodology

We propose a hybrid ANP-based model that introduces IFSs and grey relations within the standard SIR method. It should be noted that the SIR technique is superior to the TOPSIS one in terms of duration and mutual inferiority of options (Memarzade, Alvandi, & Mavi 2011). The ANP method is used to obtain the weights of the evaluation criteria, while the proposed IFG-SIR approach is introduced to account for the uncertainty and the lack of precision associated with the input information received from the experts evaluating potential 3PRLPs. More precisely

- The unique capabilities of the ANP will be properly utilised to evaluate inter-criterion interactions (Zareinejad et al., 2013).
- As already stated, systems are generally ambiguous due to the uncertainties inherent to their input information (Kumar, Bhatia, & Kaur, 2009). Therefore, we will make use of IFSs and GRA to address the potential inadequacy of the input data received from the experts (Chen & Tzeng, 2004).

The resulting hybrid model provides a proper framework to analyse the existing correlations among the decision criteria and allows us to obtain an ideal solution in a highly-complex, multi-criteria, decision-making environment. Figure 1 describes the set of steps composing the proposed hybrid model.

3.1. Definition of criteria

A recent study conducted by Govindan et al. (2012) analysed 35 decision criteria generally considered in the selection process of 3PRLPs. However, even though this study seemed to be sufficiently comprehensive, it did not consider the different stages of the product life cycle (PLC) incorporated by Meade and Sarkis (2002). Besides, potential risks should not be overlooked, since every step of the PLC is associated with specific risks (Xia & Chen, 2011). In this regard, the results of the literature review performed on 3PRLP evaluation criteria are presented in Table 3.

3.2. ANP methodology

The ANP method is an extended version of the AHP. It determines the relative significance of criteria and clusters in terms of the correlations and feedbacks

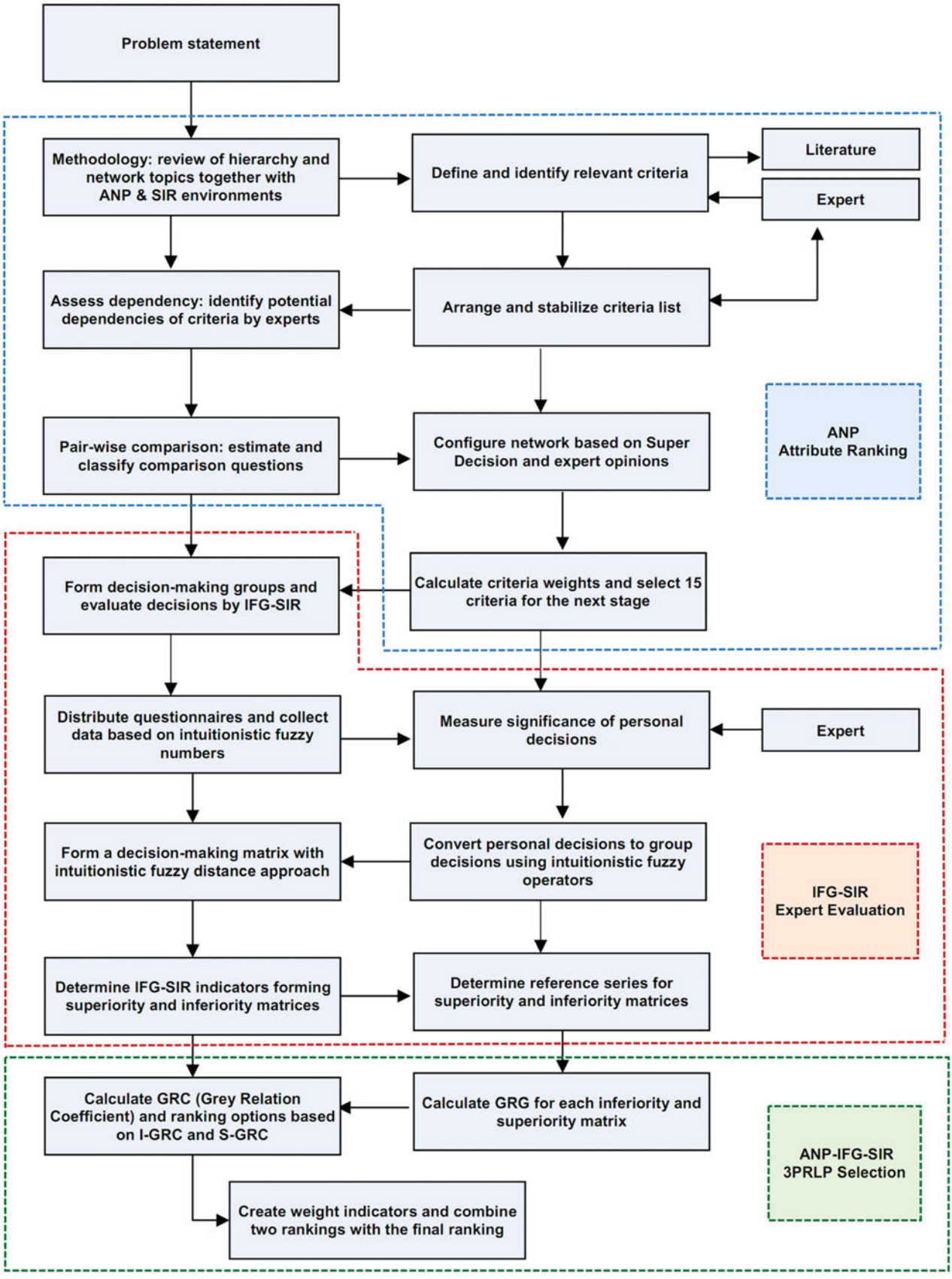

Figure 1. Proposed framework.

Table 3. Evaluation criteria.

Criterion	Sub-criterion	References
IT applications (IT) (A)	• Warehouse management (A1) • Order management (A2) • Supply chain planning (A3) • Shipment and tracking (A4) • Freight payment (A5)	Dowlatshahi (2000), Holguı'n-Veras (2002), Li, Wu, Lai, and Liu (2006), Govindan et al. (2012), Bun and Ishizuka (2006), and van den Berg and Zijm (1999)
Impact of use of 3PL (IU3PL) (B)	• Customer satisfaction (B1) • Profitability (B2) • Frequent updating (B3) • Employee morale (B4)	Boyson, Corsi, Dresner, and Rabinovich (1999), Jähn, Zimmermann, Fischer, and Käschel (2006), Govindan et al. (2012), and Lynch (2000)
Third-party logistics services (3PLS) (C)	• Inventory replenishment (C1) • Warehouse management (C2) • Shipment consolidation (C3) • Direct transportation services (C4)	Davis and Gaither (1985), Dowlatshahi (2000), Gunasekaran, Patel, and Tirtiroglu (2001), Gupta and Bagchi (1987), Holguı'n-Veras (2002), Govindan et al. (2012), Bun and Ishizuka (2006), Kleinsorge, Schary, and Tanner (1991), and van den Berg and Zijm (1999)
User satisfaction (US) (D)	• Effective communication (D1) • Service improvement (D2) • Cost saving (D3) • Overall working relations (D4)	Andersson and Norrman (2002), Boyson et al. (1999), Govindan et al. (2012), Lynch (2000), and Mohr and Spekman (1994)
RL functions (RLF) (E)	• Collection (E1) • Packing (E2) • Storage (E3) • Sorting (E4) • Transitional processing (E5) • Delivery (E6)	Dowlatshahi (2000), Cochran and Ramanujam (2006), Kaliampakos, Benardos, and Mavrikos (2002), Govindan et al. (2012), Schwartz (2000), and van Dijck (1990)
Organisational performance criteria (OPC) (F)	• Flexibility (F1) • Service (F2) • Time (F3) • Cost (F4) • Quality (F5)	Andersson and Norrman (2002), Boyson et al. (1999), Govindan et al. (2012), Kim, Park, and Jeong (2004), Kim et al. (2007), Lynch (2000), and Stock, Greis, and Kasarda (1999)
Organisational role (OR) (G)	• Reclaim (G1) • Recycle (G2) • Remanufacture (G3) • Reuse (G4) • Disposal (G5)	Dowlatshahi (2000), Demir and Orhan (2003), Govindan et al. (2012), Meade and Sarkis (2002), and Schwartz (2000)
Product life cycle stages (PLC) (H)	• Introduction (H1) • Growth (H2) • Maturity (H3) • Decline (H4)	Mead and Sarkis (2002)

existing among the different decision factors. It also extends the super matrix method (Saaty, 2001a). More importantly, this model overcomes the structural limitations of the linear AHP since it uses networks regardless of their levels. In fact, the criteria are included in clusters that replace the levels. Moreover, the ANP model considers both inter-cluster (outer-dependence) and intra-cluster (inter-dependence) interactions and feedback. Hence, it can be used to analyse the whole set of potential relationships arising among the decision factors. The ANP process is generally comprised of the following steps (Saaty, 2005):

