Transportation Research Part D 36 (2015) 29–44

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Location selection of city logistics centers under sustainability

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ARTICLE INFO

Article history:
Available online 6 March 2015

Keywords:
City logistics centers
Location selection
Sustainability
THOWA operator
TOPSIS

ABSTRACT

City Logistics Centers (CLC) are an important part of the modern urban logistics system, and the selection of the location of a CLC has become a key problem in logistics and supply chain management. Integrating the economic, environmental, and social dimensions of sustainable development, this paper presents a new evaluation system for the location selection of a CLC from a sustainability perspective. A fuzzy multi-attribute group decision making (FMAGDM) technique based on a linguistic 2-tuple is used to evaluate potential alternative CLC locations. In this method, the linguistic evaluation values of all the evaluation criteria are transformed into linguistic 2-tuples. A new 2-tuple hybrid ordered weighted averaging (THOWA) operator is presented to aggregate the overall evaluation values of all experts into a collective evaluation value for each alternative, which is then used to rank and select alternative CLC locations. An application example is provided to validate the method developed and to highlight the implementation, practicality, and effectiveness by comparing with the fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method.

Introduction

Since the start of this decade, more than 100 million people have migrated to cities globally (Lee, 2014). By 2050, the World Health Organisation estimates that at least 70% of the world's population will live in cities (Lee, 2014). Cities, being an accelerator for economic growth, will continue to grow and propel the much needed economic development for a country. Indeed, urban logistics has become an important part of a city's growth and development. An advanced and well developed city logistics system can hasten the rate of economic growth, reduce unnecessary transaction cost, enhance economic efficiency, improve investment climate, increase foreign direct investment, solve urban unemployment, and promote the development of the regional economy. However, studies also show that the last mile of the urban logistics system is the most expensive, inefficient and pollutive part of the supply chain (Gevaers et al., 2009). Thus, there is an imperative to improve urban logistics so that people can live, work and play in a high quality environment. Logistics infrastructure, notably the logistics centres servicing the logistics needs of a city, needs to be blended well with the rest of the supply chain.

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http://dx.doi.org/10.1016/j.trd.2015.02.008

As a key logistics node, the City Logistics Center (CLC) is an important part of the modern urban logistics system, and has a pivotal position in the logistics system. A CLC is described as a logistics facility that is situated in relatively close proximity to the geographic area that it serves, be that a city center, an entire town or a specific site (e.g. shopping mall), from which consolidated deliveries are performed within that vicinity (Crainic et al., 2009). A range of other value-added logistics and retail services can also be provided at the CLC. The selection of the location of a CLC has become a key concern in logistics and supply chain management practice and design. The rationality and feasibility of the location selection and layout of the CLC affects the functioning, efficiency, and external costs for the city and her residents. For a start, a well considered CLC will reduce the logistics cost, improve the efficiency of transport flows, improve a citizen's living condition, sustain the city's economic vitality and can contribute to the harmonious development of the economy, environment and society. However, a poorly designed CLC can trigger a series of negative externalities and external costs, such as greater traffic congestion, increased emissions, road safety, and damaged urban image. Hence, a study on the selection of the location of a CLC from the perspective of the different stakeholders and their conflicting objectives has valuable theoretical significance and application merit.

From the literature, the CLC location selection problem can be classified as a special case of the facility location problem (FLP) (Owen and Daskin, 1998; Melo et al., 2009; Beresnev, 2013). It is a complex decision which involves the consideration of multiple factors including politics, economics, infrastructure, environment, competition, development strategy, product features, logistics cost, and customer service levels. The study of location theory formally began in 1909 when Weber first considered how to position a single warehouse so as to minimize the total distance between it and several customers (Owen and Daskin, 1998). Since the 1970s, the literature is replete with work on location theory. We name a few recent key works for completeness, for example, the hybrid multi-start heuristic (Resende and Werneck, 2006), second-order cone programming (Wagner et al., 2009), approximation algorithms (Huang and Li, 2008; Li, 2013), greedy heuristic and fix-and-optimize heuristic (Ghaderi and Jabalameli, 2013), Lagrangian relaxation heuristic (Nezhad et al., 2013), mixed integer linear programming model (Kratica et al., 2014), discrete variant of unconscious search (Ardjmand et al., 2014), multi-objective optimization model (Tang et al., 2013), and the weighted Dantzig–Wolfe decomposition and path-relinking combined method (Li et al., 2014), which have been presented for solving an uncapacitated facility location problem. Also, some algorithms and methods have been proposed for solving the capacitated facility location problem to optimality such as the mixed integer programming formulation (Melkote and Daskin, 2001; Aros-Vera et al., 2013; Rosa et al., 2014), branch-and-price algorithm (Klose and Görtz, 2007), Lagrangian heuristic algorithm (Wu et al., 2006; Elhedhli and Merrick, 2012), kernel search heuristic (Guastaroba and Speranza, 2014), Lagrangian Heuristic and Ant Colony System (Chen and Ting, 2008), Lagrangian relaxation algorithm (Yun et al., 2014), a fix-and-optimize heuristic based on the evolutionary fire-fly algorithm (Rahmaniani and Ghaderi, 2013), hybrid Firefly-Genetic Algorithm (Rahmani and MirHassani, 2014), swarm intelligence based on sample average approximation (Aydin and Murat, 2013), modified Clarke and Wright savings heuristic algorithm (Li et al., 2015), iterated tabu search heuristic (Ho, 2015), improved approximation algorithm (Aardal et al., 2015), two-stage robust models and algorithms (An et al., 2014), and the evolutionary multi-objective optimization approach (Rakas et al., 2004; Harris et al., 2014).

Much of the literature have studied the location selection problem under a certain and deterministic environment, that is, the parameters in the problem are fixed and known. In other words, many facility location problems were characterized as static and deterministic. These problems take constant, known quantities as inputs and derive a single solution to be implemented at a point in time. In practice, due to the complexity of the decision-making environment and their ambiguity, many parameters in the FLP are difficult to obtain with certainty. To deal with the decision of the FLP under an uncertain environment, fuzzy theory is developed and applied. For example, Chu (2002) proposed a fuzzy TOPSIS method under group decisions to solve the FLP. Likewise, Kahraman et al. (2003) proposed another solution approach of fuzzy multi-attribute group decision-making to solve the FLP. Wen and Iwamura (2008) have presented a new a-cost model under the Hurwicz criterion with fuzzy demands to solve the FLP under uncertainty and produced a hybrid intelligent algorithm to solve this model. Chou et al. (2008) present a new fuzzy multiple attribute decision-making approach, i.e., fuzzy simple additive weighting system, for solving the FLP by using objective/subjective attributes under group decision-making conditions. Önüt et al. (2010) proposed a combined fuzzy multi criteria decision making (MCDM) approach based on the fuzzy AHP and fuzzy TOPSIS techniques for selecting a suitable shopping center location. Li et al. (2011) used the axiomatic fuzzy set and TOPSIS method to select the CLC location. Wang and Watada (2012) studied a facility location model with fuzzy random parameters and its swarm intelligence approach, and established a Value-at-Risk (VaR) based fuzzy random facility location model (VaR-FRFLM) in which both the costs and demands are assumed to be fuzzy random variables. Recently, Ozgen and Gulsun (2014) combined possibilistic linear programming with fuzzy AHP to solve the multi-objective capacitated multi-FLP. Mokhtarian et al. (2014) proposed an Interval Valued Fuzzy-VlseKriterijumska Optimizacija I Kompromisno Resenje (IVF-VIKOR) method based on uncertainty risk reduction in the decision making process of facility location selection.

The traditional criteria applied to the FLP have predominantly focused on minimizing the economic cost or maximizing customer service level. With the emphasis on social responsibility and greater environmental awareness, this goal has now grown to include the selection of facility location with another criterion, that of sustainability, which means we must pay greater attention to address the challenging requirements of a sustainable facility location under the considerations of economic, environmental, and social dimensions. The considerations of both economic and environmental considerations in facility location selection decisions do exist (Melo et al., 2009; Harris et al., 2014), albeit scarce. This makes the consideration of economic, environmental, and social dimensions in facility location selection under uncertain environment more pertinent. Our first contribution in this paper is therefore to include the three dimensions and provide a practical slant to the class of fuzzy MCDM problems.

