Green port performance evaluation under uncertainty: a multiple attribute group decision analysis

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Abstract: This paper aims to assess the performance of a port within the context of its supply chain on the basis of integrating a five-dimensional balanced scorecard with green performance criteria. A multiple attribute group decision-making (MAGDM) approach is proposed which encompasses both intuitionistic fuzzy set theory and evidence theory in order to properly represent and aggregate the uncertain information which prevails within any process of such an evaluation. With an empirical application, the evaluation results provide effectively not only the ranking order of all alternative port enterprises, but also the strengths and weaknesses of each one, at the detailed level of individual performance attributes.

Keywords: MAGDM; green port; supply chain management; performance evaluation; intuitionistic fuzzy set; IFS; evidence theory.

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1 Introduction

Environmental considerations have recently gained increasing attention amongst governments, companies and other organisations as a reaction to the growing proliferation of serious environmental problems such as global warming, water pollution, air pollution and energy shortages. In this respect, organisations in the maritime arena have also proposed initiatives such as alternative maritime power (AMP) technology and emissions control areas (ECAs) as methods or approaches to reduce the adverse environmental impact of maritime transportation.

The role of ports as nodes within the global maritime transportation network is pivotal, especially given the significant proportion of world freight which is carried by the international shipping industry [estimated at around 90% of world trade by volume (see ICS, 2018)]. Given this critical role of ports in facilitating international trade, the implementation of the 'green port' concept may provide an effective approach for port managers to improve environmental performance and, as a consequence, to potentially secure a competitive advantage.

In recognition of the trend towards the adoption of the 'green port' concept, a significant body of research has emerged which attempts to evaluate the performance outcomes which have resulted from its implementation. In this respect, a number of different evaluation methods have been applied; for example and *inter alia*, the Delphi technique (Chen and Pak, 2017), the fuzzy analytic hierarchy process (FAHP) (Chiu et al., 2014) and a developed assessment model (Chang and Wang, 2012).

Port supply chains which operate at a high level of efficiency will successfully integrate resources, improve the service level of the port and, as a result, enhance its competitiveness. Performance evaluation provides one of the most essential and significant sources of information for the enhancement of an enterprise's performance and competitiveness. The evaluation of green port performance within the context of its supply chain represents, therefore, information that is critical to the efforts of port management to instigate performance improvements and enhance the competitiveness of the port enterprise.

A comprehensive performance evaluation system applicable to a green port within the context of its supply chain would naturally include both quantitative and qualitative attributes which reveal the various characteristics of a green port. In order to build a reasonable performance evaluation model of a green port within the context of its supply chain, the five-dimensional balanced score card (5DBSC) can be adopted and extended to include an environmental dimension which encompasses a range of different criteria. In addition, because of the complexity of the real world problem and the subjective nature of decision makers' preferences and judgments, the performance evaluation model for a green port within the context of its supply chain also has to cater for uncertain information, multiple attributes and the judgments of an expert group.

In consequence, therefore, the performance evaluation of a green port within the context of its supply chain can be regarded as a multiple attribute group decision-making (MAGDM) problem under uncertainty. As one of the most effective ways of dealing with the subjective uncertainty of decision makers, intuitionistic fuzzy set (IFS) theory (Atanassov, 1986) has been used for handling the ambiguity of human judgments on green supply chain practices (Govindan et al., 2015). In addition, as one of the main methods in dealing with the logic of uncertainty and of great advantage in processing uncertain multi-source information, evidence theory (Dempster, 1967) is also utilised for determining different weights across decision makers based on evidence conflict, to reflect the diversity in the judgments of different decision makers.

The following section of the paper is devoted to providing a review of the literature in the field. Section 3 outlines a conceptual model for the comprehensive performance evaluation of a green port within the context of its supply chain. In so doing, it integrates environmental performance into the 5DBSC. Encompassing a MAGDM method which utilises IFS and evidence theory, the full methodology is expounded in Section 5. This is then applied empirically to evaluating the performance of a green port within the context of its supply chain under uncertainty for a sample of ports in China. The results are presented in Section 6 and conclusions are finally drawn in Section 7.

2 Literature review

The majority of the research conducted on the performance evaluation of ports has traditionally focused on the technical efficiency of port operations, mainly estimated using data envelopment analysis (DEA) (Charnes et al., 1978; Banker et al., 1984) or stochastic frontier analysis (Meeusen and van den Broeck, 1977; Aigner et al., 1977). Over the years, there have been a number of reviews of this body of work (Gonzalez and Trujillo, 2009; Cullinane, 2010; Dutra et al., 2015), with much of it revolving around the relationship between port performance and governance structures (Brooks and Cullinane, 2006; Tongzon and Heng, 2005; Vieira et al., 2014; de Langen and Heij, 2014; Brooks et al., 2017) and the issue of trade facilitation (Wu and Goh, 2010).

A recent trend has been the adoption of a more holistic approach to port performance evaluation based on a port's position within a logistics or supply chain (Carbone and Martino, 2003; Bichou and Gray, 2004; Wang and Cullinane, 2006; Almotairi and Lunsden, 2009; Woo et al., 2011; Lam and Gu, 2013; Ha et al., 2017). By analysing reference models of supply chain management, Herz and Flamig (2014) provided a conceptual overview of the role of ports within international supply chains by identifying 12 supply chain management subsystems that represent broad design areas of shippers' strategies where ports have a significant role to play. More specifically targeting the evaluation of the performance of port supply chains, Low and Lam (2013) applied DEA to evaluate the performance of 30 seaports worldwide. The efficiency scores from a network DEA model and the traditional DEA-CCR model were compared to provide valuable insights into how port operators might improve port performance from the perspective of the wider supply chain. Shao et al. (2016) established a performance evaluation index system for port supply chains based on the use of a balanced score card (BSC) (Kaplan and Norton, 1992) and then utilised fuzzy-matter-element analysis to obtain comprehensive evaluation results. Loh et al. (2017) analysed data obtained from a questionnaire survey using a fuzzy comprehensive evaluation method in order to deduce the likely impact on performance of potential disruptions to a port-centric supply chain. Another system-wide approach is that of Jula and Leachman (2011), which seeks to optimise the efficiency of containerised imports through US ports and the nation's inland transport infrastructure by applying an approach based on a mixed integer nonlinear programming model.

Another recent trend in the evaluation of port performance has been to supplement the traditional approach of evaluating technical efficiency by including environmental or sustainability criteria within the analysis. A range of different approaches and methods have been applied in order to achieve this, such as: the Delphi technique (Chen and Pak, 2017); the analytical hierarchical programming model (Asgari et al., 2015), a fuzzy analytical hierarchical programming model (Chiu et al., 2014), emissions modelling (Chang and Wang, 2012; Puig et al., 2015).

While the more generic concept of green supply chain management (GSCM) has emerged as a proactive approach and has drawn quite significant research interest (Liao et al., 2010; Lin, 2013; Shen et al., 2013; Mirhedayatian et al., 2014; Wei et al., 2014; Govindan et al., 2015; Rostamzadeh et al., 2015; Liu and Yi, 2016; Uygun and Dede, 2016; Qin et al., 2017; Zhang, 2017), there has been relatively little work undertaken at the interface where the performance evaluation considers both green port practices and port supply chain management. One notable exception is the work of Lu et al. (2016), which applies structural equation modelling to survey data in order to evaluate Taiwanese port performance within the specific context of the sustainability of the wider supply chain.

Clearly, there exists significant scope for expanding the research nexus within the area of performance evaluation of green port within the context of its supply chain, particularly in utilising the wide range of available techniques which can obviously be deployed. The analysis conducted herein, therefore, proposes the use of a MAGDM method in order to capture the wide range of potential dimensions and attributes which might have an influence on such a performance evaluation. Furthermore, because they are important and useful approaches to dealing with the uncertainty and vagueness which surrounds the use of qualitative criteria in particular, IFS theory and evidence reasoning are deemed to provide an effective means of facilitating the performance evaluation of green port in the presence of uncertainty.