(1) Construction of a network model: after identifying the main criteria, which are based on the objective of the problem, the decision elements are classified into clusters and distributed within a network structure. The network includes all mutual relationships and feedback among both elements and clusters.
(2) Performance of pair-wise comparisons: in this stage, each of the sub-criteria composing the different decision criteria is compared pair-wise. These pair-wise comparisons follow the same intuition as those performed in the AHP method.
(3) Formation of the super matrix: the relative priority eigenvectors obtained for each pair-wise comparison matrix are placed in a larger partitioned matrix. The resulting super matrix allows for the analysis of the existing interdependences among the whole set of criteria composing the network. The function of this super matrix is similar to that of a Markov chain process. Every ANP network has three super matrices associated with it, named un-weighted, weighted, or normalised and limit.
(4) Analysis of the information: all calculations regarding the super matrices are easily performed

$$
w = \begin{array}{c|c}
 & \begin{array}{cccc} C_1 & C_k & \cdots & C_N \end{array} \\
\begin{array}{c} \\ C_1 \\ \\ \\ C_k \\ \\ \\ C_N \end{array} & \begin{array}{c} e_{11}e_{12..}e_{1n1}..... \\ e_{11} \\ e_{1n1} \\ e_{k1} \\ e_{knk} \\ e_{N1} \\ e_{NnN} \end{array}
\begin{bmatrix} e_{k1}e_{k2..}e_{knk}..... & e_{N1}e_{N2..}e_{NnN} \\ W_{11} & W_{12} \quad \cdots \quad W_{1N} \\ W_{21} & W_{22} \quad \cdots \quad W_{2N} \\ \cdots & \cdots \quad \cdots \quad \cdots \\ W_{N1} & W_{N2} \quad \cdots \quad W_{NN} \end{bmatrix}
\end{array}
$$

Figure 2. Sample super matrix.

using the super decisions software. The columns of the limit super matrix, which are all identical, determine the ultimate priority of the whole set of criteria composing the network. As a result, the ANP allows us to identify and select the criterion or alternative with the highest priority.

Figure 2 describes a super matrix that contains N clusters. In particular, C_k refers to the kth cluster, composed by n_k elements or criteria, which are denoted by $e_{k1}, e_{k2}, \ldots\ldots, e_{kn_k}$. Each column (w_{ji}) in this figure describes the relation and subsequent effect that the column criterion has on the row criterion. That is, each column is a relative priority vector derived from pair-wise comparisons among the corresponding criteria using the AHP eigenvector method. If there are no relationships among the elements of two clusters, the resulting matrix will be a zero matrix (Saaty & Vargas, 2006).

The sum of the weights composing the columns of the primary or un-weighted super matrix may result in a number greater than one. Thus, a weighted or normalised super matrix must be obtained by multiplying the value of each criterion composing the un-weighted super matrix by the (eigenvector) weight assigned to its corresponding cluster. Finally, the weighted super matrix is converted into a limit super matrix by raising it to the power 2k+1, with k being a sufficiently large number.

If more than one limit matrix is obtained, it is necessary to calculate the Cesaro sum in order to establish a priority ranking among the resulting super matrices (Chen & Chen, 2012). The Cesaro sum is given by the following expression: $\mathrm{Lim}_{N\to\infty}(\frac{1}{N})\sum_{k=1}^{N} w^k$, with w referring to the weighted super matrix used to calculate the limit one.

3.3. The classic SIR technique

The classic SIR technique was first introduced by Rebai (1993). This technique was based on the construction of superiority and inferiority matrices that were used to rank the options available. Consider a decision-maker who must rank m available options, denoted by A_i, with $i = 1, 2, \ldots, m$, with respect to n cardinal criteria, denoted by g_j, with $j = 1, 2, \ldots, n$. Let $g_j(A_i)$ be a real valued function describing the criteria value or performance of the ith alternative, A_i, with respect to the jth criterion, g_j. These criteria values or performances are used to construct the decision matrix $\mathbf{D}$ as follows:

$$
\mathbf{D} = \begin{bmatrix} g_1(A_1) & g_2(A_1) & \ldots & g_n(A_1) \\ g_1(A_2) & g_2(A_2) & \ldots & g_n(A_2) \\ \vdots & \vdots & \vdots & \vdots \\ g_1(A_m) & g_2(A_m) & \ldots & g_n(A_m) \end{bmatrix}.
$$

Assume now that f_j is a generalised criterion adopted by the decision-maker in order to compare options A_i and A_k with respect to the jth criterion g_j. That is, f_j is a monotonic function from the set of real numbers in the interval [0, 1].

The intensity of preference or superiority of the alternative A_i relative to A_k based on the jth criterion is determined by the following relation $P_j\ (A_i, A_k) = f_j\ (g_j(A_i) - g_j(A_k))$ (Xu, 2001).

The superiority, $S_j(A_i)$, and the inferiority, $I_j(A_i)$, indexes for alternative A_i with respect to the jth criterion are calculated using the following equations:

$$
S_j(A_i) = \sum_{k=1}^{m} P_j(A_i, A_k) \quad \text{and} \quad I_j(A_i) = \sum_{k=1}^{m} P_j(A_k, A_i). \tag{1}
$$

Superiority and inferiority indexes are used in the construction of the superiority ($S = (S_j(A_i))_{m\times n}$) and inferiority ($I = (I_j(A_i))_{m\times n}$) matrices.

Finally, standard MCDM procedures such as SAW and TOPSIS can be implemented on the S and I matrices in order to aggregate the corresponding indexes into two different global preference indexes, namely, the superiority (S-flow) $\varphi^{>}(\cdot)$ and the inferiority (I-flow) $\varphi^{<}(\cdot)$ flows. The S and I flows reflect the global degree of superiority and inferiority of each alternative, respectively (Xu, 2001).

3.3.1. SIR ranking

Following Xu (2001), the superiority $\varphi^{>}(\cdot)$ and inferiority $\varphi^{<}(\cdot)$ flows can be used to rank the set of alternatives. Note that the higher the value of the superiority flow, the more preferred is a given alternative. Similarly, the lower the value of the inferiority flow, the more preferred is a given alternative.

Let $P_>$ and $I_>$ denote the strict preference and indifference relations relative to the superiority flow. A similar notation can be introduced for the inferiority flow. The superiority ranking ($\Re_> = \{P_>, I_>\}$) of the alternatives based on the descending order of $\varphi^>(\cdot)$ is therefore given by $A_i P_> A_k$ iff $\varphi^>(A_i) > \varphi^>(A_k)$ and $A_i I_> A_k$ iff $\varphi^>(A_i) = \varphi^>(A_k)$. Similarly, the inferiority ranking ($\Re_< = (P_<, I_<)$) of the alternatives based on the descending order of $\varphi^<(\cdot)$ is given by $A_i P_< A_k$ iff $\varphi^<(A_i) < \varphi^<(A_k)$ and $A_i I_< A_k$ iff $\varphi^<(A_i) = \varphi^<(A_k)$.