In this paper, we study the problem of location selection of a sustainable CLC under a fuzzy information environment, and present a fuzzy multi-attribute group decision making (FMAGDM) method based on a 2-tuple hybrid ordered weighted averaging (*THOWA*) operator for the location selection of a sustainable CLC. Our second contribution is thus to provide a theoretical basis and decision-making reference to help business select optimal CLC locations under sustainability.

The rest of the paper is organized as follows. Section ‘Evaluation criteria for location selection of CLC under sustainability’ describes the problem and presents the evaluation criteria for the location selection of a CLC from the dimensions of sustainable development – economic, environmental, and social. Section ‘Decision method for location selection of CLC’ presents a FMAGDM method based on the *THOWA* operator under a fuzzy environment. In Section ‘Numerical illustration’, we present a numerical application of the location selection of a sustainable CLC to show the feasibility of the proposed decision method. Section ‘Conclusion’ concludes the paper.

Evaluation criteria for location selection of CLC under sustainability

As many factors impact the location of a CLC, the location selection of a CLC can be treated as a multi-attribute decision making problem. Integrating the three dimensions of sustainability, economic, environmental, and social, this paper uses the following 13 criteria from a sustainability perspective to evaluate and select the potential location(s) for a CLC (Elhedhli and Merrick, 2012; Tang et al., 2013; Holmgren et al., 2014; Wang et al., 2014; Mohammadi et al., 2014; Chen et al., 2014).

Economic criteria

Price of acquiring land (A_1). A CLC generally covers a large area, and always requires enough surrounding space for development and to be able to run smoothly. Land price has a close relationship with location choice. A higher land price can increase the investment cost of the CLC construction, which will affect the scale of construction of the CLC.

Upside delivery flexibility (A_2) is the total elapsed time between the occurrence of an unplanned event and the achievement of a sustained delivery performance. A good location of a CLC should meet all necessary delivery activities in the least time.

Transportation conditions (A_3). Transportation is the core of logistics distribution, so a CLC must connect its location with multiple modes of transport, e.g. highways, rail, seaport, and airport to facilitate transit.

Service level (A_4) refers to the capacity of delivering goods from supply locations, or to the customer/consignee locations on time and in full. A good CLC should provide satisfactory service for a customer’s logistics demand at any time.

Human resource condition (A_5) pertains to the quantity and quality of manpower. The operation of a modern CLC requires automation and robotics, which in turn calls for an adequate level of labor, which has become an important location selection factor for a CLC. Generally, the technical level, source, and wage levels of staff must be considered.

Environmental criteria

Environmental protection level (A_6). The location selection of a CLC must consider how to protect the natural environment, and to reduce urban pollution as much as possible. Pollution includes vehicle noise and air pollution caused by vehicular emissions.

Impact on ecological landscape (A_7). When selecting the location of a CLC, sufficient space should be allowed for the development of the CLC to harmonise with the surrounding landscape and to make the CLC architecture merge into the living environment of the local residents, and to maintain or improve the original landscape without damaging a city’s image.

Natural conditions (A_8). When selecting the location of CLC, we should comprehensively know the local natural environment such as temperature, wind, and rainfall, which helps to reduce the risk of the CLC construction. For example, the region’s climatic conditions will directly affect employee health and work efficiency. As the CLC is a staging area for a large amount of goods which requires a higher soil bearing capacity, it must locate away from a flood prone river basin.

Social criteria

Public facilities condition (A_9). The location of a CLC requires public goods such as roads, communication, power supply, and water to function properly.

Security (A_{10}) refers to the security of the location from accidents, theft, and vandalism.

Comply with environmental laws and regulations (A_{11}). The location selection of a CLC must comply with local laws and regulations, and comprehensively consider the city and region’s overall planning and resource space, and the selected location must conform to the city spatial structure and land use planning.

Impact on nearby residents (A_{12}). The location selection of a CLC must consider the social environment. It should not only reduce the disturbance to city life, but also relieve the pressure on urban congestion and promote healthy development for urban residents.

Impact on traffic congestion (A_{13}). The influence of a CLC on traffic must be considered when selecting the CLC location. Given the large amount of traffic through a CLC, any poor arrangement will deteriorate the local traffic conditions. To operate the CLC smoothly, we must plan for the surrounding traffic environment.

The above thirteen criteria form the evaluation index system to evaluate and select the potential locations for a CLC, as listed in Fig. 1. A decision maker can synthetically consider the performance of many criteria and provide the evaluation value for each potential location as fuzzy linguistic variables namely, "Very poor, Poor, Medium, Good, Very good" or "Very low, Low, Medium, High, Very high". Table 1 shows the detailed scale for the performance values of the criteria.

Further, the above criteria can be classified as either a cost type or a benefit type. Criteria A_1, A_7, A_{12}, and A_{13} are cost type attributes, i.e., the smaller the criteria value, the better is the corresponding CLC location. The rest are benefit type criteria, i.e., the higher the criteria value, the better is the corresponding CLC location.

Decision method for location selection of CLC

Problem description

The problem of the location selection of a CLC is described as follows. Suppose we want to select an optimal location among m potential CLC locations to construct a new CLC. The set of the potential CLC locations is denoted as $B = \{B_1, B_2, \ldots, B_m\}$. The set of evaluation criteria of Section 'Evaluation criteria for location selection of CLC under sustainability' used to evaluate the potential CLC locations is denoted as $A = \{A_1, A_2, \ldots, A_{13}\}$, and the set of weights for these criteria is denoted as $W = \{w_1, \ldots, w_{13}\}$, with $0 \leqslant w_j \leqslant 1$ and $\sum_{j=1}^{13} w_j = 1$.

Suppose l experts participate in the evaluation decision and provide the performance ratings for each potential CLC location. The weight vector of these experts is $V = \{v_1, \ldots, v_l\}$, with $0 \leqslant v_j \leqslant 1$ and $\sum_{k=1}^{l} v_k = 1$. The performance ratings for alternative B_i ($i = 1, \ldots, m$) with respect to criteria A_j ($j = 1, \ldots, 13$) given by expert E_k ($k = 1, \ldots, l$) is denoted as a fuzzy linguistic variable r_{ij}^k such as Very poor, Poor, Good, and so on (see the scale method in Table 1). The decision matrix given by expert E_k is denoted as $R_k = (r_{ij}^k)_{i \times 13}$, ($k = 1, \ldots, l$). Now our goal is to select an optimal location of a sustainable CLC according to the information given by l decision matrices $R_1, R_2, \ldots, R_l$.

2-tuple linguistic representation model

As the evaluation results of all potential CLC locations given by the experts are fuzzy linguistic variables, we employ a FMAGDM method based on the 2-tuple linguistic representation model to evaluate all alternatives and select the optimal CLC location. The 2-tuple linguistic representation model is based on fuzzy linguistic variables and the concept called Symbolic Translation (Herrera and Martinez, 2000). It is ideal for decision making problems with linguistic assessment information.

Definitions and operations of linguistic 2-tuple

Herrera and Martinez (2000) first proposed the definition of a linguistic 2-tuple based on a set of fuzzy linguistic variables $S = \{s_0, s_1, \ldots, s_t\}$ which is formed by $t + 1$ linguistic fuzzy variables, where s_k satisfies the following characteristics.

(i) Property of ordering, i.e., if $k \geqslant l$, then $s_k \geqslant s_l$.
(ii) Negation operator. $Neg(s_k) = s_l$, where $l = t - k$.

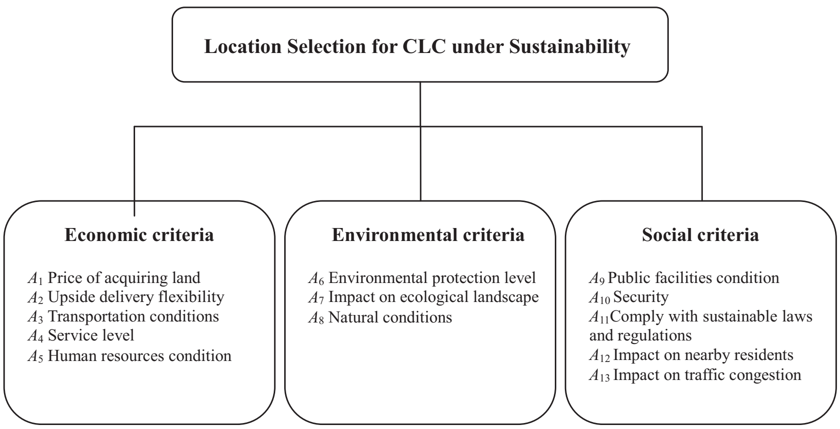

Fig. 1. Evaluation criteria under sustainability.