In recent years, IFS theory and evidence theory have both been widely applied in the MAGDM field. For example, Chen and Yang (2011) investigated MAGDM problems with intuitionistic fuzzy information and built some optimisation models for determining the attribute weights. Wan et al. (2013) investigated MAGDM with triangular intuitionistic fuzzy numbers based on the VIKOR method and determined the weights of decision makers objectively by combining evidence theory with Bayesian approximation. Ye (2013) proposed MAGDM methods with completely unknown weights of both experts and attributes in IFS and interval-valued IFS. Liu et al. (2015) employed the evidential reasoning approach (ERA) to aggregate the uncertain information represented by the belief structure in the MAGDM problems. Fu et al. (2015) investigated MAGDM problems on the basis of the belief structure and combined group assessments by utilising the evidential reasoning rule. Mousavi et al. (2016) developed a VIKOR method based on IFS for solving MAGDM problems and utilised an intuitionistic fuzzy weighted averaging operator to aggregate decision makers' judgments. Xu et al. (2016) solved the heterogeneous MAGDM problem based on TOPSIS, in which heterogeneous decision information was transformed into IFS. Liu et al. (2017) extended the partitioned Bonferroni mean operator and the partitioned geometric Bonferroni mean operator for IFS and used them to process MAGDM problems. Liu and Chen (2017) constructed the intuitionistic fuzzy Heronian aggregation operators based on the Archimedean T-conorm and T-norm and further proposed a corresponding MAGDM method.

3 A conceptual model for green port performance evaluation

Performance evaluation can reveal a lot about the management capability of a company and represents a critical means by which corporate competitiveness can be enhanced. As supplements to traditional financial assessment, some more comprehensive methods of enterprise assessment have come into being over recent years. As first expounded by Kaplan and Norton (1992), the BSC is one of the most widely utilised of these. As initially expounded, it comprises four dimensions:

a the finance dimension

b the customer dimension

c the internal business process dimension

d the learning and growth dimension.

By adding in supplier performance, the five-dimensional balanced scorecard (5DBSC) was proposed specifically for supply chain performance evaluation (Shao et al., 2016; Liu and Yi, 2016).

According to the OECD, green port environmental concerns can be summarised into three types:

a shipping emissions

b port activity

c hinterland transportation (Du et al., 2019).

In practice, the hinterland transport system, including trucks, railways and inland waterways, is a key link in the port supply chain and connects ports with inland origins or destinations. Therefore, hinterland transportation can be regarded as the supplier of the green port. In fact, green port performance is not only influenced by internal management but also by external supplier, so the 5DBSC is suitable for assessing the performance of port activity and hinterland transportation for a green port. However, the 5DBSC does not contain any environmental criteria. It is necessary to introduce green performance indicators into the 5DBSC to represent the performance of shipping emissions. In so doing, the performance evaluation model for a green port within the context of its supply chain conducted within this study now consists of six dimensions: finance dimension (D1), customer dimension (D2), business process dimension (D3), learning and development dimension (D4), supplier dimension (D5) and green performance dimension (D6). Together with the individual attributes associated with each of them, these dimensions are described in Table 1 and summarised in Figure 1.

In order to derive empirical assessments of the level of performance of organisational entities with respect to each of the listed attributes across all six dimensions, a formal and generally applicable methodological approach is now espoused, which is later implemented within the context of a specific empirical context.

Figure 1 The performance evaluation model for green port within the context of its supply chain (see online version for colours)

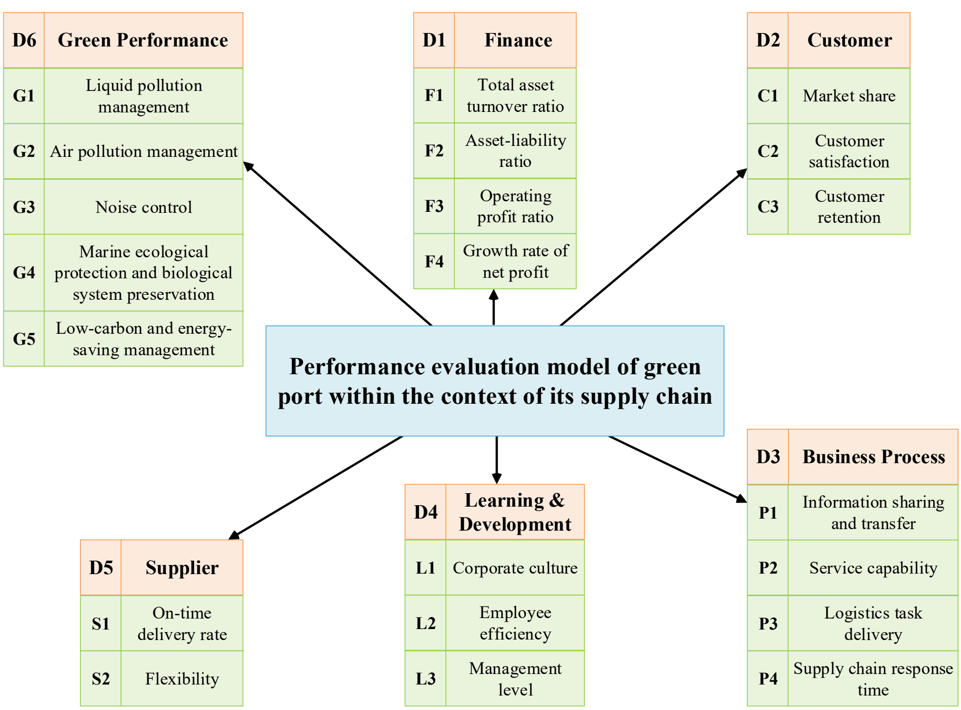


Table 1 Represented attributes for the performance evaluation model of green port within the context of its supply chain

Codes	*Attributes*	*Property*	*Formulas or implications*
F1	Total asset turnover ratio	Quantitative	Operating revenue/average total assets
F2	Asset-liability ratio	Quantitative	Total liabilities/total assets
F3	Operating profit ratio	Quantitative	Operating profit/operating revenue
F4	Growth rate of net profit	Quantitative	Net profit growth/net profit
C1	Market share	Quantitative	Sales volume/total sales of market
C2	Customer satisfaction	Qualitative	To estimate the service level of an enterprise
C3	Customer retention	Qualitative	To measure the customer loyalty
P1	Information sharing and transfer	Qualitative	To evaluate information sharing degree and level of information transfer
P2	Service capability	Qualitative	To measure the efficiency of cargo-handling, throughput of berth, facility utilisation, etc.
P3	Logistics task delivery	Qualitative	To assess completion of task delivery, accuracy of delivery, etc.
P4	Supply chain response time	Quantitative	To calculate the time required to meet the sudden demand
L1	Corporate culture	Qualitative	To evaluate the brand influence
L2	Employee efficiency	Qualitative	To service efficiency of human resource
L3	Management level	Qualitative	To express the corporate governance system, organisational structure, etc.
S1	On-time delivery rate	Quantitative	Punctual delivery times/ total delivery times
S2	Flexibility	Qualitative	To evaluate SC's capability of handing the special business and meeting the requirement
G1	Liquid pollution management	Qualitative	To assess fuel spill, ballast water pollutant, sewage treatment, solid waste dumping, etc.
G2	Air pollution management	Qualitative	To describe the use of low-sulphur fuel, the emissions of toxic gas, cold ironing, etc.
G3	Noise control	Qualitative	To monitor noise and vibration from cargo-handling equipment and vessels
G4	Marine ecological protection and biological system preservation	Qualitative	To evaluate the preservation of wetland and marine habitat, port entrance sediment and coastal erosion control
G5	Low-carbon and energy-saving management	Qualitative	To assess substitute energy and energy-saving devices, new energy-saving operational processes, renewable energy resources, etc.

4 Research methodology

4.1 Intuitionistic fuzzy theory

IFS were developed and proposed by Atanassov (1986) as an extension to fuzzy set theory as originally promulgated by Zadeh (1965). Since they were first introduced, IFS have become acknowledged as one of the most important tools for dealing with the subjective uncertainty and vagueness of decision makers. The characteristics of IFS are their membership degree, non-membership degree and hesitancy degree. As such, in comparison to classical fuzzy set theory, IFS provide an expanded perspective on the uncertainty surrounding any decision. Atanassov (1986) provides the following definition:

Definition 1: Let X be a finite universal set, $A = \{\langle x, \mu_A(x), \upsilon_A(x) \mid x \in X\rangle\}$ that is defined as an IFS in X, where υ_A, $\mu_A \in [0, 1]$, with the condition $0 \leq \mu_A(x) + \upsilon_A(x) \leq 1$, for all $x \in X$. $\mu_A(x)$ and $\upsilon_A(x)$ represent the degree of membership and non-membership respectively of the element x to A, and $\pi_A(x) = 1 - \mu_A(x) - \upsilon_A(x)$ is the degree of hesitancy. Then, an intuitionistic fuzzy number (IFN) can be denoted by $a = (\mu_a, \upsilon_a)$.