3.4. Grey relation analysis (GRA)

The first researcher to theorise grey systems was Deng (1988). The theory of grey systems yields satisfactory outputs using relatively little information and highly variable criteria. Similarly to the theory of fuzzy systems, this theory also provides an effective mathematical tool to solve uncertain and ambiguous problems (Deng, 1988).

GRA is a part of the theory of grey systems that is generally used to solve problems with complex interfactor and inter-variable relationships (Moran, Granada, Míguez, & Porteiro, 2006). In particular, GRA has been widely used in data processing and modelling activities, systems analysis, as well as to solve MCDM problems (Deng, 1988; Memarzade et al., 2011; Wei, 2011; Zare Mehrjerdi, 2014). In a grey relation environment, a collection of non-functional models can be used to meet the requirements of statistical methods for the analysis of large sample volumes (Chen & Tzeng, 2004).

The main definitions commonly employed in GRA are presented below.

Definition 3.4.1 (Chen & Tzeng, 2004)**:** Let X be a set of grey relation coefficients (GRCs) of determination, $x_0 \in X$ the referential sequence, and $x_i \in X$ the comparative sequence, with $x_0(j)$ and $x_i(j)$ representing the numerical values of x_0 and x_i at point j.

Definition 3.4.2 (Chen & Tzeng, 2004)**:** The GRC, which determines the proximity between $x_i(j)$ and $x_0(j)$, is given by

$$\gamma(x_0(j), x_i(j)) = \frac{\Delta\min + \zeta\,\Delta\max}{\Delta_{ij} + \zeta\,\Delta\max}\ ; \quad i = 1, \ldots, m \ \ j = 1, \ldots, n, \tag{2}$$

where the sub-index i refers to the options available, j accounts for the selection criteria,

$$\Delta_{ij} = |x_0(j) - x_i(j)|$$

$$\Delta\min = \min\left\{\Delta_{ij}, i = 1, 2, \ldots, m;\ j = 1, 2 \ldots, n\right\}$$

$$\Delta Max = Max\left\{\Delta_{ij}, i = 1, 2, \ldots, m;\ j = 1, 2 \ldots, n\right\}$$

and $\zeta \in [0, 1]$ is the distinguished coefficient used to expand or contract the range of the GRC. Note that the value of the GRC increases as $x_i(j)$ approaches $x_0(j)$.

Definition 3.4.3 (Chen & Chen, 2012)**:** Let w_j denote the weight of the jth criterion. The grey relation grade (GRG) is given by

$$\Gamma(x_0, x_i) = \sum_{j=1}^{n} w_j \gamma\left(x_0(j), x_i(j)\right). \tag{3}$$

The GRC relation describes the existing correlation between the target referential and the comparative sequence. The best alternative is the one endowed with the highest GRG.

3.5. Intuitionistic fuzzy set (IFS)

Atanassov (1986) extended the fuzzy model developed by Zadeh (1965). Together with the degrees of membership and non-membership defining the elements of a fuzzy set, Atanassov introduced a degree of hesitancy as a main characteristic of the elements within the set. This degree of hesitancy accounts for the fact that a decision-maker is not always able to determine definite membership degrees. Hence, an IFS is defined as follows.

Definition 3.5.1 (Atanassov, 1986)**:** Let X be a non-empty finite set. An IFS A in X is given by

$$A = \{x,\ \mu_A(x), \upsilon_A(x) \,|x \in X\}, \tag{4}$$

with $\mu_A, \upsilon_A : X \to [0,\ 1]$ denoting the degree of membership and non-membership of x to A, respectively, and $0 \le \mu_A(x) + \upsilon_A(x) \le 1, \forall\, x \in X$.

Szmidt and Kacprzyk (2000) introduced an intuitionistic index of x in A, defined by $\pi_A(x) = 1 - \mu_A(x) - \upsilon_A(x)$ for each IFS in X. This index determines the hesitancy degree of x to A. Given this index and the parameters composing it, an IFS performs better than a fuzzy one in uncertain situations.

3.5.1. Measuring the intuitionistic fuzzy distance

Following Szmidt and Kacprzyk (2000) and Chai, Liu, and Xu (2012), we propose two different ranges based on the $\mu_A(x)$, $\upsilon_A(x)$ and $\pi_A(x)$ parameters to measure the distance between two IFSs. Assume that A and B are two IFSs in $X = \{x_1, x_2, \ldots, x_n\}$, the following distances are proposed:

(1) The Hamming distance,

$$h(A, B) = 1/2 \sum_{i=1}^{n} (|\mu_A(x_i) - \mu_B(x_i)| + |v_A(x_i) - v_B(x_i)| + |\pi_A(x_i) - \pi_B(x_i)|). \tag{5}$$

(2) The Euclidean distance,

$$d(A,B)=\sqrt{1/2\sum_{i=1}^{n}(\mu_A(x_i)-\mu_B(x_i))^2+(\nu_A(x_i)-\nu_B(x_i))^2+(\pi_A(x_i)-\pi_B(x_i))^2}. \quad (6)$$

Generally, decisions are made by a group of decision-makers, so the aggregation of opinions is an essential component of any decision-making method (Wei, Zhao, & Wang, 2012). Recently, Xu (2007a), Chai et al. (2012), Wei and Zhao (2012), and Zhao and Wei (2013) have developed several operators (such as IFHA, IFHG; IFWA, IFWG; I-IFCA, I-IFCG; IFEHA, IFEHG) to aggregate opinions within an intuitionistic fuzzy space. These operators can be used to aggregate the intuitionistic fuzzy values obtained by a specific alternative in relation to each criterion. The result of these calculations is also an intuitionistic fuzzy value that helps the decision-maker to select the best alternative available.

Definition 3.5.1.1: Let $\alpha_i = (\mu_{\alpha_i}, \upsilon_{\alpha_i})$ $(i = 1, \ldots, n)$ be a set of intuitionistic fuzzy values, then IFWA: $\Theta^n \to \Theta$ is defined as follows (Xu, 2007b):

$$\mathrm{IFWA}_\omega = \bigoplus_{i=1}^{n}(\omega_i\alpha_i) = \left(1-\prod_{i=1}^{n}(1-\mu_{\alpha_i})^{\omega_i}, \prod_{i=1}^{n}(\upsilon_{\alpha_i})^{\omega_i}\right). \quad (7)$$

Definition 3.5.1.2: Let $\alpha_i = (\mu_{\alpha_i}, \upsilon_{\alpha_i})$ $(i = 1, \ldots, n)$ be a set of intuitionistic fuzzy values, then IFWG: $\Theta^n \to \Theta$ is defined as follows (Xu & Yager, 2006):

$$\mathrm{IFWG}_\omega = \bigoplus_{i=1}^{n}(\alpha_i^{\omega_i}) = \left(\prod_{i=1}^{n}(\mu_{\alpha_i})^{\omega_i}, 1-\prod_{i=1}^{n}(1-\upsilon_{\alpha_i})^{\omega_i}\right), \quad (8)$$

where $\omega_i = (\omega_1, \omega_2, \ldots, \omega_n)^T$ is the weight vector of α_i $(i = 1, \ldots, n)$ with $\omega_i \in [0, 1]$ and $\sum_{i=1}^{n}\omega_i = 1$.

3.6. The proposed IFG-SIR methodology

The following inputs are required to implement the method proposed:

Input 1: The weights assigned to the kth expert: $w_k = (\mu_k, \nu_k)$, with $k = 1, \ldots, L$;

Input 2: The weights of the criteria: W_j, with $j = 1, \ldots, n$;

Input 3: The value of the report provided by the kth expert: $d_{ij}^{(k)} = (\mu_{ij}^{(k)}, \upsilon_{ij}^{(k)})$, with $i = 1, \ldots, m$.

Chai et al. (2012) developed the SIR method on the basis of IFSs. In the proposed model, the weights of the criteria correspond to those obtained after implementing the ANP, from where they are directly imported.