Table 1
Scale and type for evaluation criteria.

Criteria	Evaluation scale for performance values	Criteria type
A_1 Price of acquiring land	Very low, Low, Medium, High, Very high	Cost
A_2 Upside delivery flexibility	Very poor, Poor, Medium, Good, Very good	Benefit
A_3 Transportation conditions	Very poor, Poor, Medium, Good, Very good	Benefit
A_4 Service level	Very low, Low, Medium, High, Very high	Benefit
A_5 Human resources condition	Very poor, Poor, Medium, Good, Very good	Benefit
A_6 Environmental protection level	Very low, Low, Medium, High, Very high	Benefit
A_7 Impact on ecological landscape	Very low, Low, Medium, High, Very high	Cost
A_8 Natural conditions	Very poor, Poor, Medium, Good, Very good	Benefit
A_9 Public facilities condition	Very poor, Poor, Medium, Good, Very good	Benefit
A_{10} Security	Very low, Low, Medium, High, Very high	Benefit
A_{11} Comply with sustainability laws and regulations	Very poor, Poor, Medium, Good, Very good	Benefit
A_{12} Impact on nearby residents	Very low, Low, Medium, High, Very high	Cost
A_{13} Impact on traffic congestion	Very low, Low, Medium, High, Very high	Cost

(iii) Max operator and Min operator. If $s_k > s_l$, then $\max(s_k, s_l) = s_k,\ \min(s_k, s_l) = s_l$.

As the evaluation scale for the performance values given in Section 'Evaluation criteria for location selection of CLC under sustainability' are all linguistic fuzzy variables, $S = \{s_0, s_1, \ldots, s_t\}$ is defined as follows.

(i) For the benefit type attribute, we define
S = {s_0 = Very low/poor, s_1 = Low/poor, s_2 = Medium, s_3 = High/good, s_4 = Very high/good},
(ii) For the cost type attribute, we define
S = {s_0 = Very high, s_1 = High, s_2 = Medium, s_3 = Low, s_4 = Very low}.
The definition of a linguistic 2-tuple is also given based on the following concept of symbolic translation (Herrera and Martinez, 2000).

Definition 1. Let β be the result of an aggregation of the indices of a set of labels assessed on a linguistic term set S, i.e., the result of a symbolic aggregation operation. $\beta \in [0, t],\ t + 1$ being the cardinality of S. Let I = round (β) and $a = \beta - i$ be two values such that $i \in [0, t]$ and $a \in [-0.5, 0.5)$, where round$(\cdot)$ is the usual rounding operation. Then a is called a *symbolic translation*.

Using $S = \{s_0, s_1, \ldots, s_t\}$ and symbolic translation, Herrera and Martinez (2000) defined a linguistic 2-tuple as follows.

Definition 2. A dual combination (s_k, a_k) is a linguistic 2-tuple if s_k is the k-th linguistic fuzzy variable in a predefined linguistic evaluation set $S = \{s_0, s_1, \ldots, s_t\}$, and a_k is a numerical value expressing the value of the translation from the original result β to the closest index label i in S, i.e., the symbolic translation, such that $a_k \in [-0.5, 0.5)$.

Herrera and Martinez (2000) also define the transformation function between the numeric values and the 2-tuples, and the transformation function between the linguistic fuzzy variables and the 2-tuples. They are shown in Definitions 3 and 4.

Definition 3. Let $S = \{s_0, s_1, \ldots, s_t\}$ be a known linguistic evaluation set, and $\beta \in [0, t]$ be a real number which is a value supporting the result of a symbolic aggregation operation, then β can be transformed into an equivalent linguistic 2-tuple by the function Δ:

$$\Delta:\ [0, t] \to S \times [-0.5, 0.5), \quad \Delta(\beta) = (s_k, a_k),$$

where

$$\begin{cases} k = rnd(\beta) \\ a_k = \beta - k, \quad a_k \in [-0.5, 0.5) \end{cases} \tag{1}$$

and "rnd" is the usual rounding operation. Conversely, for a known linguistic 2-tuple (s_k, a_k), there is an inverse function Δ^{-1} such that from a 2-tuple (s_k, a_k) it returns its equivalent numerical value $\beta \in [0, t]$, i.e.,

$$\Delta^{-1} : S \times [-0.5, 0.5) \to [0, t],$$
$$\Delta^{-1}(s_k, a_k) = k + a_k = \beta. \tag{2}$$

Definition 4. Let $s_k \in S$ be a linguistic fuzzy variable, then its corresponding linguistic 2-tuple can be obtained by the following function θ.

$$\theta : S \rightarrow S \times [-0.5, 0.5), \quad \theta(s_k) = (s_k, 0), \ s_k \in S.$$

This suggests that the corresponding linguistic 2-tuple for a linguistic fuzzy variable $s_k \in S$ is just $(s_k, 0)$.

In addition, the comparison operations of linguistic 2-tuples are defined as follows.

Definition 5. For any two linguistic 2-tuples (s_k, a_k) and (s_l, a_l), the comparison rules are as follows. If $k > l$, then $(s_k, a_k) > (s_l, a_l)$. If $k = l$, three cases exist, i.e., (i) $a_k = a_l$, then $(s_k, a_k) = (s_l, a_l)$; (ii) $a_k > a_l$, then $(s_k, a_k) > (s_l, a_l)$; (iii) $a_k < a_l$, then $(s_k, a_k) < (s_l, a_l)$.

Aggregation operator with 2-tuple linguistic information

In a practical group multi-attribute decision making, if the evaluation values are in the form of linguistic 2-tuples, then we must aggregate all the expert evaluation information into collective overall preference information, and aggregate all the evaluation values under the different attributes into a comprehensive evaluation value for each alternative.

Using Definitions 1–5, the arithmetic aggregation operators with 2-tuple linguistic information are presented as follows.

Definition 6. Let $(s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)$ be n linguistic 2-tuples, then the 2-tuple arithmetic averaging (TAA) operator is defined as

$$TAA((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)) = \Delta\left(\frac{1}{n}\sum_{j=1}^{n}\Delta^{-1}(s_j, a_j)\right) \tag{3}$$

In the above TAA operator, when aggregating the n linguistic 2-tuples, the weights of all the linguistic 2-tuples $(s_j, a_j), \ j = 1, \ \ldots, \ n$ are given the same value $1/n$. When the weights of the n linguistic 2-tuples are different, the following TWA operator (Herrera and Martinez, 2000) can be used to aggregate multiple linguistic 2-tuples.

Definition 7. Let $(s_1, a_1), \ (s_2, a_2), \ \ldots, \ (s_n, a_n)$ be n linguistic 2-tuples, then the 2-tuple weighted averaging (TWA) operator is defined as

$$TWA_W((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)) = \Delta\left(\sum_{j=1}^{n} w_j\Delta^{-1}(s_j, a_j)\right) \tag{4}$$

where $W = \{w_1, w_2, \ldots, w_n\}$ is the weight vector of 2-tuples $(s_j, a_j), \ j = 1, \ \ldots, \ n$, which satisfies $0 \leqslant w_j \leqslant 1$ and $\sum_{j=1}^{n} w_j = 1$.

Obviously, when $w_j = 1/n, \ j = 1, \ \ldots, \ n$, the TWA operator is reduced to the TAA operator. Further, ordering the TWA operator (Yager, 1988), a 2-tuple ordered weighted averaging ($TOWA$) operator is presented by Herrera and Martinez (2000). On the TWA and $TOWA$ operators, the TWA operator considers the importance of each given linguistic 2-tuple, but the $TOWA$ operator weights all the ordered positions of the linguistic 2-tuple instead of weighting the given linguistic 2-tuple themselves.