The notion of an intuitionistic fuzzy number was further elaborated upon by Xu et al. (2016) by the following:

Definition 2: For an IFN $a = (\mu_a, \upsilon_a)$, a score function is defined as $S(a) = \mu_a - \upsilon_a$, and an accuracy function can be defined as $\mathcal{H}(a) = \mu_a + \upsilon_a$. For two IFNs $a_1 = (\mu_1, \upsilon_1)$ and $a_2 = (\mu_2, \upsilon_2)$, then:

1 $a_1 > a_2$, if $S(a_1) > S(a_2)$ or $S(a_1) = S(a_2) \wedge \mathcal{H}(a_1) > \mathcal{H}(a_2)$

2 $a_1 < a_2$, if $S(a_1) < S(a_2)$ or $S(a_1) = S(a_2) \wedge \mathcal{H}(a_1) < \mathcal{H}(a_2)$

3 $a_1 = a_2$, if $S(a_1) = S(a_2) \wedge \mathcal{H}(a_1) = \mathcal{H}(a_2)$.

4.2 Evidence theory

Also known as the *theory of belief functions* or the *Dempster-Shafer theory* after its originators (Dempster, 1967; Shafer, 1976), *evidence theory* is founded on the precept of making the maximum use of all available information while taking care not to distort uncertainty and unknown information. Based on evidence theory, Yang and Xu (2002) advocated an ERA to the solution of MADM problems with uncertainty. The basic algorithm of the ERA is as follows:

1 Assume that $E = \{e_i \mid i = 1, 2, \cdots, L\}$ is an attribute that is evaluated through L sub-criteria. The attribute e_i can be assessed by using a set of grades $H = \{H_n \mid n = 1, 2, \cdots, N\}$ with a set of associated belief degrees $B_i = \{\beta_{n,i} \mid n = 1, 2, \cdots, N\}$. Belief degrees are a type of probability, satisfying $0 \leq \beta_{n,i} \leq 1$ and $\sum_{n=1}^{N} \beta_{n,i} \leq 1$. Then, $\beta_{H,i} = 1 - \sum_{n=1}^{N} \beta_{n,i}$ is the belief degree unassigned to any grades, representing the uncertain information. Therefore, the assessment of attribute e_i can be denoted by:

$$S(e_i) = \left\{ (H_n, \beta_{n,i}) \middle| n = 1, 2, \cdots, N \right\}, i = 1, 2, \cdots, L \tag{1}$$

2 Let ω_i be the weight of attribute e_i, satisfying $0 \le \omega_i \le 1$ and $\sum_{i=1}^{L} \omega_i = 1$. Then the basic probability mass $m_{n,i}$ and the remaining probability mass $m_{H,i}$, representing the mass to grade H_n and the mass to neither grade on the i^{th} attribute e_i, can be obtained as follows:

$$m_{n,i} = \omega_i \beta_{n,i} \tag{2}$$

$$m_{H,i} = 1 - \sum_{n=1}^{N} m_{n,i} \tag{3}$$

3 Let $\bar{m}_{H,i} = 1 - \omega_i$ and $\tilde{m}_{H,i} = \omega_i \beta_{H,i}$, then the probability mass $m_{n,(i+1)}$ and the remaining probability mass $m_{H,(i+1)}$, which represent the mass to grade H_n and the mass to neither grade on the first j aggregated attributes, respectively, can be determined as:

$$m_{n,(i+1)} = K_{(i+1)} \left[m_{n,(i)} m_{n,i+1} + m_{H,(i)} m_{n,i+1} + m_{n,(i)} m_{H,(i+1)} \right] \tag{4}$$

$$\tilde{m}_{H,(i+1)} = K_{(i+1)} \left[\tilde{m}_{H,(i)} \tilde{m}_{H,i+1} + \bar{m}_{H,(i)} \tilde{m}_{H,i+1} + \tilde{m}_{H,(i)} \bar{m}_{H,i+1} \right] \tag{5}$$

$$\bar{m}_{H,(i+1)} = K_{(i+1)} \bar{m}_{H,(i)} \bar{m}_{H,i+1} \tag{6}$$

$$m_{H,(i+1)} = \tilde{m}_{H,(i+1)} + \bar{m}_{H,(i+1)} \tag{7}$$

where $K_{(i+1)} = \left[1 - \sum_{t=1}^{N} \sum_{j=1, j \ne t}^{N} m_{t,(i)} m_{j,i+1} \right]^{-1}$.

4 Finally, the combined degree of belief in the assessment of attribute E, which is denoted by $S(E) = \{(H_n, \beta_n) \mid n = 1, 2, \cdots, N\}$, can be calculated as:

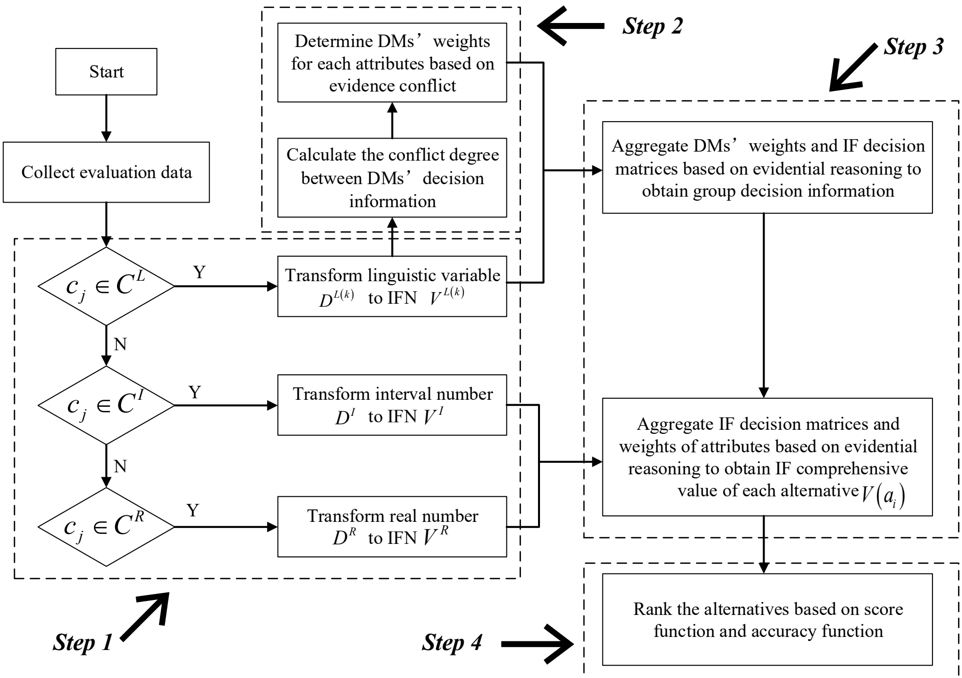
$$\beta_n = m_{n,(L)} \big/ \left(1 - \bar{m}_{H,(L)}\right), n = 1, 2, \cdots, N \tag{8}$$

$$\beta_H = \tilde{m}_{H,(L)} \big/ \left(1 - \bar{m}_{H,(L)}\right), n = 1, 2, \cdots, N \tag{9}$$

4.3 A proposed MAGDM approach

Because of the advantages they offer in representing and aggregating uncertain information, intuitionistic fuzzy theory and evidence theory have been combined to solve multiple attribute decision-making (MADM) problems in an uncertain environment (Bao et al., 2017). For the purposes of the analysis undertaken within this study, a MAGDM approach is proposed which is based on intuitionistic fuzzy theory and evidence theory, as shown in Figure 2. Because there are both quantitative and qualitative attributes which will affect the performance evaluation of green port within the context of its supply chain, the values of the quantitative attributes are collected in the form of real numbers and/or interval numbers (ranges) and decision makers provide the required information on qualitative attributes through the use of linguistic variables.