Our model is defined in nine sequential stages. However, before starting with the initial one, we determine the value of the intuitionistic weights, w_k, associated to each expert. In this regard, it should be emphasised that the first six stages have been defined to account for the reliability of the experts and their reports.

Stage 1: The main objective of the initial stage is to ascertain the significance of the personal decisions of each expert, ξ_k, with $k = 1, \ldots, L$. To this end, we will compute the relative distance between the weight assigned to the kth expert, $\mathrm{w_k} = (\mu_k, \upsilon_k)$, and the corresponding ideal value, $w^+{}_k = (\mu^+{}_k, \upsilon^+{}_k, \pi^+{}_k)$, using Equations (5) and (6). We will denote the distance functions defined in these equations by $D_k(\cdot)$, when applied to the kth expert.

The positive-ideal intuitionistic fuzzy weight, $w^+{}_k = (\mu^+{}_k, \upsilon^+{}_k, \pi^+{}_k)$, and the negative-ideal intuitionistic fuzzy weight, $w^-{}_k = (\mu^-{}_k, \upsilon^-{}_k, \pi^-{}_k)$, are given by $w^+ = (1, 0, 0)$, and $w^- = (0, 1, 0)$, respectively. The significance of the report provided by the kth expert is therefore given by the relative closeness of his weight to the positive-ideal one,

$$\xi_k\left(w_k, w^+\right) = D_k\left(w_k, w^-\right)/D_k\left(w_k, w^-\right) + D_k\left(w_k, w^-\right) \quad (9)$$

Stage 2: The second stage consists of computing the group aggregated decision values, $\bar{d}_{ij} = (\bar{\mu}_{ij}, \bar{\upsilon}_{ij})$, which are based on the intuitionistic fuzzy aggregation operators defined in Equations (7) and (8). According to Chai et al. (2012), IFWA should be used when the aggregation of the decision values aims at preserving the subjective judgments of the experts, and therefore it is the criterion we use,

$$\bar{d}_{ij} = IFWA_{\xi k} = \xi_1\, d_{ij}^{(1)} \oplus \ldots \oplus \xi_L d_{ij}^{(L)}$$

Stage 3: In this stage, the group aggregated decision values, $\bar{d}_{ij} = (\bar{\mu}_{ij}, \bar{\upsilon}_{ij})$, are transformed into the entries defining the performance decision matrix **D**. Therefore, $g_j(S_i)$ behaves as an operational performance function mapping relative ideal distances into the [0, 1] interval. The procedure is similar to the one described in the first stage and has therefore been omitted.

Stage 4: The IFG-SIR index and the corresponding superiority and inferiority matrices are constructed in this stage. As described in Section 3.3, the degree of preference $P_j(S_i, S_t)$ reflecting the superiority of alternative S_i

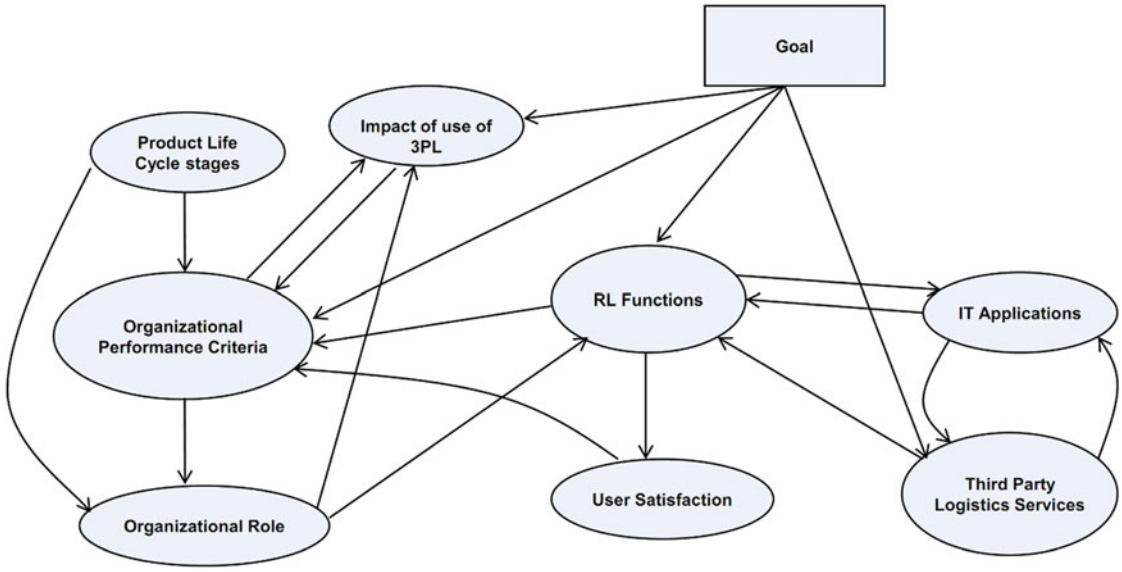

Figure 3. Network model.

relative to S_t based on the jth criterion is given by

$$P_j\ (S_i, S_t) = f_j\ \left(g_j(S_i) - g_j\ (S_t)\right), \quad \text{with} \quad j = 1, \ldots, n;\ i, t = 1, \ldots, m \text{ and i } \neq t, \tag{10}$$

where f_j is a monotonic function that can be determined by each decision-maker.

The corresponding superiority (Su) and inferiority (I) indices based on the jth criterion will be defined as follows:

$$Su_j\ (\mathrm{S_i}) = \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{P_j}\ (\mathrm{S_i}, \mathrm{S_t}) \tag{11}$$

$$I_j\ (\mathrm{S_i}) = \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{P_j}\ (\mathrm{S_t}, \mathrm{S_i})\,. \tag{12}$$

Stage 5: In this stage, the maximum values obtained by the alternatives for each criterion within the superiority matrix and the minimum values obtained by the alternatives for each criterion within the inferiority matrix will be used to define superiority and inferiority reference series for each respective matrix.

Stage 6: In this stage, we use Equation (2) to calculate the GRC for each one of the elements composing the superiority and inferiority matrices.

Stage 7: The weights of the criteria obtained from the ANP are inputted into the GRA model, using Equation (3) to calculate the GRG of each alternative within the superiority and inferiority matrices.

Stage 8: The alternatives are ranked based on the GRGs obtained in the previous stage for the superiority (Su-GRG) and inferiority (I-GRG) matrices. In each case, the best alternative is the one whose GRG is closer to 1 (Zareinejad, 2013).

Stage 9: In the final stage, the Su-GRG and the I-GRG rankings are combined. To this end, we define a problem-weighted index that behaves similarly to the V-weighted index introduced in the VIKOR technique (Opricovic & Tzeng, 2004). The V index is designed to achieve maximum group desirability and is usually equal to 0.5 (Opricovic & Tzeng, 2004; Zareinejad, 2013). Thus, the final weight assigned to each alternative is obtained using the following equation:

$$\Gamma_{Su_i, I_i}(x_{0j}, x_{ij}) = V \times \Gamma_{Su_i}(x_{0j}, x_{ij}) + \left((1 - V) \times \Gamma_{Ii}(x_{0j}, x_{ij})\right). \tag{13}$$

The final ranking is determined by the $\Gamma_{Su_i,\ I_i}(\mathrm{x_{0j}}, \mathrm{x_{ij}})$ value obtained by each alternative.

4. The conceptual model

Without understanding the interactions and relationships among the various criteria defining each alternative, it is not possible to properly select a 3PRLP. Therefore, when preparing, designing, and providing a formal framework for our decision-making model, it should be acknowledged that RL services must focus on non-linear relationships instead of linear ones. Consequently, a powerful decision-making method is required to account for the opinions of experts and integrate abstract ideas with concrete criteria. In order to gain a better understanding of the problem being analysed and the type of MCDM structure required, the conceptual model is illustrated in Figure 3.