Definition 8. Let $(s_1, a_1), \ (s_2, a_2), \ \ldots, \ (s_n, a_n)$ be linguistic 2-tuples, then the $TOWA$ operator is defined as:

$$TOWA_\omega((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)) = \Delta\left(\sum_{j=1}^{n}\omega_j\Delta^{-1}(s_{\tau(j)}, a_{\tau(j)})\right) \tag{5}$$

where $\omega = \{\omega_1, \omega_2, \ldots, \omega_n\}$ is the weighted vector correlating with $TOWA$, which satisfies $0 \leqslant \omega_j \leqslant 1$ and $\sum_{j=1}^{n}\omega_j = 1$. $(\tau(1), \ \tau(2), \ \ldots, \ \tau(n))$ is a permutation of $(1, 2, \ldots, n)$ which satisfies $(s_{\tau(j-1)}, a_{\tau(j-1)}) \geqslant (s_{\tau(j)}, a_{\tau(j)})$ for any j.

Based on the $TOWA$ operator, we present a new 2-tuple hybrid ordered weighted averaging ($THOWA$) operator, which weights the given linguistic 2-tuple and their ordered positions.

Definition 9. Let $(s_1, a_1), \ (s_2, a_2), \ \ldots, \ (s_n, a_n)$ be linguistic 2-tuples, and $W = \{w_1, \ldots, w_n\}$ be the weight vector of 2-tuples $(s_j, a_j)(j = 1, \ldots, n)$ such that $0 \leqslant w_j \leqslant 1$ and $\sum_{j=1}^{n} w_j = 1$, then the $THOWA$ operator is defined as

$$THOWA_\omega((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)) = \Delta\left(\sum_{j=1}^{n}\omega_j\Delta^{-1}(\dot{s}_{\tau(j)}, \dot{a}_{\tau(j)})\right) \tag{6}$$

where $\omega = \{\omega_1, \omega_2, \ldots, \omega_n\}$ is the weighted vector correlating with $THOWA$, which satisfies $0 \leqslant \omega_j \leqslant 1$ and $\sum_{j=1}^{n}\omega_j = 1$. $(\dot{s}_{\tau(j)}, \dot{a}_{\tau(j)})$ is the j-th largest 2-tuple of the weighted linguistic 2-tuples $(\dot{s}_j, \dot{a}_j), \ j = 1, \ \ldots, \ n$, and $(\dot{s}_j, \dot{a}_j) = \Delta(Qw_j\Delta^{-1}(s_j, a_j)), \ j = 1, \ \ldots, \ n$, where Q is the balancing coefficient such that $Q = \frac{1}{\sum_{j=1}^{n}\omega_j w_j}$.

In Definition 9, the determination methods of the weighted vector $\omega = \{\omega_1, \omega_2, \ldots, \omega_n\}$ correlating with $THOWA$ are similar with the methods for the $TOWA$ operator. That is, it can be determined by using a weight determining method such as the Normal distribution based method (Xu, 2005; Sadiq and Tesfamariam, 2007). Following Xu (2005), the weighted vector ω as determined by a Normal distribution is as follows:

$$\omega_j = \frac{1}{\sigma_n\sqrt{2\pi}} e^{-(j-\mu_n)^2/2\sigma_n^2}, \quad j = 1,\ 2,\ \ldots,\ n,$$

where μ_n is the mean of the collection of $1, 2, \ldots, n$, and $\sigma_n(\sigma_n > 0)$ is the standard deviation of the collection of $1, 2, \ldots, n$. μ_n and σ_n are obtained by

$$\mu_n = \frac{1}{n}\cdot\frac{n(1+n)}{2} = \frac{1+n}{2}, \quad \sigma_n = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(i-\mu_n)^2}.$$

We now discuss some properties of the *THOWA* operator given in Definition 9.

Theorem 1. *The TWA and TOWA operators are special cases of the THOWA operator.*

Proof. For the above *THOWA* operator, let $w_j = \frac{1}{n},\ j = 1,\ 2,\ \ldots,\ n$, then from the balancing coefficient $Q = \frac{1}{\sum_{j=1}^{n}\omega_j w_j} = n$, we have

$$(\dot{s}_j, \dot{a}_j) = \Delta(Qw_j\Delta^{-1}(s_j, a_j)) = \Delta\left(n\cdot\frac{1}{n}\Delta^{-1}(s_j, a_j)\right) = (s_j, a_j), \quad j = 1,\ 2,\ \ldots,\ n,$$

which means that the *THOWA* operator is reduced to the *TOWA* operator.

Let $w_j = \frac{1}{n}$ and $\omega_j = \frac{1}{n}$, then by the above proof process, the *THOWA* operator is reduced to the*TWA* operator. This completes the proof of Theorem 1. □.

In addition, we can prove that the *THOWA* operator has the properties of idempotency, commutativity, monotonicity and boundedness, which is shown in Theorem 2.

Theorem 2. *Let* $(s_1, a_1),\ (s_2, a_2),\ \ldots,\ (s_n, a_n)$ *be n linguistic 2-tuples, and* $W = \{w_1, \ldots, w_n\}$ *be the weight vector of 2-tuples* (s_j, a_j) $(j = 1, \ldots, n)$ *with* $0 \leqslant w_j \leqslant 1$ *and* $\sum_{j=1}^{n} w_j = 1$, *then the THOWA operator has the following properties.*

(i) *Idempotency. If* $(s_1, a_1) = (s_2, a_2) = \cdots = (s_n, a_n) = (s, a)$, *then*

$$THOWA_\omega((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)) = (s, a).$$

(ii) *Commutativity.*

$$THOWA_\omega((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)) = TOWA_\omega\left((s'_1, a'_1),\ (s'_2, a'_2),\ \ldots,\ (s'_n, a'_n)\right),$$

where $(s'_1, a'_1),\ (s'_2, a'_2),\ \ldots,\ (s'_n, a'_n)$ *is any permutation of* $(s_1, a_1),\ (s_2, a_2),\ \ldots,\ (s_n, a_n)$.

(iii) *Monotonicity. If* $(s_j, a_j) \leqslant \left(s'_j, a'_j\right)$ *for any j, then*

$$THOWA_\omega((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)) \leqslant TOWA_\omega\left((s'_1, a'_1), (s'_2, a'_2), \ldots, (s'_n, a'_n)\right).$$

(iv) *Boundedness.*

$$\min\ ((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)) \leqslant THOWA_\omega((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)) \leqslant \max\ ((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n))$$

Proof. Let $\omega = \{\omega_1, \omega_2, \ldots, \omega_n\}$ be an associated vector of the *THOWA* operator s.t. $0 \leqslant \omega_j \leqslant 1$ and $\sum_{j=1}^{n}\omega_j = 1$.

(i) If $(s_1, a_1) = (s_2, a_2) = \cdots = (s_n, a_n) = (s, a)$, then we have $(\dot{s}_j, \dot{a}_j) = \Delta(Qw_j\Delta^{-1}(s, a))$.
Together with $Q = \frac{1}{\sum_{j=1}^{n}\omega_j w_j}$, so we obtain

$$\begin{aligned} THOWA_\omega((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)) &= \Delta\left(\sum_{j=1}^{n}\omega_j\Delta^{-1}(\dot{s}_{\tau(j)}, \dot{a}_{\tau(j)})\right) = \Delta\left(\sum_{j=1}^{n}\omega_j\Delta^{-1}\Delta(Qw_j\Delta^{-1}(s, a))\right) \\ &= \Delta\left(\Delta^{-1}(s, a)Q\sum_{j=1}^{n}\omega_j w_j\right) = \Delta\left(\Delta^{-1}(s, a)\right) = (s, a). \end{aligned}$$

(ii) Since $(s'_1, a'_1),\ (s'_2, a'_2),\ \ldots,\ (s'_n, a'_n)$ is any permutation of $(s_1, a_1),\ (s_2, a_2),\ \ldots,\ (s_n, a_n)$, the corresponding weighting vector is denoted as $(w'_1, w'_2, \ldots, w'_n)$, together with