Figure 2 The proposed MAGDM algorithm



For a multi-attribute group decision-making problem, suppose that there are m alternatives denoted by $A = \{a_i \mid i = 1, 2, \cdots, m\}$ and n attributes represented by $C = \{c_i \mid j = 1, 2, \cdots, n\}$. The attribute weights are $W = \{\omega_j \mid j = 1, 2, \cdots, n\}$, satisfying $0 \leq \omega_j \leq 1$ and $\sum_{j=1}^{n} \omega_j = 1$. For quantitative attributes, the subsets of attributes in the form of real numbers and interval numbers can be denoted by C^R and C^I, respectively. Then, the decision matrices for C^R and C^I can be expressed as $D^R = [d_{ij}^R]_{mn^R}$ and $D^I = [d_{ij}^I]_{mn^I}$, respectively. For qualitative attributes, the subsets of attributes based on linguistic variables can be denoted by C^L. The decision information on qualitative attributes are provided by a group of decision makers, denoted by $T = \{t_k \mid k = 1, 2, \cdots, K\}$. Let $\lambda_j = \{\lambda_j^k \mid k = 1, 2, \cdots, K\}$ be a weight vector associated with decision makers for $c_j \in C^L$. Then the decision matrix provided by decision maker t_k can be denoted by $D^{L(k)} = [d_{ij}^{(k)}]_{mn^L}$. More specifically, therefore, the MAGDM algorithm can be described in four steps:

Step 1: aggregating information for the IFS

The evaluation criteria can be divided into two sets: the benefit criteria set $C_{Benefit}$ (where the higher the value, the better) and the cost criteria set C_{Cost} (where the smaller the value, the better), satisfying $C_{Benefit} \cap C_{Cost} = \varnothing$ and $C_{Benefit} \cup C_{Cost} = C$. In practice, the units in which attributes are measured are varied and non-standard. Therefore, the values within the decision matrices have to be normalised and transformed into IFNs, by implementing the following procedure:

1 For $c_j \in C^R$, the decision value d_{ij}^R is a positive real number. The corresponding intuitionistic fuzzy decision matrix $V^R = [V_{ij}^R]_{mn^R}$, in which $V_{ij}^R = (\mu_{ij}^R, \upsilon_{ij}^R)$, is calculated using the following formulae:

$$\mu_{ij}^R = \begin{cases} \dfrac{d_{ij}^R - \min d_j^R}{\max d_j^R - \min d_j^R} & c_j \in C_{Benefit} \\ \dfrac{\max d_j^R - d_{ij}^R}{\max d_j^R - \min d_j^R} & c_j \in C_{Cost} \end{cases} \tag{10}$$

$$\upsilon_{ij}^R = 1 - \mu_{ij}^R \tag{11}$$

where $\max d_j^R = \max\{d_{ij}^R \mid i = 1, 2, \cdots, m\}$ and $\min d_j^R = \min\{d_{ij}^R \mid i = 1, 2, \cdots, m\}$.

2 For $c_j \in C^I$, the decision value $d_{ij}^I = [d_{ij}^{IL}, d_{ij}^{IR}]$ is a positive interval number. Then, d_{ij}^I can be transformed into an IFN $V_{ij}^I = (\mu_{ij}^I, \upsilon_{ij}^I)$ based on equations (12) and (13), which is then an element within the intuitionistic fuzzy decision matrix $V^I = [V_{ij}^I]_{mn^I}$.

$$\mu_{ij}^I = \begin{cases} \dfrac{d_{ij}^{IL} - \min d_j^{IL}}{\max d_j^{IR} - \min d_j^{IL}} & c_j \in C_{Benefit} \\ \dfrac{\max d_j^{IR} - d_{ij}^{IR}}{\max d_j^{IR} - \min d_j^{IL}} & c_j \in C_{Cost} \end{cases} \tag{12}$$

$$\upsilon_{ij}^I = \begin{cases} \dfrac{\max d_j^{IR} - d_{ij}^{IR}}{\max d_j^{IR} - \min d_j^{IL}} & c_j \in C_{Benefit} \\ \dfrac{d_{ij}^{IL} - \min d_j^{IL}}{\max d_j^{IR} - \min d_j^{IL}} & c_j \in C_{Cost} \end{cases} \tag{13}$$

where $\max d_j^{IR} = \max\{d_{ij}^{IR} \mid i = 1, 2, \cdots, m\}$ and $\min d_j^{IL} = \min\{d_{ij}^{IL} \mid i = 1, 2, \cdots, m\}$.

3 For $c_j \in C^L$, assume that $L = (l_0, l_1, l_2, l_3, l_4, l_5, l_6)$ is the set of linguistic variables and that the decision value provided by decision maker t_k can be elicited as $d_{ij}^{(k)} = [d_{ij}^{L(k)}, d_{ij}^{R(k)}]$, where $d_{ij}^{L(k)}, d_{ij}^{R(k)} \in L$ and $d_{ij}^{L(k)} \prec d_{ij}^{R(k)}$. Based on the bipolar scaling transformation shown in Table 2 (Li, 2002), the value $d_{ij}^{(k)}$ can be quantified as an interval number $d_{ij}^{I(k)} = [d_{ij}^{IL(k)}, d_{ij}^{IR(k)}]$. The decision matrix $V^{L(k)} = [V_{ij}^{L(k)}]_{mn^L}$ can, therefore, be obtained by using equations (14) and (15).

$$\mu_{ij}^{L(k)} = \frac{d_{ij}^{IL(k)} - \min d_j^{IL(k)}}{\max d_j^{IR(k)} - \min d_j^{IL(k)}} \tag{14}$$

$$\upsilon_{ij}^{L(k)} = \frac{\max d_j^{IR(k)} - d_{ij}^{IR(k)}}{\max d_j^{IR(k)} - \min d_j^{IL(k)}} \tag{15}$$

where $\max d_j^{IR(k)} = \max\{d_{ij}^{IR(k)} \mid i = 1, 2, \cdots, m\}$ and $\min d_j^{IL(k)} = \min\{d_{ij}^{IL(k)} \mid i = 1, 2, \cdots, m\}$.

Table 2 Transformation of bipolar scaling

Benefit attribute	*ML*	*VL*	*L*	*M*	*H*	*VH*	*MH*
Cost attribute	MH	VH	H	M	L	VL	ML
Quantitative value	0	1	3	5	7	9	10
Standard value	0	0.0286	0.0857	0.1429	0.2000	0.2571	0.2857

Step 2: determination of decision makers' weights

In practice, decision makers provide the evaluation information on qualitative attributes according to their own knowledge, experience and preferences. Different decision makers may attach different weights (or values) to the different attributes affecting their decisions. This will inevitably influence the aggregation of individual decision information and, thus, the final result of the group decision. Obviously, there may exist some divergence between the opinions of the different decision makers and this could lead to some conflict in the decision information and arriving at the decision value of qualitative attributes. In this step, therefore, the decision makers' weights are determined by applying evidence theory to resolve such conflicts amongst individual decision makers.

In order to measure the evidence conflict as utilised in evidence theory, the degree of conflict between evidence bodies is calculated in accordance with the novel approach developed in Bao et al. (2017). By mixing Jousselme's et al. (2001) distance, probabilistic-based distance and the divergence degree between evidences by applying the Harnacher (1978) T-conorm, then the conflict function between evidence bodies can be defined. For two evidence bodies m_1 and m_2 in the identification framework $\Theta = \{\theta_1, \cdots, \theta_n, \cdots, \theta_N\}$, the degree of conflict, $CM(m_1, m_2)$, can be calculated as follows (Bao et al., 2017):

$$CM\left(m_1, m_2\right) = S^{(1/2)}\left(S^{(1/2)}\left(d_J^{(O)}, DiffP^{(2)}\right), CE_{BPA}\right) \tag{16}$$

where $S^{(1/2)}(x, y)$ is a function of the Harnacher T-conorm, $d_J^{(O)}$, $DiffP^{(2)}$ and CE_{BPA} are measures of Jousselme's distance, probabilistic-based distance and divergence degree, respectively. Their individual formulae can be defined as follows:

$$S^{(1/2)}(x, y) = \frac{2x + 2y - 3xy}{2 - xy} \tag{17}$$

$$d_J^{(O)}\left(m_1, m_2\right)=\sqrt{\frac{1}{2}\left(m_1-m_2\right) F_D\left(m_1-m_2\right)^T}, F_D(A, B)=\frac{|A \cap B|}{\sqrt{|A||B|}}, A, B \in 2^{\Theta} \tag{18}$$

$$DiffP^{(2)}\left(m_1, m_2\right)=\left[1-\sum_{\theta_i \in \Theta} \sqrt{P_1\left(\theta_i\right) P_2\left(\theta_i\right)}\right]^2 \tag{19}$$

$$\begin{aligned} E_{BPA}\left(m_1, m_2\right)=\sum\nolimits_{i=1}^{n} & \left\{\left(1+P_1\left(\theta_i\right)\right) \ln \frac{2\left(1+P_1\left(\theta_i\right)\right)}{\left(1+P_1\left(\theta_i\right)\right)+\left(1+P_2\left(\theta_i\right)\right)}\right. \\ & \left.\left[1+\left(1-P_1\left(\theta_i\right)\right)\right] \ln \frac{2\left[1+\left(1-P_1\left(\theta_i\right)\right)\right]}{\left[1+\left(1-P_1\left(\theta_i\right)\right)\right]+\left[1+\left(1-P_2\left(\theta_i\right)\right)\right]}\right\} \end{aligned} \tag{20}$$

$$CE_{BPA}\left(m_1, m_2\right)=\frac{1}{2T}\left(E_{BPA}\left(m_1, m_2\right)+E_{BPA}\left(m_2, m_1\right)\right) \tag{21}$$

where T = 2ln2 – 3(ln3 – ln2), $P_1(\theta_i)$ and $P_2(\theta_i)$ are the transformed probabilities of evidence bodies m_1 and m_2 and can be calculated according to Ma and An (2015), as follows:

$$P\left(\theta_i\right)=Bel\left(\theta_i\right)+\frac{BEL \cdot Bel\left(\theta_i\right)+(1-BEL) \cdot Pl\left(\theta_i\right)}{\sum_{\theta_i \in \Theta}\left[BEL \cdot Bel\left(\theta_i\right)+(1-BEL) \cdot Pl\left(\theta_i\right)\right]} \cdot(1-BEL) \tag{22}$$

where $BEL=\sum_{\theta_i \in \Theta} Bel(\theta_i)$ and $Bel(A)=\sum_{B \subseteq A} m(B)$ define the belief function associated with a BPA and $Pl(A)=\sum_{B \cap A \neq \varnothing} m(B)$ defines its plausibility function.