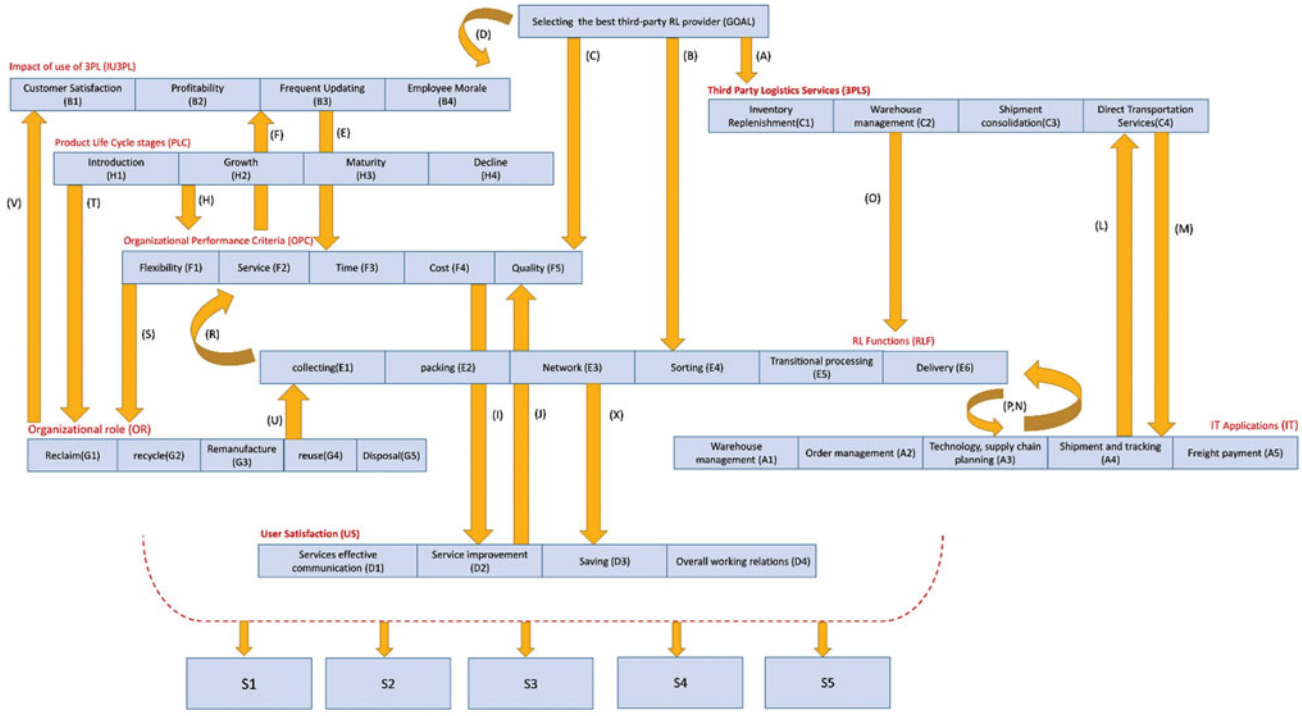

Figure 4. General relations between criteria and sub-criteria in the ANP model.

This model describes the selection process in terms of inter-factor relationships, dependencies, and feedback. It applies holism and systems theory resulting from the characteristics of the ANP.

5. Case study

In this paper, we apply the proposed framework to Pipex[1], a manufacturer of flexible and reinforced composite pipes in West Virginia. Pipex is the leading manufacturer of pipes, joints, and composite tanks in West Virginia. The corrosion and damage of composite tanks and fiberglass materials pose serious threats to the environment. Composites contain carbon fibres and are coated with chrome linings. Composites with hexavalent chromium coatings are known to be hazardous wastes. Therefore, since chromium may be leached into the ground, it is not possible to dispose of these coatings in the environment.

One of the main priorities of Pipex is the reduction of the costs derived from the collection and return of composites. Hence, one of the main objectives of the company is the selection of a 3PRLP to handle its collection and return operations. As a result of the conflicts arising among the different selection indices, the company is looking for a systematic method to select 3PRLPs.

5.1. Inter-criterion dependencies

All of the relationships defined among the different criteria and sub-criteria determining the choice of an alternative are based on the information retrieved from seven half-matrix questionnaires. The resulting network structure illustrated in Figure 4 follows from the relations described in Figure 3 and the opinions of the experts.

5.2. Pair-wise comparisons and determination of local weight

After building the ANP network, experts perform pair-wise comparisons among all the sub-criteria on the basis of the nine-point scale of preference proposed by Saaty (2000). We distributed copies of the pair-wise comparison questionnaires to 10 logistic specialists, out of which only seven responded. The opinions of the experts were aggregated using the geometric mean method (Saaty, 2001a).

5.3. Formation of a super-matrix

The weights assigned to each sub-criterion are obtained using special vectors (Saaty, 1980), whose values form the columns of a larger matrix that reflects the effect of each sub-criterion composing each cluster on all the other elements of the system. The formation of a super matrix allows for the analysis of the correlations existing among all the elements composing the ANP model. The primary (or un-weighted) super matrix, which is described in Figure 5, is composed of letters and zero values. The letters represent the relationships shown in Figure 4. If an

Criterion								
IT	IU3PL	3PLS	US	RLF	OPC	OR	Goal	PLC
0	0	M	0	P	0	0	0	0
0	0	0	0	0	F	V	D	0
L	0	0	0	0	0	0	A	0
0	0	0	0	X	I	0	0	0
N	0	O	0	0	0	U	B	0
0	E	0	J	R	0	0	C	H
0	0	0	0	0	S	0	0	T
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0

Figure 5. Sub-matrices in the super matrix.

element does not influence another element, its relative impact priority is set equal to zero.

In order to provide more insight, a subset of the calculations of block H, i.e. those involving the introduction stage (H1) of the PLC and the elements of cluster F, are presented in Figure 6. The calculations of the weights assigned to each criterion are performed using the super decisions software.

It should be highlighted that the final limit matrix (Saaty, 2001b) determines the weights associated to each criterion that will be used in the following stages of the model.

5.4. Results of weight calculations

In this stage, the 15 sub-criteria with the highest relative global significance are selected from the limit matrix for inclusion in the proposed IFG-SIR model. The weights associated to each one of these decision criteria are presented in Table 4.

5.5. Deciding on the final ranking using IFG-SIR

Four qualified experts are selected to provide subjective evaluations of the five 3PRLPs available for selection by the company. The experts are also evaluated and a weight w_k is assigned to each one of them in order to estimate the relative significance of their decisions. The input information provided by the experts as well as the evaluations used to describe their significance are presented in the form of verbal descriptions. The expressions employed together with their corresponding IFVs are presented in Table 5.

Table 4. The final normalised weights of the criteria.

Sub-criterion	Initial values of the final weight	Values of the final normalised weight
A4	0.0310	0.0486
A2	0.0299	0.0469
A1	0.0367	0.0575
F5	0.0399	0.0625
F4	0.0428	0.0671
F3	0.0333	0.0522
F2	0.0617	0.0967
F1	0.0920	0.1442
E2	0.0345	0.0541
E1	0.0379	0.0594
D3	0.0454	0.0711
D2	0.0453	0.0710
B3	0.0496	0.0777
B2	0.0277	0.0434
B1	0.0303	0.0475

5.5.1. Intuitionistic fuzzy evaluation matrices

In this stage, we build the intuitionistic fuzzy matrices describing the linguistic evaluations of each 3PRLP provided by the experts based on each of the selection criterion considered. These matrices are presented in Table 6.