$(\dot{s}_j, \dot{a}_j) = \Delta(Qw_j\Delta^{-1}(s_j, a_j)), \quad j = 1, 2, \ldots, n,$
$\left(\dot{s}'_j, \dot{a}'_j\right) = \Delta\left(Qw'_j\Delta^{-1}\left(s'_j, a'_j\right)\right), \quad j = 1, 2, \ldots, n,$

we can conclude that the j-th largest 2-tuple $(\dot{s}_{\tau(j)}, \dot{a}_{\tau(j)})$ of the weighted linguistic 2-tuples $(\dot{s}_j, \dot{a}_j)$ $(j = 1, \ldots, n)$ for the linguistic 2-tuples $(s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)$ is equal to the j-th largest 2-tuple $\left(\dot{s}'_{\tau(j)}, \dot{a}'_{\tau(j)}\right)$ of the weighted linguistic 2-tuples $\left(\dot{s}'_j, \dot{a}'_j\right)$ $(j = 1, \ldots, n)$ for permutation $(s'_1, a'_1), (s'_2, a'_2), \ldots, (s'_n, a'_n)$. So, we have

$$THOWA_\omega((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)) = TOWA_\omega\left(\left(s'_1, a'_1\right), \left(s'_2, a'_2\right), \ldots, \left(s'_n, a'_n\right)\right).$$

(iii) Let $\Delta^{-1}(\dot{s}'_{\tau(j)}, \dot{a}'_{\tau(j)}) = \beta'_{\tau(j)}$ and $\Delta^{-1}(\dot{s}_{\tau(j)}, \dot{a}_{\tau(j)}) = \beta_{\tau(j)}$ for any j. As $(s_j, a_j) \leqslant \left(s'_j, a'_j\right)$ for any j, we have $\Delta^{-1}(\dot{s}_{\tau(j)}, \dot{a}_{\tau(j)}) = \beta_{\tau(j)} \leqslant \beta'_{\tau(j)} = \Delta^{-1}\left(\dot{s}'_{\tau(j)}, \dot{a}'_{\tau(j)}\right)$. Hence

$$\begin{aligned} THOWA_\omega((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)) &= \Delta\left(\sum_{j=1}^{n}\omega_j\Delta^{-1}(\dot{s}_{\tau(j)}, \dot{a}_{\tau(j)})\right) \leqslant \Delta\left(\sum_{j=1}^{n}\omega_j\Delta^{-1}\left(\dot{s}'_{\tau(j)}, \dot{a}'_{\tau(j)}\right)\right) \\ &= TOWA_\omega\left(\left(s'_1, a'_1\right), \left(s'_2, a'_2\right), \ldots, \left(s'_n, a'_n\right)\right). \end{aligned}$$

(iv) Let $\max_j(s_j, a_j) = (s_k, a_k)$, $\min_j(s_j, a_j) = (s_l, a_l)$, then for the collection of linguistic 2-tuples $(s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)$, and another collection of linguistic 2-tuples $(s_k, a_k), (s_k, a_k), \ldots, (s_k, a_k)$ which is formed by n times the same 2-tuple (s_k, a_k), the condition $(s_j, a_j) \leqslant \left(s'_j, a'_j\right) = (s_k, a_k)$ is satisfied for any j, by the property of monotonicity proven in (iii), we have

$$THOWA_\omega((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)) \leqslant TOWA_\omega\left(\left(s'_1, a'_1\right), \left(s'_2, a'_2\right), \ldots, \left(s'_n, a'_n\right)\right) = TOWA_\omega((s_k, a_k), (s_k, a_k), \ldots, (s_k, a_k)),$$

Using the property of idempotency proven in (i), we obtain

$$TOWA_\omega((s_k, a_k), (s_k, a_k), \ldots, (s_k, a_k)) = (s_k, a_k).$$

Thus, $THOWA_\omega((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)) \leqslant (s_k, a_k) = max((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n))$.
Using the above proof method, we obtain

$$\min((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)) \leqslant THOWA_\omega((s_1, a_1), (s_2, a_2), \ldots, (s_n, a_n)).$$

This completes the proof of Theorem 2. □

Generally, in group multi-attribute decision making, the *TWA* operator is suitable for aggregating all the evaluation values under the different attributes into a comprehensive evaluation value for each alternative. The *THOWA* operator is suitable for aggregating the evaluation values given by the experts into the collective overall preference values. In fact, in practical group decision making, experts often have a strong personal bias and preference, or some might be irrational and provide unreasonable evaluation scores for the alternatives, i.e., they will give high evaluation values of the 2-tuple to their preferential alternatives, and low evaluation values of the 2-tuple to their repugnant alternatives. This thwarts the optimal solution. Therefore, in the process of aggregating the decision-making data, we need to lessen irrationality, and make the decision result fair (Wei, 2010; Wan, 2013; Park et al., 2013). As such, if we use the *THOWA* operator to aggregate the decision-making information, the high scores from the expert's preference or the low scores from the expert's aversion will be ranked with relatively smaller weights.

Location evaluation decision based on 2-tuple linguistic representation model

We now present a FMAGDM method based on a 2-tuple linguistic representation model given in Section '2-tuple linguistic representation model' to solve the problem of the location selection of a sustainable CLC. An algorithm and decision process of the FMAGDM problems with 2-tuple linguistic evaluation information is given as follows.

Step 1: l experts rate the performance for m potential CLC locations, and l original linguistic decision matrices $R_1, R_2, \ldots, R_l$ are found, where $R_k = (r_{ij}^k)_{i\times 13}$, $k = 1, 2, \ldots, l$. The performance rating r_{ij}^k for alternative B_i $(i = 1, \ldots, m)$ with respect to criteria A_j $(j = 1, \ldots, 13)$ given by expert E_k $(k = 1, \ldots, l)$ is determined by the following rules.

(i) For the cost type attributes, A_1 Price of acquiring land, A_7 impact on the ecological landscape, A_{12} impact on surrounding residents and A_{13} impact on traffic congestion, the values of the performance rating r_{ij}^k $(j = 1, 7, 12, 13,$ $i = 1, 2, \ldots, m$, $k = 1, 2, \ldots, l)$ are determined by s_4 = Very low, s_3 = Low, s_2 = Medium, s_1 = High, s_0 = Very high.

(ii) For the benefit type attributes A_j $(j = 2, 3, 4, 5, 6, 8, 9, 10, 11)$, the values of the performance rating r_{ij}^k $(i = 1, 2, \ldots,$ m, $k = 1, 2, \ldots, l)$ are determined by

$$\text{Very low} = s_0,\ \text{Low} = s_1,\ \text{Medium} = s_2,\ \text{High} = s_3, \text{Very high} = s_4,$$
$$\text{Very poor} = s_0,\ \text{Poor} = s_1,\ \text{Medium} = s_2,\ \text{Good} = s_3,\ \text{Very good} = s_4.$$

Step 2: Use the transformation method in Definition 4 to transform each original linguistic decision matrix $R_k = (r_{ij}^k)_{i\times 13}$ into a linguistic 2-tuple decision matrix $\widetilde{R}_k = ((r_{ij}^k, 0))_{i\times 13}$, $k = 1, 2, \ldots, l$.

Step 3: Use the *TWA* operator given in Definition 7 to aggregate all evaluation values under 13 evaluation criteria in matrix R_k into an overall evaluation value y_i^k of alternative B_i ($i = 1, 2, \ldots, m$) corresponding to expert E_k, that is,

$$y_i^k = (s_i^k, a_i^k) = TWA_W((r_{i1}^k, 0), (r_{i2}^k, 0), \ldots, (r_{i13}^k, 0)) = \Delta\left(\sum_{j=1}^{13} w_j \Delta^{-1}(r_{ij}^k, 0)\right), \quad k = 1, 2, \ldots, l,$$

where $W = \{w_1, w_2, \ldots, w_{13}\}$ is the weight vector of 13 evaluation criteria such that $0 \leqslant w_j \leqslant 1$ and $\sum_{j=1}^{13} w_j = 1$.