Within the context of the MAGDM problem analysed herein, the alternatives can be considered as identifiable objects. Thus, let $\Theta = \{a_1, \cdots, a_i, \cdots, a_m\}$ be the identification framework. The values provided by decision maker t_k on attribute c_j, denoted by $V_j^{L(k)}=[V_{ij}^{L(k)}]_{m \times 1}$, can be regarded as an evidence body. Then, the mass function can be calculated by:

$$m_j^k(\delta)=\begin{cases} 0 & \delta=\varnothing \\ \dfrac{\mu_{ij}^{L(k)}}{\sum_{i=1}^{m}\left(1-\upsilon_{ij}^{L(k)}\right)} & \delta=a_i \\ 1-\sum_{i=1}^{m} m_j^k\left(a_i\right) & \delta=\Theta \end{cases} \tag{23}$$

where $m_j^k(\Theta)$ can represent the uncertain information provided by decision maker t_k.

In group decision-making on qualitative attributes, a few decision makers' judgements may be significantly different from the majority of expert perspectives. Thus, these decision makers get less support from other decision makers and have higher conflict with most decision makers. In order to minimise the adverse effect of these outlying views on the final decision result, these decision makers should be allocated lower weights. In contrast, some decision makers' judgements are very similar and by supporting each other, these views should attract higher weights. In other words, the smaller is the degree of conflict, the higher is the value of the weight attached to the decision maker's view.

Let Sup_j^k be the degree of support for m_j^k, which is the degree of decision maker t_k supported by other decision makers and can be expressed as follows:

$$Sup_j^k = \sum_{l=1,l\neq k}^{K}\left(1-CM\left(m_j^k, m_j^l\right)\right) \tag{24}$$

Hence, the decision makers' weight vector $\lambda_j = \{\lambda_j^k \mid k = 1, 2, \cdots, K\}$ for $c_j \in C^L$ can be obtained:

$$\lambda_j^k = \frac{Sup_j^k}{\sum_{t=1}^{K} Sup_j^t} \tag{25}$$

Step 3: aggregation across attributes for each alternative

The intuitionistic fuzzy decision information in the matrices V^R, V^I and $V^{L(k)}$ (k = 1, 2, $\cdots$, K) needs to be aggregated to yield a comprehensive evaluation value of each alternative based on the algorithm of the ERA.

Firstly, the individual decision information of qualitative attributes and decision makers' weights can be integrated into group decision information based on equations (1)–(9). The intuitionistic fuzzy decision value $V_{ij}^{L(k)}$ can be considered as the performance value provided by decision maker t_k for alternative a_i in relation to qualitative attribute c_j. Because the value $V_{ij}^{L(k)}$ is represented by an IFN, a grade set can be defined as $H = \{H_h \mid h = 1, 2\}$, where $H_1 = (\mu^v, \upsilon^v) = (1, 0)$ when the performance is exactly the same as what the decision maker expected, and $H_2 = (\mu^v, \upsilon^v) = (0, 1)$ when the performance is worse. The assessment provided by decision maker t_k on qualitative attribute c_j for alternative a_i can be expressed as follows:

$$S\left(t_k\left(a_i, c_j\right)\right) = \left\{\left(H_h, \beta_{h,ij}^k\right) \middle| h = 1, 2\right\} \tag{26}$$

where $\beta_{1,ij}^k = \mu_{ij}^{L(k)}$ and $\beta_{2,ij}^k = \upsilon_{ij}^{L(k)}$.

If $\sum_{h=1}^{2} \beta_{h,ij}^k = 1$, i.e., $\mu_{ij}^{L(k)} + \upsilon_{ij}^{L(k)} = 1$ and $\pi_{ij}^{L(k)} = 1 - \mu_{ij}^{L(k)} - \upsilon_{ij}^{L(k)} = 0$, there is no hesitancy on the part of decision maker t_k with respect to the judgement of alternative a_i on attribute c_j. If $\sum_{h=1}^{2} \beta_{h,ij}^k < 1$, there exists uncertainty in the assessment $S(t_k(a_i, c_j))$. Let $H_H = (0, 0)$ represent the evaluation grade of hesitancy. Then we can obtain $\beta_{H,ij}^k$, the degree of belief for alternative a_i belonging to the grade of hesitancy as $\beta_{H,ij}^k = 1 - \sum_{h=1}^{2} \beta_{h,ij}^k$. Therefore, the assessment provided by a group of decision makers can be denoted as a belief structure shown in equation (26). The ERA algorithm can be used to calculate the group decision values $S^L(c_j(a_i))$ by aggregating $S(t_k(a_i, c_j))$ and the decision maker' weights λ_j.

$$S^L\left(c_j\left(a_i\right)\right)=\left\{\left(H_h, \beta_{h,ij}^L\right)\middle| h=1,2\right\}, c_j \in C^L \tag{27}$$

Secondly, the evaluation information of the quantitative criteria which are contained in the intuitionistic fuzzy decision matrices V_{ij}^R and V_{ij}^I can be expressed as:

$$S^R\left(c_j\left(a_i\right)\right)=\left\{\left(H_h, \beta_{h,ij}^R\right)\middle| h=1,2\right\}, c_j \in C^R \tag{28}$$

$$S^I\left(c_j\left(a_i\right)\right)=\left\{\left(H_h, \beta_{h,ij}^I\right)\middle| h=1,2\right\}, c_j \in C^I \tag{29}$$

where $\beta_{1,ij}^R=\mu_{ij}^R$, $\beta_{2,ij}^R=\upsilon_{ij}^R$, $\beta_{1,ij}^I=\mu_{ij}^I$ and $\beta_{2,ij}^I=\upsilon_{ij}^I$.

Thirdly, the assessment $S^R(c_j(a_i))$, $S^I(c_j(a_i))$ and $S^L(c_j(a_i))$ can be synthesised into the decision values for alternative a_i in relation to attribute c_j, as follows:

$$S\left(c_j\left(a_i\right)\right)=S^R\left(c_j\left(a_i\right)\right)\cup S^I\left(c_j\left(a_i\right)\right)\cup S^L\left(c_j\left(a_i\right)\right)=\left\{\left(H_h, \beta_{h,ij}\right)\middle| h=1,2\right\} \tag{30}$$

Finally, based on equations (1)–(9), the aggregation process for decision values on criteria for each alternative can be completed and then the alternative a_i is assessed to grade H_h with degree of belief $\beta_{h,i}$, as follows:

$$S\left(a_i\right)=\left\{\left(H_h, \beta_{h,i}\right)\middle| h=1,2\right\}, i=1,2,\cdots,m \tag{31}$$

Therefore, the intuitionistic fuzzy comprehensive value of alternative a_i is stated as:

$$V\left(a_i\right)=\left(\mu_i^v, \upsilon_i^v\right), i=1,2,\cdots,m \tag{32}$$

where, $\mu_i^v=\beta_{1,i}$ and $\upsilon_i^v=\beta_{2,i}$.

Step 4: ranking the alternatives

After the aggregation of the decision information in the matrices V^R, V^I and $V^{L(k)}$, a set of comprehensive values can be obtained for each alternative $a_i \in A$, which is denoted by $V=\{\langle a_i, \mu_i^v, \upsilon_i^v\rangle, i=1,2,\cdots,m\}$. Using Definition 2, the ranking and prioritisation of alternatives can be determined by comparing the intuitionistic fuzzy values in V.