5.5.2. Measuring the significance of personal decisions

The following linguistic weights are ascribed to the opinions of the experts: (1) expert one: very important (VI); (2) expert two: extremely important (EI); (3) expert three:

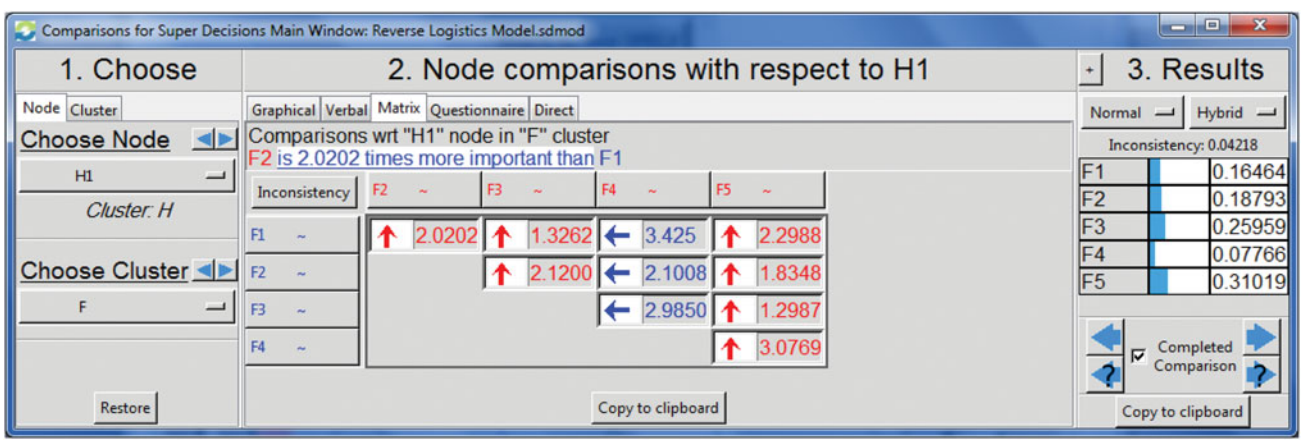

Figure 6. Pair-wise comparison matrix of organisational performance criteria with respect to the introduction sub-criterion (H1).

altogether important (AI); (4) expert four: very, very important (VVI).

The relative closeness of the above values to the positive-ideal solution, $w^+ = (1, 0, 0)$, is calculated using Equation (9). The resulting significance levels assigned to the subjective decisions made by each expert are given by

$$\xi_k = (\xi_1, \xi_2, \xi_3, \xi_4) = (0.7405, 1.000, 0.9000, 0.8314).$$

5.5.3. Aggregation decision-making

The group aggregated decision values, $\bar{d}_{ij} = (\bar{\mu}_{ij}, \bar{\upsilon}_{ij})$, are obtained after applying the intuitionistic fuzzy aggregation operator defined in Equation (7). The corresponding intuitionistic decision-making matrix is presented in Table 7.

5.5.4. Calculation of the performance function matrix

The group aggregated decision values are now transformed, using Equations (5) and (9), into the entries defining the performance (relative to the positive-ideal solution) decision matrix **D**. The resulting decision matrix, $[g_j(S_i)]$, which is entirely composed by crisp numbers, is given by

$$g_j(S_i) = \begin{bmatrix} 0.9975 & 0.9986 & 0.9840 & 0.9905 & 0.9931 & 0.9912 & 0.9834 & 0.9862 & 0.9744 & 0.9987 & 0.9684 & 0.9929 & 0.9807 & 0.9409 & 0.9896 \\ 0.9755 & 0.9969 & 0.9641 & 0.9889 & 0.9894 & 0.9796 & 0.9774 & 0.9907 & 0.9954 & 0.9857 & 0.9971 & 0.9896 & 0.9969 & 0.9755 & 0.9866 \\ 0.9986 & 0.9894 & 0.9437 & 0.9992 & 0.9533 & 0.9755 & 0.9443 & 0.9969 & 0.9969 & 0.9906 & 0.9930 & 0.9842 & 0.9824 & 0.9248 & 0.9754 \\ 0.9971 & 0.9182 & 0.9814 & 0.9533 & 0.9960 & 0.9846 & 0.7471 & 0.9437 & 0.9931 & 0.9921 & 0.9858 & 0.9755 & 0.9537 & 0.9866 & 0.9473 \\ 0.9422 & 0.8994 & 0.9989 & 0.9951 & 0.9981 & 0.9889 & 0.9969 & 0.9712 & 0.9994 & 0.9973 & 0.9947 & 0.9987 & 0.9282 & 0.9547 & 0.9920 \end{bmatrix}.$$

5.5.5. Formation of superiority and inferiority matrices

The degree of preference, $P_j(S_i, S_t)$, is now calculated for each jth criterion using Equation (10). The resulting superiority and inferiority matrices follow after applying the superiority (Su) and inferiority (I) indices described in Equations (11) and (12), respectively,

Table 5. Verbal expressions and their respective intuitionistic fuzzy number.

Description of the importance of experts		Description of the option performance		Intuitionistic fuzzy number
Extremely important	EI	Extremely positive	EP	(1.00, 0.00)
Altogether important	AI	Altogether positive	AP	(0.90, 0.10)
Very very Important	VVI	Very very positive	VVP	(0.80, 0.10)
Very important	VI	Very positive	VP	(0.70, 0.20)
Important	I	Positive	P	(0.60, 0.30)
Medium	M	Medium	M	(0.50, 0.40)
Less important	LS	Negative	N	(0.40, 0.50)
Non-important	NI	Very negative	VN	(0.10, 0.80)
Inconsiderable	UC	Extremely negative	EN	(0.00, 1.00)

Table 6. Expert opinions represented by verbal expressions.

	Expert 1					Expert 2					Expert 3					Expert 4				
Sub-criterion	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5
A1	P	M	P	VP	VVP	VP	VP	P	VVP	VP	VP	P	VP	VP	VP	P	VVP	VP	VVP	VP
A2	VP	VP	N	VN	AP	VVP	VVP	N	N	VVP	P	P	M	VN	VVP	P	VP	VVP	M	VP
A4	VP	P	VVP	M	M	P	VP	VVP	M	P	VVP	VVP	VP	M	VP	VP	VVP	AP	VP	VP
B1	P	VP	VVP	VP	AP	VP	AP	VP	VVP	AP	VP	VVP	AP	VVP	AP	P	VP	VVP	VP	VVP
B2	AP	VVP	AP	AP	VVP	VVP	VP	VVP	AP	AP	AP	P	M	VP	VP	VVP	VP	P	AP	VVP
B3	P	VP	P	VVP	VP	P	VVP	VP	VP	P	P	VVP	AP	VP	AP	VP	AP	VP	P	VVP
D2	AP	VVP	VP	VVP	AP	AP	VP	VVP	P	VVP	VP	P	M	P	VVP	VP	VVP	VP	P	P
D3	VP	VVP	P	M	M	VP	VVP	P	M	M	P	VP	VP	P	M	VP	AP	VVP	VP	AP
E1	M	P	N	P	M	M	P	M	VP	P	P	VP	N	VP	M	P	VP	VP	VVP	VVP
E2	VP	VP	P	N	VVP	VP	VP	P	M	VP	VVP	VVP	VP	P	VP	VP	P	VP	VP	VP
F1	AP	VVP	VP	VP	M	VP	P	AP	VVP	P	AP	P	AP	VV	M	VP	P	VP	AP	AP
F2	VP	VVP	P	N	M	AP	VVP	VP	M	M	AP	VP	VP	M	N	VVP	AP	AP	P	M
F3	P	M	M	VP	VVP	VVP	VP	M	P	AP	P	P	M	P	VVP	VP	P	VP	VVP	P
F4	VVP	VP	AP	N	AP	VVP	VP	AP	M	VVP	VP	VP	AP	M	VP	P	VP	VP	VVP	VP
F5	VP	P	N	VVP	VP	VVP	P	M	AP	AP	VVP	P	M	VVP	AP	VP	AP	VVP	M	VP

Table 7. Aggregation decision-making matrix.