Step 4: Use the *THOWA* operator given in Definition 9 to aggregate the overall evaluation value y_i^k corresponding to expert E_k ($k = 1, \ldots, l$) to yield the collective overall evaluation value for alternative B_i, $i = 1, 2, \ldots, m$,

$$y_i = (s_i, a_i) = THOWA_\omega((s_i^1, a_i^1), (s_i^2, a_i^2), \ldots, (s_i^l, a_i^l)) = \Delta\left(\sum_{k=1}^{l} \omega_k \Delta^{-1}(\dot{s}_i^{\tau(k)}, \dot{a}_i^{\tau(k)})\right),$$

where $\omega = \{\omega_1, \omega_2, \ldots, \omega_l\}$ is the weighted vector correlating with *THOWA*, which satisfies $0 \leqslant \omega_k \leqslant 1$ and $\sum_{k=1}^{l} \omega_k = 1$. $\left(\dot{s}_i^{\tau(k)}, \dot{a}_i^{\tau(k)}\right)$ is the k-th largest 2-tuple of the weighted linguistic 2-tuples $(\dot{s}_i^k, \dot{a}_i^k)$, $k = 1, 2, \ldots, l$, and

$$(\dot{s}_i^k, \dot{a}_i^k) = \Delta(Q v_k \Delta^{-1}(s_i^k, a_i^k)), \quad k = 1,\ 2,\ \ldots,\ l,$$

where $V = \{v_1, v_2, \ldots, v_l\}$ is the weight vector of the experts such that $0 \leqslant v_k \leqslant 1$ and $\sum_{k=1}^{l} v_k = 1$. Q is the balancing coefficient with $Q = \frac{1}{\sum_{j=1}^{n} \omega_j v_j}$.

Step 5: Rank all potential CLC locations in accordance with the 2-tuple $y_i = (s_i, a_i)$ ($i = 1, 2, \ldots, m$), and select the optimal location. The greater the value of $y_i = (s_i, a_i)$, the better is the CLC location i.

Numerical illustration

We now give a decision making example of the location selection of a sustainable CLC under a fuzzy information environment to demonstrate the effectiveness and implementation of this method.

Suppose we want to select an optimal location among four potential CLC locations to create a new CLC. The CLC locations are B_1, B_2, B_3 and B_4 (see Fig. 2). Fig. 2 shows that B_1 is located outside the city and far from highways and near a main road; B_2 is located in the center of city close to the consignees (such as retailers, shopping mall) but far from the highways; B_3 is located in the city and near the highway and close to the consignees; B_4 is located outside the city and near a highway.

Three experts participate in the evaluation decision for four potential CLC locations, and the weight vector of the experts is V=$(v_1, v_2, v_3) = (0.35, 0.4, 0.25)$. The experts evaluate the potential CLC locations' sustainability performance from the dimensions of sustainable development – economic, environmental, and social. We use the 13 evaluation criteria in Table 1 and we let the weight set of the evaluation criteria be $W = (0.1, 0.1, 0.1, 0.1, 0.025, 0.1, 0.05, 0.025, 0.05, 0.1, 0.1, 0.05, 0.1)$. The experts rate the performance of the evaluation criteria for the potential CLC locations using the rating scales of Table 1. The original decision matrix $R_k = (r_{ij}^k)_{4\times 13}$, ($k = 1, 2, 3$) as given by the experts is listed in Tables 2–4.

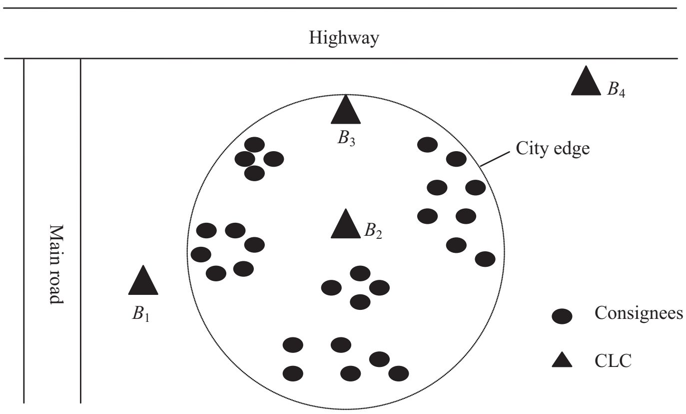

Fig. 2. Potential CLC locations.

Table 2
Original decision matrix R_1.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}
B_1	s_4	s_2	s_1	s_2	s_2	s_3	s_4	s_1	s_2	s_3	s_4	s_4	s_2
B_2	s_0	s_2	s_2	s_3	s_3	s_0	s_1	s_3	s_3	s_1	s_0	s_0	s_1
B_3	s_2	s_4	s_4	s_4	s_3	s_1	s_3	s_3	s_4	s_2	s_3	s_1	s_2
B_4	s_3	s_3	s_3	s_2	s_2	s_4	s_4	s_4	s_3	s_4	s_4	s_4	s_3

Table 3
Original decision matrix R_2.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}
B_1	s_4	s_2	s_1	s_2	s_3	s_3	s_4	s_1	s_1	s_4	s_4	s_3	s_2
B_2	s_1	s_3	s_1	s_2	s_2	s_1	s_0	s_3	s_4	s_1	s_1	s_1	s_1
B_3	s_2	s_3	s_2	s_3	s_3	s_2	s_1	s_4	s_3	s_2	s_2	s_2	s_3
B_4	s_3	s_3	s_3	s_3	s_3	s_4	s_3	s_3	s_4	s_4	s_4	s_3	s_4

Table 4
Original decision matrix R_3.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}
B_1	s_4	s_2	s_1	s_2	s_2	s_2	s_4	s_2	s_1	s_3	s_4	s_3	s_1
B_2	s_0	s_1	s_2	s_3	s_3	s_0	s_1	s_3	s_3	s_0	s_1	s_1	s_0
B_3	s_2	s_3	s_3	s_3	s_3	s_1	s_2	s_3	s_4	s_2	s_2	s_2	s_2
B_4	s_3	s_3	s_3	s_2	s_4	s_4	s_3	s_4	s_3	s_4	s_4	s_4	s_4

We want to select an optimal location to construct a sustainable CLC according to the information given by the above three decision matrices R_1, R_2, and R_3.

Decision making process

Using the decision method of Section 'Decision method for location selection of CLC', we invoke the following steps to select the best CLC location.

(1) We use the transformation method in Definition 4 to transform R_1, R_2 and R_3 into a linguistic 2-tuple decision matrix $\widetilde{R}_k = \left(\left(r_{ij}^k, 0\right)\right)_{4\times 13}$, $k = 1, 2, 3$ (see Tables 5–7).

(2) Use the *TWA* operator given in Definition 7 to aggregate all evaluation values under the evaluation criteria in matrix $R_k = \left(\left(r_{ij}^k, 0\right)\right)_{4\times 13}$ corresponding to expert E_k ($k = 1, 2, 3$) into one overall evaluation value $y_i^k = \left(s_i^k, a_i^k\right)$ of alternative B_i ($i = 1, 2, 3, 4$), the computation results are as follows.

$$y_1^1 = \left(s_1^1, a_1^1\right) = (s_3, -0.125),\ y_2^1 = \left(s_2^1, a_2^1\right) = (s_1, 0.25),\ y_3^1 = \left(s_3^1, a_3^1\right) = (s_3, -0.25),$$
$$y_4^1 = \left(s_4^1, a_4^1\right) = (s_3, 0.3),\ y_1^2 = \left(s_1^2, a_1^2\right) = (s_3, -0.4),\ y_2^2 = \left(s_2^2, a_2^2\right) = (s_1, 0.475),$$
$$y_3^2 = \left(s_3^2, a_3^2\right) = (s_2, 0.375),\ y_4^2 = \left(s_4^2, a_4^2\right) = (s_3, 0.45),\ y_1^3 = \left(s_1^3, a_1^3\right) = (s_2, 0.4),$$
$$y_2^3 = \left(s_2^3, a_2^3\right) = (s_1, 0.1),\ y_3^3 = \left(s_3^3, a_3^3\right) = (s_2, 0.35),\ y_4^3 = \left(s_4^3, a_4^3\right) = (s_3, 0.4).$$

(3) Use the *THOWA* operator given in Definition 9 to aggregate the overall evaluation value y_i^k corresponding to expert E_k ($k = 1, 2, 3$). Here, the weighted vector correlating with *THOWA* is $\omega = \{0.24, 0.52, 0.24\}$, which is determined by using the Normal distribution based method (see the solution steps in Section 'Aggregation operator with 2-tuple linguistic information'). We obtain the collective overall evaluation value $y_i = (s_i, a_i)$ of alternative B_i ($i = 1, 2, 3, 4$) as follows.