5 Empirical application

5.1 Problem description

The uncertain and fuzzy information which pervades the performance evaluation of green port within the context of its supply chain can be aggregated and analysed through the application of the proposed algorithm founded on evidence theory. To demonstrate the proposed procedure, four Chinese port companies provide the basis for an empirical example. To maintain anonymity, these are referred to as port companies A1 to A4. The numerical values relating to their quantitative attributes have been collected from their corporate annual reports and through a detailed analysis of each of their supply chains. In addition, three decision makers t_1, t_2 and t_3 have been invited to carry out an evaluation of their qualitative attributes by utilising linguistic variables, i.e., the linguistic terms of benefit attributes shown in Table 2. The decision matrices for the qualitative and quantitative attributes are listed in Table 3 and Table 4, respectively. The weights of the criteria, in the form of real numbers, are also determined based on three decision makers' judgements, as follows:

- $W = \{0.3, 0.2, 0.15, 0.15, 0.1, 0.1\}$, for six dimensions D1 to D6
- $W(D1) = \{0.2, 0.2, 0.3, 0.3\}$, for finance attributes F1 to F4
- $W(D2) = \{0.4, 0.3, 0.3\}$, for customer attributes C1 to C3
- $W(D3) = \{0.3, 0.2, 0.3, 0.2\}$, for business process attributes P1 to P4
- $W(D4) = \{0.2, 0.4, 0.4\}$, for learning and development attributes L1 to L3
- $W(D5) = \{0.5, 0.5\}$, for supplier attributes S1 to S2
- $W(D6) = \{0.2, 0.2, 0.2, 0.2, 0.2\}$, for green performance G1 to G5.

Table 3 The decision values of quantitative attributes

	F1	*F2*	*F3*	*F4*	*C1*	*P4*	*S1*
A1	0.21	41.49	28.02	20.67	0.28	[24, 48]	0.98
A2	0.22	36.20	23.60	22.31	0.15	[24, 48]	0.92
A3	0.19	41.13	7.97	12.24	0.08	[48, 72]	0.95
A4	0.17	30.40	19.16	18.79	0.04	[48, 72]	0.96

5.2 Application of proposed approach

Step 1 In general, port companies would like to pursue smaller values of attributes F2 and P4 and higher values of other attributes to improve their competitiveness. Therefore, attributes F2 and P4 are regarded as cost attributes, while other attributes are benefit attributes. The decision matrices are firstly normalised and transformed into intuitionistic fuzzy numbers based on equations (10)–(15) and Table 2, and are listed in Tables 5 and 6.

Step 2 For each qualitative attribute, the decision makers' weights are determined based on the degree of conflict between the decision makers' decision values [see equations (16)–(25)] and are presented in Table 7.

Step 3 The comprehensive value of each alternative is calculated, based on the algorithm of the ERA:

a In accordance with equations (1)–(9) and equation (26), the individual intuitionistic fuzzy decision matrix $V^{L(k)}$ shown in Table 5 and the decision makers' weight vector λ_j presented in Table 7, can be aggregated into the group decision values of qualitative attributes, listed in Table 8.

b For each dimension, the intuitionistic fuzzy decision values of related attributes shown in Table 1 or Table 2 and the weights of these attributes, can be integrated into the intuitionistic fuzzy values of dimensions by using equations (1)–(9) and equations (27)–(29). For example, there exist four attributes for the finance dimension, which are F1, F2, F3 and F4. Based on the intuitionistic fuzzy values of these attributes (see Table 3) and the weight vector *W*(*D*1) (see *Step 1*), the intuitionistic fuzzy values of the finance dimension can be determined by adopting the algorithm of the ERA and are shown in Table 9.

c Aggregating the intuitionistic fuzzy values and the weights of dimensions (see Table 1 and *Step 1*), the comprehensive value of each alternative $V(a_i)$ can be calculated by using equations (1)–(9) and equations (31)–(32), as follows.

$$V(A1) = (0.75, 0.16); V(A2) = (0.67, 0.24);$$
$$V(A3) = (0.25, 0.65); V(A4) = (0.49, 0.4)$$

Step 4 All the alternatives can then be ranked in accordance with their comprehensive intuitionistic fuzzy values $V(a_i)$ based on the score function and the accuracy function of the IFS (see Definition 2), as shown in Figure 3. It is then obvious that $S(A1) > S(A2) > S(A4) > S(A3)$ and that, therefore, the ranking of the four Chinese port companies can be obtained: $\mathrm{A1} \succ \mathrm{A2} \succ \mathrm{A4} \succ \mathrm{A3}$, where the symbol '$\succ$' means 'superior to'.

Figure 3 The comprehensive evaluation results of alternatives (see online version for colours)

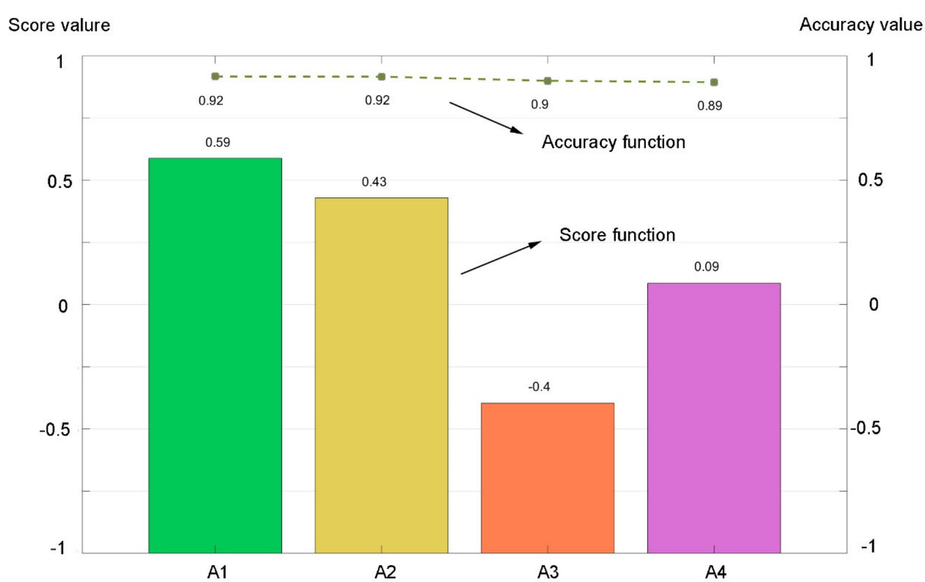


Table 4 The decision values of qualitative attributes provided by three decision makers

	t_1				t_2				t_3			
	A1	*A2*	*A3*	*A4*	*A1*	*A2*	*A3*	*A4*	*A1*	*A2*	*A3*	*A4*
C2	[VH, MH]	[VH, MH]	[L, M]	[VH, MH]	[VH, MH]	[M, MH]	[H, VH]	[L, M]	[L, M]	[VH, MH]	[L, M]	[VH, MH]
C3	[H, VH]	[L, M]	[M, H]	[H, VH]	[VH, MH]	[M, H]	[H, VH]	[H, VH]	[H, MH]	[VH, MH]	[L, H]	[M, MH]
P1	[VH, MH]	[VH, MH]	[L, H]	[VH, MH]	[VH, MH]	[VH, MH]	[H, VH]	[L, M]	[L, VH]	[VH, MH]	[L, M]	[VH, MH]
P2	[VH, MH]	[M, H]	[VH, MH]	[L, M]	[L, M]	[M, H]	[VH, MH]	[M, H]	[VH, MH]	[VH, MH]	[L, M]	[M, H]
P3	[M, H]	[VH, MH]	[VH, MH]	[VH, MH]	[VH, MH]	[L, M]	[VH, MH]	[M, H]	[M, MH]	[VH, MH]	[M, H]	[VH, MH]
L1	[H, VH]	[L, M]	[VH, MH]	[VH, MH]	[L, MH]	[M, VH]	[H, VH]	[M, H]	[L, M]	[M, H]	[L, M]	[L, M]
L2	[H, VH]	[VH, MH]	[H, VH]	[M, H]	[M, H]	[VH, MH]	[H, MH]	[H, VH]	[VH, MH]	[H, VH]	[H, VH]	[L, VH]
L3	[H, VH]	[L, M]	[H, VH]	[L, VH]	[VH, MH]	[M, H]	[VH, MH]	[VH, MH]	[VH, MH]	[H, VH]	[M, H]	[H, VH]
S2	[M, H]	[L, M]	[L, VH]	[VH, MH]	[M, H]	[H, VH]	[L, M]	[L, MH]	[M, MH]	[L, H]	[L, VH]	[L, M]
G1	[H, VH]	[M, MH]	[VH, MH]	[L, M]	[H, VH]	[VH, MH]	[VH, MH]	[L, VH]	[L, M]	[L, VH]	[M, H]	[L, M]
G2	[M, H]	[M, H]	[VH, MH]	[VH, MH]	[H, VH]	[M, H]	[L, M]	[M, H]	[VH, MH]	[VH, MH]	[M, VH]	[M, VH]
G3	[L, M]	[M, H]	[M, VH]	[H, VH]	[L, M]	[VH, MH]	[M, H]	[H, VH]	[M, H]	[VH, MH]	[M, H]	[L, M]
G4	[H, VH]	[VH, MH]	[M, H]	[H, VH]	[L, M]	[H, VH]	[M, VH]	[H, MH]	[VH, MH]	[M, H]	[L, M]	[M, H]
G5	[H, VH]	[L, MH]	[L, M]	[M, H]	[H, MH]	[H, VH]	[M, H]	[L, M]	[L, M]	[L, MH]	[VH, MH]	[VH, MH]