Sub-criterion	S1	S2	S3	S4	S5
A1	(0.9911,0.0040)	(0.9793,0.0051)	(0.9751,0.0076)	(0.9844,0.0033)	(0.9888,0.0028)
A2	(0.9832,0.0037)	(0.9769,0.0027)	(0.9422,0.0193)	(0.7163,0.1619)	(0.9969,0.0006)
A4	(0.9860,0.0030)	(0.9906,0.0015)	(0.9969,0.0006)	(0.9417,0.0233)	(0.9706,0.0094)
B1	(0.9739,0.0081)	(0.9954,0.0013)	(0.9969,0.0007)	(0.9930,0.0010)	(0.9994,0.0003)
B2	(0.9987,0.0003)	(0.9855,0.0032)	(0.9909,0.0029)	(0.9919,0.0012)	(0.9973,0.0006)
B3	(0.9677,0.0109)	(0.9971,0.0006)	(0.9930,0.0027)	(0.9856,0.0031)	(0.9946,0.0017)
D2	(0.9978,0.0011)	(0.9895,0.0018)	(0.9840,0.0035)	(0.9751,0.0067)	(0.9987,0.0004)
D3	(0.9804,0.0054)	(0.9969,0.0006)	(0.9822,0.0043)	(0.9523,0.0180)	(0.9251,0.0323)
E1	(0.9387,0.0249)	(0.9751,0.0076)	(0.9214,0.0337)	(0.9865,0.0028)	(0.9534,0.0175)
E2	(0.9895,0.0020)	(0.9865,0.0028)	(0.9750,0.0076)	(0.9455,0.0213)	(0.9919,0.0013)
F1	(0.9975,0.0012)	(0.9751,0.0067)	(0.9986,0.0006)	(0.9971,0.0006)	(0.9401,0.0242)
F2	(0.9986,0.0006)	(0.9969,0.0006)	(0.9865,0.0028)	(0.9143,0.0381)	(0.8938,0.0508)
F3	(0.9838,0.0036)	(0.9632,0.0125)	(0.9417,0.0233)	(0.9811,0.0046)	(0.9989,0.0003)
F4	(0.9904,0.0015)	(0.9888,0.0037)	(0.9992,0.0006)	(0.9518,0.0151)	(0.9955,0.0011)
F5	(0.9930,0.0010)	(0.9894,0.0061)	(0.9518,0.0155)	(0.9960,0.0011)	(0.9981,0.0010)

$$Su = \begin{bmatrix} 0.5500 & 1.6020 & 0.3548 & 0.2423 & 0.2743 & 0.0844 & 1.2710 & 0.3472 & 0.0000 & 0.0533 & 0.0000 & 0.0760 & 0.5594 & 0.0511 & 0.3422 \\ 0.1990 & 1.5718 & 0.0799 & 0.2239 & 0.2294 & 0.0034 & 1.1970 & 0.4344 & 0.0845 & 0.0000 & 0.1816 & 0.0448 & 1.0150 & 0.6977 & 0.2905 \\ 0.5721 & 1.4386 & 0.0000 & 0.3832 & 0.0000 & 0.0000 & 0.9995 & 0.5863 & 0.0996 & 0.0048 & 0.1243 & 0.0105 & 0.5968 & 0.0000 & 0.1461 \\ 0.5418 & 0.0682 & 0.3055 & 0.0000 & 0.3160 & 0.0214 & 0.0000 & 0.0000 & 0.0675 & 0.0086 & 0.0587 & 0.0000 & 0.1220 & 1.1061 & 0.0000 \\ 0.0000 & 0.0000 & 0.7743 & 0.3068 & 0.3503 & 0.0561 & 1.5339 & 0.1404 & 0.1298 & 0.0409 & 0.1455 & 0.1664 & 0.0000 & 0.2011 & 0.3900 \end{bmatrix}$$

$$I = \begin{bmatrix} 0.0240 & 0.0000 & 0.0434 & 0.0192 & 0.0067 & 0.0000 & 0.0358 & 0.0267 & 0.3658 & 0.0000 & 0.4539 & 0.0067 & 0.0517 & 0.6135 & 0.0012 \\ 0.2826 & 0.0006 & 0.3494 & 0.0292 & 0.0264 & 0.0487 & 0.0804 & 0.0077 & 0.0036 & 0.0727 & 0.0000 & 0.0186 & 0.0000 & 0.0244 & 0.0076 \\ 0.0000 & 0.0280 & 1.0613 & 0.0000 & 1.1368 & 0.1032 & 0.8852 & 0.0000 & 0.0013 & 0.0225 & 0.0040 & 0.0620 & 0.0412 & 0.6168 & 0.1171 \\ 0.0005 & 2.0727 & 0.0608 & 0.3912 & 0.0009 & 0.0124 & 3.9989 & 1.2329 & 0.0118 & 0.0141 & 0.0513 & 0.2148 & 0.5991 & 0.0000 & 1.0421 \\ 1.5800 & 2.5810 & 0.0000 & 0.0034 & 0.0000 & 0.0011 & 0.0000 & 0.2410 & 0.0000 & 0.0004 & 0.0012 & 0.0000 & 1.6010 & 0.2671 & 0.0000 \end{bmatrix}.$$

Moreover, in the current stage we also define the reference series for the superiority and inferiority matrices,

- Reference series for the superiority matrix (RS),

$$\{\max SU_1(A_i), \max SU_2(A_i), \ldots, \max SU_n(A_i)\}$$
$$RS = \{0.5721, 1.6020, 0.7743, 0.3832, 0.3503, 0.0844, 1.5339, 0.5863, 0.1298, 0.0533, 0.1816, 0.1664, 1.0150, 1.1061, 0.3900\}$$

- Reference series for the inferiority matrix (RI),

$$\{\min I_1(A_i), \min I_2(A_i), \ldots, \min I_n(A_i)\}$$
$$RI = \{0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000\}$$

5.5.6. Grey relation coefficient (GRC)

The GRC is calculated for each of the entries composing the superiority and inferiority matrices using Equation (2). A summary of the numerical results obtained is presented in Table 8. For instance, the $[Su_{\mathrm{F1}}(S_1)]$ coefficient for the F1 criterion represented in the first column of the superiority matrix is calculated as follows:

$$\gamma_{Su} = \gamma(x_0(j),$$
$$x_{S1}(j)) = \frac{0 + \zeta 0.5721}{(0.5721 - 0.5500) + \zeta 0.5721} = 0.92828,$$

where $\zeta = 0.5$.

5.5.7. Grey relation grade (GRG)

In this stage, we introduce the weights calculated for each decision criterion using the ANP into Equation (3) in order to obtain the GRG of each available option. Table 9 presents the results of these calculations.

5.5.8. Comparison of rankings

Given the fact that the best GRG is the one whose value is closer to 1, the resulting superiority and inferiority rankings are

$$Su - GRG: \quad 3PRLP - 1 \succ 3PRLP - 5 \succ 3PRLP - 3 \succ 3PRLP - 2 \succ 3PRLP - 4$$

$$I - GRG: \quad 3PRLP - 2 \succ 3PRLP - 1 \succ 3PRLP - 3 \succ 3PRLP - 4 \succ 3PRLP - 5.$$

Table 8. Grey relation coefficients of superiority and inferiority matrixes.

	Superiority matrix					Inferiority matrix				
Criterion	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5
A1	1	0.34253	0.33333	0.40114	0.59858	1	0.51394	0.33333	0.80625	0.97913
A2	0.74472	0.69479	0.58935	0.33333	1	0.98241	0.96134	0.69313	0.33333	1
A4	0.55077	0.65869	1	0.33333	0.39666	0.95849	0.98766	1	0.33333	0.71893
B1	0.33333	0.58893	0.68244	0.51022	1	0.33333	0.9807	0.99294	0.93939	1
B2	1	0.33333	0.35462	0.37351	0.68246	1	0.33333	0.61767	0.72051	0.98912
B3	0.33333	1	0.614	0.4249	0.71552	0.33333	1	0.98268	0.81563	0.99474
D2	0.47926	0.40625	0.34797	0.33333	1	0.94128	0.85238	0.634	0.33333	1
D3	0.52694	1	0.54823	0.36237	0.33333	0.93933	1	0.95105	0.57195	0.33333
E1	0.34393	0.57522	0.33333	1	0.37931	0.33453	0.92668	0.33333	1	0.53588
E2	0.80313	0.66214	0.4443	0.33333	1	0.997	0.98562	0.8165	0.33333	1
F1	0.92828	0.43397	1	0.90422	0.33333	0.97052	0.73653	1	0.99937	0.33333
F2	1	0.96366	0.83057	0.33813	0.33333	1	0.99953	0.97876	0.38371	0.33333
F3	0.47995	0.35796	0.33333	0.4523	1	0.9244	0.60298	0.33333	0.8972	1
F4	0.57624	0.54602	1	0.33333	0.71493	0.91061	0.87011	1	0.33333	0.98291
F5	0.69739	0.59162	0.33333	0.83624	1	0.98835	0.95562	0.33333	0.99842	1

Table 9. Grey relation grade for S and I matrices.