Table 5
Linguistic 2-tuple decision matrix $\widetilde{R}_1$.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}
B_1	$(s_4, 0)$	$(s_2, 0)$	$(s_1, 0)$	$(s_2, 0)$	$(s_2, 0)$	$(s_3, 0)$	$(s_4, 0)$	$(s_1, 0)$	$(s_2, 0)$	$(s_3, 0)$	$(s_4, 0)$	$(s_4, 0)$	$(s_2, 0)$
B_2	$(s_0, 0)$	$(s_2, 0)$	$(s_2, 0)$	$(s_3, 0)$	$(s_3, 0)$	$(s_0, 0)$	$(s_1, 0)$	$(s_3, 0)$	$(s_3, 0)$	$(s_1, 0)$	$(s_0, 0)$	$(s_0, 0)$	$(s_1, 0)$
B_3	$(s_2, 0)$	$(s_4, 0)$	$(s_4, 0)$	$(s_4, 0)$	$(s_3, 0)$	$(s_1, 0)$	$(s_3, 0)$	$(s_3, 0)$	$(s_4, 0)$	$(s_2, 0)$	$(s_3, 0)$	$(s_1, 0)$	$(s_2, 0)$
B_4	$(s_3, 0)$	$(s_3, 0)$	$(s_3, 0)$	$(s_2, 0)$	$(s_2, 0)$	$(s_4, 0)$	$(s_4, 0)$	$(s_4, 0)$	$(s_3, 0)$	$(s_4, 0)$	$(s_4, 0)$	$(s_4, 0)$	$(s_3, 0)$

Table 6
Linguistic 2-tuple decision matrix $\widetilde{R}_2$.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}
B_1	$(s_4,0)$	$(s_2,0)$	$(s_0,0)$	$(s_2,0)$	$(s_3,0)$	$(s_3,0)$	$(s_4,0)$	$(s_1,0)$	$(s_1,0)$	$(s_4,0)$	$(s_4,0)$	$(s_3,0)$	$(s_2,0)$
B_2	$(s_1,0)$	$(s_3,0)$	$(s_1,0)$	$(s_2,0)$	$(s_2,0)$	$(s_1,0)$	$(s_0,0)$	$(s_3,0)$	$(s_4,0)$	$(s_1,0)$	$(s_1,0)$	$(s_1,0)$	$(s_1,0)$
B_3	$(s_2,0)$	$(s_3,0)$	$(s_2,0)$	$(s_3,0)$	$(s_3,0)$	$(s_2,0)$	$(s_1,0)$	$(s_4,0)$	$(s_3,0)$	$(s_2,0)$	$(s_2,0)$	$(s_2,0)$	$(s_3,0)$
B_4	$(s_3,0)$	$(s_3,0)$	$(s_3,0)$	$(s_3,0)$	$(s_3,0)$	$(s_4,0)$	$(s_3,0)$	$(s_3,0)$	$(s_4,0)$	$(s_4,0)$	$(s_4,0)$	$(s_3,0)$	$(s_4,0)$

Table 7
Linguistic 2-tuple decision matrix $\widetilde{R}_3$.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}
B_1	$(s_4,0)$	$(s_2,0)$	$(s_1,0)$	$(s_2,0)$	$(s_2,0)$	$(s_2,0)$	$(s_4,0)$	$(s_2,0)$	$(s_1,0)$	$(s_3,0)$	$(s_4,0)$	$(s_3,0)$	$(s_1,0)$
B_2	$(s_0,0)$	$(s_1,0)$	$(s_2,0)$	$(s_3,0)$	$(s_3,0)$	$(s_0,0)$	$(s_1,0)$	$(s_3,0)$	$(s_3,0)$	$(s_0,0)$	$(s_1,0)$	$(s_1,0)$	$(s_0,0)$
B_3	$(s_2,0)$	$(s_3,0)$	$(s_3,0)$	$(s_3,0)$	$(s_3,0)$	$(s_1,0)$	$(s_2,0)$	$(s_3,0)$	$(s_4,0)$	$(s_2,0)$	$(s_2,0)$	$(s_2,0)$	$(s_2,0)$
B_4	$(s_3,0)$	$(s_3,0)$	$(s_3,0)$	$(s_2,0)$	$(s_4,0)$	$(s_4,0)$	$(s_3,0)$	$(s_4,0)$	$(s_3,0)$	$(s_4,0)$	$(s_4,0)$	$(s_4,0)$	$(s_4,0)$

$$y_1 = (s_1, a_1) = (s_3, -0.395),\ y_2 = (s_2, a_2) = (s_1, 0.236),$$
$$y_3 = (s_3, a_3) = (s_2, 0.460),\ y_4 = (s_4, a_4) = (s_3, 0.227).$$

(4) Rank all potential CLC locations based on the 2-tuple $y_i = (s_i, a_i)$ (i = 1, 2, 3, 4). As $y_4 > y_1 > y_3 > y_2$, the optimal CLC location is B_4.

Discussion

The evaluation result of the CLC locations in the above example is found by considering the economic, environmental, and social criteria from a sustainability perspective. In this case, B_1 and B_4 are located outside the city, and B_2 and B_3 are located in the city. As $B_4 \succ B_1 \succ B_3 \succ B_2$, constructing a CLC outside of the city is better than in the city.

If we only consider the economic criteria $A_1 - A_5$, we set $w_6 = w_7 = \cdots = w_{13} = 0$, and reset the weight set of the evaluation criteria $A_1 - A_5$ as $W = (w_1, w_2, \ldots, w_5) = (0.2, 0.2, 0.25, 0.3, 0.05)$. By using the same decision method in Section 'Decision making process', we obtain the collective overall evaluation value $y_i = (s_i, a_i)$ of the four alternatives as follows.

$$y_1 = (s_1, a_1) = (s_2, 0.01), y_2 = (s_2, a_2) = (s_2, -0.216),$$
$$y_3 = (s_3, a_3) = (s_3, -0.169), y_4 = (s_4, a_4) = (s_3, -0.343).$$

which shows the ranking order of four potential alternative CLC locations to be $B_3 \succ B_4 \succ B_1 \succ B_2$. Thus, the optimal CLC location is B_3, i.e. B_3 can be selected to construct a new CLC. From Fig. 1, as B_3 is located in the city and near the highway and close to the consignees, some external costs will be triggered, for example, more traffic congestion, more emissions, and so on. Moreover, it cannot afford enough land for future development. This decision result will run counter to the sustainable development strategy.

Comparison with fuzzy TOPSIS

Fuzzy TOPSIS has been used to solve the facility location problem (Chu, 2002; Önüt et al., 2010; Awasthi et al., 2011). We compare our location evaluation decision method based on a linguistic 2-tuple with the method based on fuzzy TOPSIS. The location evaluation decision method based on fuzzy TOPSIS is given as follows:

Step 1: Use the following transformation method (Awasthi et al., 2011) to transform each original linguistic decision matrix $R_k = \left(r_{ij}^k\right)_{4\times13}$ into a triangular fuzzy number decision matrix $\widetilde{R}_k = \left(\tilde{x}_{ij}^k\right)_{4\times13} = \left(\left(a_{ij}^k, b_{ij}^k, c_{ij}^k\right)\right)_{4\times13}$, k = 1, 2, 3, where $\tilde{x}_{ij}^k = \left(a_{ij}^k, b_{ij}^k, c_{ij}^k\right)$ is determined by $s_0 = (1,1,3)$, $s_1 = (1,3,5)$, $s_2 = (3,5,7)$, $s_3 = (5,7,9)$, $s_4 = (7,9,9)$. The triangular fuzzy number decision matrices are listed in the following Tables 8–10.

Step 2: Aggregate three triangular fuzzy number decision matrices $\widetilde{R}_1,\ \widetilde{R}_2,\ \widetilde{R}_3$ of the three experts into a comprehensive decision matrix $\widetilde{R} = (\tilde{y}_{ij})_{4\times13} = ((a_{ij}, b_{ij}, c_{ij}))_{4\times13}$, where

$$a_{ij} = \min_k a_{ij}^k, \quad b_{ij} = \frac{1}{3}\sum_{k=1}^{3} b_{ij}^k, \quad c_{ij} = \max_k c_{ij}^k, \quad i = 1, \ldots, 4,\ j = 1, \ldots, 13, \quad k = 1, 2, 3.$$

By this aggregation method, we obtain the comprehensive decision matrix in Table 11.