Table 5 The intuitionistic fuzzy decision values of qualitative attributes

	t_1				t_2				t_3			
	A1	*A2*	*A3*	*A4*	*A1*	*A2*	*A3*	*A4*	*A1*	*A2*	*A3*	*A4*
C2	(0.86, 0)	(0.86, 0)	(0, 0.71)	(0.86, 0)	(0.86, 0)	(0.29, 0)	(0.57, 0.14)	(0, 0.71)	(0, 0.71)	(0.86, 0)	(0, 0.71)	(0.86, 0)
C3	(0.67, 0)	(0, 0.67)	(0.33, 0.33)	(0.67, 0)	(0.8, 0)	(0, 0.6)	(0.4, 0.2)	(0.4, 0.2)	(0.57, 0)	(0.86, 0)	(0, 0.43)	(0.29, 0)
P1	(0.86, 0)	(0.86, 0)	(0, 0.43)	(0.86, 0)	(0.86, 0)	(0.86, 0)	(0.57, 0.14)	(0, 0.71)	(0, 0.14)	(0.86, 0)	(0, 0.71)	(0.86, 0)
P2	(0.86, 0)	(0.29, 0.43)	(0.86, 0)	(0, 0.71)	(0, 0.71)	(0.29, 0.43)	(0.86, 0)	(0.29, 0.43)	(0.86, 0)	(0.86, 0)	(0, 0.71)	(0.29, 0.43)
P3	(0, 0.6)	(0.8, 0)	(0.8, 0)	(0.8, 0)	(0.86, 0)	(0, 0.71)	(0.86, 0)	(0.29, 0.43)	(0, 0)	(0.8, 0)	(0, 0.6)	(0.8, 0)
L1	(0.57, 0.14)	(0, 0.71)	(0.86, 0)	(0.86, 0)	(0, 0)	(0.29, 0.14)	(0.57, 0.14)	(0.29, 0.43)	(0, 0.5)	(0.5, 0)	(0, 0.5)	(0, 0.5)
L2	(0.4, 0.2)	(0.8, 0)	(0.4, 0.2)	(0, 0.6)	(0, 0.6)	(0.8, 0)	(0.4, 0)	(0.4, 0.2)	(0.86, 0)	(0.57, 0.14)	(0.57, 0.14)	(0, 0.14)
L3	(0.67, 0)	(0, 0.67)	(0.67, 0)	(0, 0)	(0.8, 0)	(0, 0.6)	(0.8, 0)	(0.8, 0)	(0.8, 0)	(0.4, 0.2)	(0, 0.6)	(0.4, 0.2)
S2	(0.29, 0.43)	(0, 0.71)	(0, 0.14)	(0.86, 0)	(0.29, 0.43)	(0.57, 0.14)	(0, 0.71)	(0, 0)	(0.29, 0)	(0, 0.43)	(0, 0.14)	(0, 0.71)
G1	(0.57, 0.14)	(0.29, 0)	(0.86, 0)	(0, 0.71)	(0.57, 0.14)	(0.86, 0)	(0.86, 0)	(0, 0.14)	(0, 0.67)	(0, 0)	(0.33, 0.33)	(0, 0.67)
G2	(0, 0.6)	(0, 0.6)	(0.8, 0)	(0.8, 0)	(0.67, 0)	(0.33, 0.33)	(0, 0.67)	(0.33, 0.33)	(0.8, 0)	(0.8, 0)	(0, 0.2)	(0, 0.2)
G3	(0, 0.67)	(0.33, 0.33)	(0.33, 0)	(0.67, 0)	(0, 0.71)	(0.86, 0)	(0.29, 0.43)	(0.57, 0.14)	(0.29, 0.43)	(0.86, 0)	(0.29, 0.43)	(0, 0.71)
G4	(0.4, 0.2)	(0.8, 0)	(0, 0.6)	(0.4, 0.2)	(0, 0.71)	(0.57, 0.14)	(0.29, 0.14)	(0.57, 0)	(0.86, 0)	(0.29, 0.43)	(0, 0.71)	(0.29, 0.43)
G5	(0.57, 0.14)	(0, 0)	(0, 0.71)	(0.29, 0.43)	(0.57, 0)	(0.57, 0.14)	(0.29, 0.43)	(0, 0.71)	(0, 0.71)	(0, 0)	(0.86, 0)	(0.86, 0)

Table 6 The intuitionistic fuzzy decision values of quantitative attributes

	F1	*F2*	*F3*	*F4*	*C1*	*P4*	*S1*
A1	(0.8, 0.2)	(0, 1)	(1, 0)	(0.84, 0.16)	(1 ,0)	(0.5, 0)	(1, 0)
A2	(1, 0)	(0.48, 0.52)	(0.78, 0.22)	(1, 0)	(0.46, 0.54)	(0.5, 0)	(0, 1)
A3	(0.4, 0.6)	(0.03, 0.97)	(0, 1)	(0, 1)	(0.17, 0.83)	(0, 0.5)	(0.5, 0.5)
A4	(0, 1)	(1, 0)	(0.56, 0.44)	(0.65, 0.35)	(0,1)	(0, 0.5)	(0.67, 0.33)

Table 7 The decision makers' weights for each qualitative attribute

	C2	*C3*	*P1*	*P2*	*P3*	*L1*	*L2*	*L3*	*S2*	*G1*	*G2*	*G3*	*G4*	*G5*
t_1	0.38	0.35	0.36	0.36	0.37	0.31	0.35	0.34	0.31	0.34	0.28	0.33	0.36	0.35
t_2	0.30	0.35	0.31	0.33	0.29	0.37	0.32	0.34	0.34	0.34	0.37	0.35	0.33	0.34
t_3	0.32	0.3	0.33	0.31	0.34	0.32	0.33	0.32	0.35	0.32	0.35	0.32	0.31	0.31

Table 8 The group decision values of qualitative attributes for each alternative

	C2	*C3*	*P1*	*P2*	*P3*	*L1*	*L2*
A1	(0.65, 0.2)	(0.77, 0)	(0.69, 0.04)	(0.64, 0.2)	(0.3, 0.26)	(0.22, 0.25)	(0.48, 0.26)
A2	(0.78, 0)	(0.26, 0.48)	(0.9, 0)	(0.51, 0.29)	(0.64, 0.17)	(0.29, 0.31)	(0.8, 0.04)
A3	(0.15, 0.61)	(0.29, 0.36)	(0.18, 0.5)	(0.66, 0.19)	(0.61, 0.18)	(0.54, 0.2)	(0.53, 0.12)
A4	(0.67, 0.18)	(0.55, 0.07)	(0.66, 0.19)	(0.17, 0.6)	(0.73, 0.1)	(0.41, 0.33)	(0.14, 0.39)
	L3	*S2*	*G1*	*G2*	*G3*	*G4*	*G5*
A1	(0.83, 0)	(0.32, 0.32)	(0.42, 0.32)	(0.61, 0.14)	(0.08, 0.69)	(0.45, 0.31)	(0.44, 0.28)
A2	(0.12, 0.57)	(0.2, 0.48)	(0.51, 0)	(0.45, 0.29)	(0.76, 0.09)	(0.63, 0.16)	(0.27, 0.07)
A3	(0.57, 0.18)	(0, 0.44)	(0.76, 0.08)	(0.24, 0.37)	(0.34, 0.33)	(0.09, 0.57)	(0.37, 0.42)
A4	(0.51, 0.07)	(0.31, 0.29)	(0, 0.62)	(0.41, 0.21)	(0.46, 0.28)	(0.48, 0.21)	(0.38, 0.41)

Table 9 The intuitionistic fuzzy decision values of dimensions for each alternative

	D1	*D2*	*D3*	*D4*	*D5*	*D6*
A1	(0.69, 0.31)	(0.88, 0.04)	(0.61, 0.12)	(0.65, 0.14)	(0.75, 0.12)	(0.43, 0.37)
A2	(0.85, 0.15)	(0.53, 0.37)	(0.75, 0.09)	(0.47, 0.3)	(0.07, 0.81)	(0.61, 0.12)
A3	(0.08, 0.92)	(0.18, 0.7)	(0.41, 0.36)	(0.62, 0.15)	(0.28, 0.52)	(0.39, 0.38)
A4	(0.56, 0.44)	(0.34, 0.54)	(0.51, 0.3)	(0.38, 0.27)	(0.54, 0.32)	(0.38, 0.38)

6 Results

According to the ranking of alternatives $A1 \succ A2 \succ A4 \succ A3$, it is clear that port company A1 has the best performance level in terms of a comprehensive consideration of all the relevant attributes identified for the six dimensions of the conceptual model. In addition, the ranking order for each of the six dimensions can be seen in Figure 4.