3PRLP	S-GRG	Normal S-GRG	I-GRG	Normal I-GRG
3PRLP-1	0.677563	1	0.850531	0.996145
3PRLP-2	0.62243	0.918631	0.853823	1
3PRLP-3	0.628292	0.927281	0.771205	0.903238
3PRLP-4	0.51655	0.762365	0.743139	0.870367
3PRLP-5	0.64761	0.955793	0.728873	0.853659

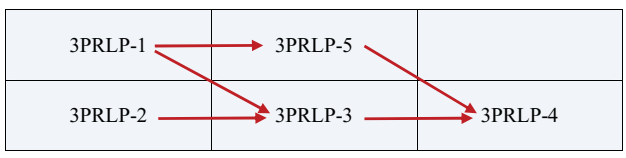

Figure 7. Priorities of options.

Table 10. Final rankings.

3PRLP	$V = 0$	$V = 1$	$V = 0.5$	Norm. $V = 0.5$
3PRLP-1	0.850531	0.677563	0.764047	1
3PRLP-2	0.853823	0.62243	0.738127	0.966074
3PRLP-3	0.771205	0.628292	0.699748	0.915844
3PRLP-4	0.743139	0.51655	0.629845	0.824353
3PRLP-5	0.728873	0.64761	0.688242	0.900784

The above results suggest that Options 1 and 2 are the best choices. Figure 7 illustrates how the available options can be prioritised according to the two aforementioned rankings.

5.5.9. Final decisive ranking

Finally, the Su-GRG and I-GRG rankings are combined using Equation (13), and the final ranking is obtained based on the problem-weighted V indexes presented in Table 10.

$$3PRLP - 1 \succ\succ 3PRLP - 2 \succ\succ 3PRLP - 3 \succ\succ 3PRLP - 5 \succ\succ 3PRLP - 4$$

6. Discussion and managerial insights

The main feature of the hybrid ANP-IFG-SIR model is its focus on the reliability of the reports received from the experts. That is, the evaluations of the initial group of experts, who must determine the relative importance of the attributes of the RLPs, are inherently imprecise and could be processed using a fuzzy version of the ANP. However, these experts do not have a direct incentive to misrepresent the information provided. On the other hand, the second group of experts evaluates directly the set of 3PRLPs based on the selection criteria obtained from the ANP. The potential incentives of the experts within this second group to bias their evaluations must be accounted for by any decision-maker facing a strategic reporting scenario.

As a result, the first six stages of the current model have been explicitly defined to smooth potential biases in the evaluations received from the second group of experts. This is why we have considered the credibility of the experts together with their evaluations from the very beginning of the decision-making process. The aggregation of intuitionistic fuzzy reports introduced in the first two stages of the model weights down potential biases using the credibility of the experts. The decision-maker is therefore endowed with the resulting matrix of subjective fuzzy aggregated evaluations describing the performance of each alternative for all the selection criteria.

Given its advantages over the standard TOPSIS approach, we have applied the SIR technique to the matrix of aggregated evaluations and generated the superiority and inferiority matrices to further smooth the biases in the evaluations received regarding the relative performance of the potential 3PRLPs. It should also be emphasised that the amount of numerical computations required increases considerably if a TOPSIS-type

approach would have been followed, which has motivated the use of GRA to derive the relative evaluations of each alternative.

Note that we have implemented two filters to account for potential biases in the subjective reports received. The first one softens strategic evaluation peaks while the second classifies the alternatives based on their relative superiority and inferiority performances. After both filters have been implemented, the decision-maker can derive the corresponding GRGs and generate two different rankings that will be subjectively combined in order to make a final decision.

The main consequence of the model from a strategic management perspective implies that managers should be particularly careful when selecting the experts given the possibility of being subject to strategic manipulation when receiving the reports. Moreover, managers should have a ranking method at their disposal that is both easy to compute and implement but sufficiently flexible so as to account for strategically biased evaluations. Clearly, the capacity of a model to smooth the biased evaluations of experts depends on the relative number of experts reporting strategically.

From an applied viewpoint, it should be highlighted that the literature is focusing on the implementation of environmentally friendly RLs policies in developing countries. For example, the Brazilian government has recently enacted the National Policy of Solid Waste (Bouzon et al., 2016), encouraging companies to incorporate RLs practices in their business processes (Guarnieri et al., 2015). A similar framework has been described for the Indian electronics industry (Prakash & Barua, 2015, 2016). However, both countries are constrained by weak institutional and regulatory systems that impose considerable barriers to the implementation of these policies, starting with the selection of adequate providers.

We conclude by emphasising that the results obtained are not only sensitive to the subjective evaluations of the experts but also to those of the decision-maker selecting a 3PRLP. Note, in particular, that the subjective preferences of the decision-maker play a fundamental role in two distinct stages of the model: when assigning credibility scores to the experts and when deciding the weights of the superiority and inferiority rankings, V and $(1 - V)$, whose convex combination determines the final choice being made.

7. Conclusion

The importance of RL processes has been recently stressed due to the existence of factors that directly influence customers' decisions when making a purchase in a competitive environment. Organisations generally outsource RL to reduce costs, focus on their core business, and avoid the complexities associated with these processes. Consequently, the selection of a third-party RL provider is an essential element of the supply chain and organisations require a proper decision-making model to address this problem. At the same time, the literature has also emphasised the important consequences that the implementation of RL processes has for developing countries designing sustainable environmentally friendly policies while facing considerable internal barriers to the adoption of such processes. The proposed hybrid MCDM model obtained by combining the ANP and IFG-SIR methods is used in this study to evaluate and select the best 3PRLP in the presence of strategic uncertainty.

The present research includes a case study aimed at assessing the reliability of the proposed hybrid model. Among the numerous interrelated criteria involved in the selection of a 3PRLP, flexibility, a sub-criterion of organisational performance, has been shown to be the most important one, followed by services (a sub-criterion of organisational performance) and profitability (a sub-criterion of the impact of using 3PLs). Given these evaluations, the IFG-SIR part of the model was used to create the final ranking of alternatives and select one of them.

The selection process is subject to a substantial amount of ambiguity and subjectivity that has to be dealt with by the decision-making model, which must also provide a relatively simple computational approach that can be easily understood and implemented by the managers. In this regard, the use of any combination of techniques – other than IFG-SIR – designed to smooth the influence of subjective biases on the final decision should be encouraged so as to prevent the potential manipulation derived from strategic reporting.

The advantages of the proposed model are sevenfold. The ANP and IFG-SIR method: (1) applies to both qualitative and quantitative structures; (2) handles inter-criterion mutual effects based on systems theory; (3) enhances group decision-making while accounting for the credibility of the experts; (4) allows for a simultaneous comparison of the superiority and inferiority evaluations of the alternatives; (5) does not require the demanding TOPSIS and SAW calculations performed in the classic SIR method; (6) accounts for the lack of adequate information and inexperienced experts through GRA; (7) allows to manage ambiguous and strategically biased information.

Note

1. The name has been changed to protect the anonymity of the manufacturing company.

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