As seen from Figure 4:

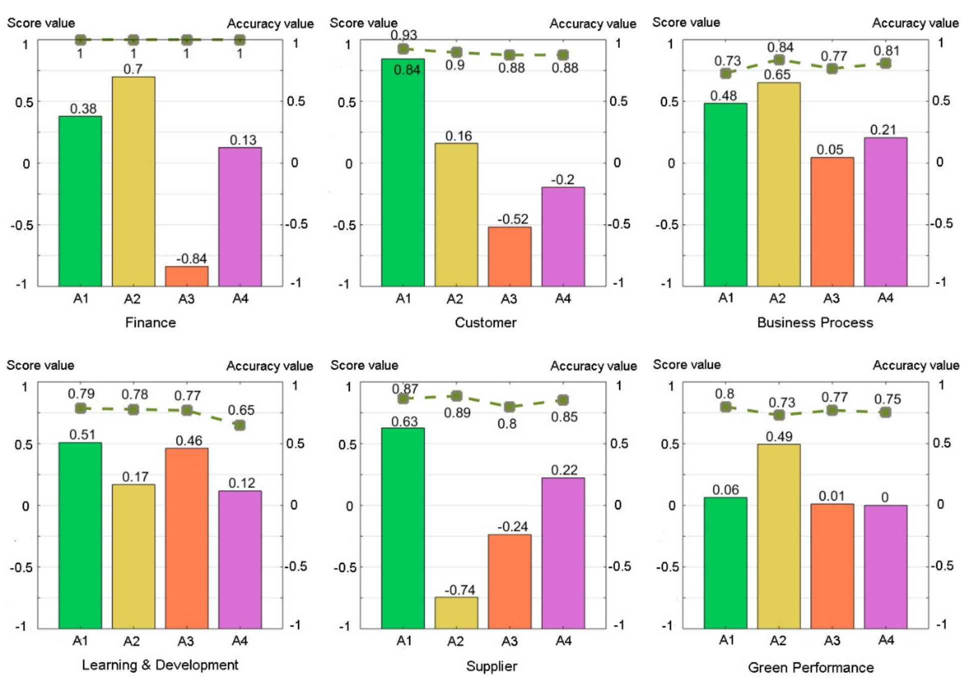
1 For both finance dimension (D1) and business process dimension (D3), the order of ranking is $A2 \succ A1 \succ A4 \succ A3$; the ranking of alternatives with respect to customer dimension (D2) is $A1 \succ A2 \succ A4 \succ A3$; the ranking for learning and growth (D4) is $A1 \succ A3 \succ A2 \succ A4$; the order with respect to suppliers (D5) and green performance (D6) are $A1 \succ A4 \succ A3 \succ A2$ and $A2 \succ A1 \succ A3 \succ A4$, respectively.

2 For the finance dimension (D1), business process dimension (D3) and green performance dimension (D6), the optimal alternative is port company A2. Alternative A1 has the best performance level for the customer dimension (D2), learning and growth dimension (D4) and the supplier dimension (D5). However, port company A1 ranks first or second for all dimensions, so it is hardly surprising that A1 is the optimum solution for overall performance evaluation.

3 Due to the inherent uncertainty associated with the use of interval numbers and linguistic variables, there exists uncertainty in the evaluation results for the customer dimension (D2), the business process dimension (D3), the learning and growth dimension (D4), the supplier dimension (D5) and the green performance dimension (D6). Obviously, the accuracy values of the intuitionistic fuzzy evaluation results for these dimensions are less than 1. However, because the decision values are real numbers for the finance dimension (D1), the evaluation results for D1 are certain, that is:

$$\mathcal{H}_{D1}(A1) = \mathcal{H}_{D1}(A2) = \mathcal{H}_{D1}(A3) = \mathcal{H}_{D1}(A4) = 1$$

Figure 4 The evaluation results of alternatives for each dimension (see online version for colours)



7 Conclusions

By extending the 5DBSC model (Liu and Yi, 2016) to encompass green performance, this paper develops and expounds a performance evaluation model for green port within the context of its supply chain. The model accounts for uncertainty in the evaluations of both quantitative and qualitative attributes from six dimensions: finance, customer, business process, learning and growth, supplier and green performance. In order to solve this sort of MAGDM problem which caters for uncertainty in the evaluations, an approach based on integrating IFS theory and evidential reasoning is proposed. Such an approach is deemed to effectively represent the subjective uncertainty and vagueness of decision makers in making evaluations, while at the same time minimising the loss of decision-making information. An empirical application to Chinese port companies provides evidence of the suitability of both the evaluation model and the proposed approach to its solution. The objective of this empirical application is to determine a ranking of the port company alternatives in terms of a holistic performance evaluation of green port within the context of its supply chain which encompasses both environmental and non-environmental criteria.

The evaluation results provide not only the ranking order of all alternative port enterprises, but also the strengths and weaknesses of each alternative enterprise, at the detailed level of individual performance attributes. The results have several potential implications for managers in the port and shipping industry:

- Most importantly, putting into practice the performance evaluation of any green port within the context of its supply chain is a complex matter, since it involves catering for multiple performance attributes, uncertain information and the aggregation of the diverse opinions of an expert group. By utilising the approach advocated herein, managers can effectively deal with this complexity and proceed to formally evaluate the performance of their green port within the context of its supply chain.
- Port companies can identify the direction of future development and prioritise improvement strategies for the greening of their port supply chain. The performance values for both the dimensions and attributes can assist port managers to define which aspects within their organisation require most attention and, therefore, where resources should be most appropriately allocated. For example, according to the evaluation results for each dimension (see Figure 4), although port company A1 is the best performing alternative overall (see Figure 3), there is still room for improvement in the dimensions of green performance, finance and business process. For port company A2, although its performance in terms of the finance, business process and green performance dimensions is ranked highest amongst all alternative port enterprises, there remains an obvious gap between A2 and other port companies in the supplier dimension. Thus, the management of port company A2 should prioritise and focus on improving those attributes related to the supplier dimension. Moreover, for port companies A3 and A4 respectively, the level of performance in the finance and customer dimensions should be paid greater attention as this is where the largest gaps exist between these two companies and the alternative with the best performance in these dimensions.
- The ranking of alternative enterprises that results from the analysis has the potential to provide managers of port companies with the basis for benchmarking against other

port companies and, thereby, secure continuous improvements in operational, environmental and economic performance.

- Indeed, by emphasising the relevance and importance of the environmental attributes of port supply chains, the results from this form of performance evaluation could actually encourage managers to actively develop, implement and inculcate green practices within the process of port supply chain management in which they are engaged.

Finally, it is important to emphasise that the approach and methodology outlined and applied within this work is not limited solely to evaluate the performance of green port within the context of its supply chain. The proposed approach is sufficiently flexible to be utilised in numerous other MAGDM contexts where uncertainty is present. The proposed MAGDM approach also has its limitations. For example:

1 Due to the complicated computations of the MAGDM algorithm, it is difficult for port managers who have no professional and theoretical decision knowledge to understand and apply the MAGDM approach to evaluate green port performance.

2 As the number of decision makers increases, the evaluation process will be more complex, and the proposed MAGDM approach may not cope with these problems effectively and quickly.

Therefore, the auxiliary decision system based on the MAGDM approach will be constructed to simplify calculations and facilitate the decisions of port managers. It will also be further extended to address the more complicated problems with more decision makers.

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