Step 3: Normalize the comprehensive decision matrix $\widetilde{R} = (\tilde{y}_{ij})_{4\times13}$ as $\widetilde{Z} = (\tilde{z}_{ij})_{4\times13}$, with

Table 8
Triangular fuzzy number decision matrix $\widetilde{R}_1$.

	B_1	B_2	B_3	B_4
A_1	(7, 9, 9)	(1, 1, 3)	(3, 5, 7)	(5, 7, 9)
A_2	(3, 5, 7)	(3, 5, 7)	(7, 9, 9)	(5, 7, 9)
A_3	(1, 3, 5)	(3, 5, 7)	((7, 9, 9)	(5, 7, 9)
A_4	(3, 5, 7)	(5, 7, 9)	(7, 9, 9)	(3, 5, 7)
A_5	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)
A_6	(5, 7, 9)	(1, 1, 3)	(1, 3, 5)	(7, 9, 9)
A_7	(7, 9, 9)	(1, 3, 5)	(5, 7, 9)	(7, 9, 9)
A_8	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)
A_9	(3, 5, 7)	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)
A_{10}	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(7, 9, 9)
A_{11}	(7, 9, 9)	(1, 1, 3)	(5, 7, 9)	(7, 9, 9)
A_{12}	(7, 9, 9)	(1, 1, 3)	(1, 3, 5)	(7, 9, 9)
A_{13}	(3, 5, 7)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)

Table 9
Triangular fuzzy number decision matrix $\widetilde{R}_2$.

	B_1	B_2	B_3	B_4
A_1	(7, 9, 9)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)
A_2	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)
A_3	(1, 1, 3)	(1, 1, 3)	(3, 5, 7)	(5, 7, 9)
A_4	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)
A_5	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)
A_6	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(7, 9, 9)
A_7	(7, 9, 9)	(1, 1, 3)	(1, 3, 5)	(5, 7, 9)
A_8	(1, 3, 5)	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)
A_9	(1, 3, 5)	(7, 9, 9)	(5, 7, 9)	(7, 9, 9)
A_{10}	(7, 9, 9)	(1, 3, 5)	(3, 5, 7)	(7, 9, 9)
A_{11}	(7, 9, 9)	(1, 3, 5)	(3, 5, 7)	(7, 9, 9)
A_{12}	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)
A_{13}	(3, 5, 7)	(1, 3, 5)	(5, 7, 9)	(7, 9, 9)

Table 10
Triangular fuzzy number decision matrix $\widetilde{R}_3$.

	B_1	B_2	B_3	B_4
A_1	(7, 9, 9)	(1, 1, 3)	(3, 5, 7)	(5, 7, 9)
A_2	(3, 5, 7)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)
A_3	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)
A_4	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)
A_5	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)
A_6	(3, 5, 7)	(1, 1, 3)	(1, 3, 5)	(7, 9, 9)
A_7	(7, 9, 9)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)
A_8	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)
A_9	(1, 3, 5)	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)
A_{10}	(5, 7, 9)	(1, 1, 3)	(3, 5, 7)	(7, 9, 9)
A_{11}	(7, 9, 9)	(1, 3, 5)	(3, 5, 7)	(7, 9, 9)
A_{12}	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(7, 9, 9)
A_{13}	(1, 3, 5)	(1, 1, 3)	(3, 5, 7)	(7, 9, 9)

$$\tilde{z}_{ij} = \left(\frac{a_{ij}}{\max\limits_i c_{ij}}, \frac{b_{ij}}{\max\limits_i c_{ij}}, \frac{c_{ij}}{\max\limits_i c_{ij}}\right), \quad i = 1,2,3,4;\ j = 1,2,\ldots,13.$$

Based on $\widetilde{Z} = (\tilde{z}_{ij})_{4\times13}$, construct the weighted normalized comprehensive decision matrix $\widetilde{V} = (\tilde{v}_{ij})_{4\times13}$, where $\tilde{v}_{ij} = w_j \cdot \tilde{z}_{ij}$, i = 1, 2, 3, 4; j = 1, 2, ..., 13, as shown in Table 12.

Step 4: Determine the fuzzy positive-ideal solution (FPIS) A^+ and fuzzy negative-ideal solution (FNIS) A^- as follows.

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_{13}^+),\ \text{where}\ \tilde{v}_j^+ = \max_i(\tilde{v}_{ij}),\ j = 1,2,\ldots,13.$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_{13}^-),\ \text{where}\ \tilde{v}_j^- = \min_i(\tilde{v}_{ij}),\ j = 1,2,\ldots,13.$$

Table 11
Comprehensive decision matrix $\widetilde{R}$.

	B_1	B_2	B_3	B_4
A_1	(7, 9, 9)	(1, 1.667, 5)	(3, 5, 7)	(5, 7, 9)
A_2	(3, 5, 7)	(1, 5, 9)	(5, 7.667, 9)	(5, 7, 9)
A_3	(1, 2.333, 5)	(1, 3.667, 7)	(3, 7, 9)	(5, 7, 9)
A_4	(3, 5, 7)	(3, 6.333, 9)	(5, 7.667, 9)	(3, 5.667, 9)
A_5	(3, 5.667, 9)	(3, 6.333, 9)	(5, 7, 9)	(3, 7,9)
A_6	(3, 6.333, 9)	(1, 1.667, 5)	(1, 3.667, 7)	(7, 9, 9)
A_7	(7, 9, 9)	(1, 2.333, 5)	(1, 5, 9)	(5, 7.667, 9)
A_8	(1, 3.667, 7)	(5, 7, 9)	(5, 7.667, 9)	(5, 8.333, 9)
A_9	(1, 3.667, 7)	(5, 7.667, 9)	(5, 8.333, 9)	(5, 7.667, 9)
A_{10}	(5, 7.667, 9)	(1, 2.333, 5)	(3, 5, 7)	(7, 9, 9)
A_{11}	(7, 9, 9)	(1, 2.333, 5)	(3, 5.667, 9)	(7, 9, 9)
A_{12}	(5, 7.667, 9)	(1, 2.333, 5)	(1, 4.333, 7)	(5, 8.333, 9)
A_{13}	(1, 4.333, 7)	(1, 2.333, 5)	(3, 5.667, 9)	(5, 8.333, 9)

Table 12
Weighted normalized comprehensive decision matrix $\widetilde{V}$.

	B_1	B_2	B_3	B_4
A_1	(0.078, 0. 1, 0. 1)	(0.011, 0.018, 0.056)	(0.033, 0.056, 0.078)	(0.056, 0.078, 0.1)
A_2	(0.033, 0.056, 0.078)	(0.011, 0.056, 0.1)	(0.056, 0.085, 0.1)	(0.056, 0.078, 0.1)
A_3	(0.011, 0.026, 0.056)	(0.011, 0.040, 0.078)	(0.033, 0.078, 0.1)	(0.056, 0.078, 0.1)
A_4	(0.033, 0.056, 0.078)	(0.033, 0.070, 0.1)	(0.056, 0.085, 0.1)	(0.033, 0.063, 0.1)
A_5	(0.008, 0.016, 0.025)	(0.008, 0.018, 0.025)	(0.014, 0.019, 0.025)	(0.008, 0.019, 0.025)
A_6	(0.033, 0.070, 0.1)	(0.011, 0.018, 0.056)	(0.011, 0.041, 0.078)	(0.078, 0.1, 0.1)
A_7	(0.039, 0.05, 0.05)	(0.006, 0.013, 0.028)	(0.006, 0.028, 0.05)	(0.028, 0.043, 0.05)
A_8	(0.003, 0.010, 0.019)	(0.014, 0.019, 0.025)	(0.014, 0.021, 0.025)	(0.014, 0.023, 0.025)
A_9	(0.006, 0.020, 0.039)	(0.028, 0.043, 0.05)	(0.028, 0.046, 0.05)	(0.028, 0.043, 0.05)
A_{10}	(0.056, 0.085, 0.1)	(0.011, 0.026, 0.056)	(0.033, 0.056, 0.078)	(0.078, 0.1, 0.1)
A_{11}	(0.078, 0.1, 0.1)	(0.011, 0.026, 0.056)	(0.033, 0.063, 0.1)	(0.078, 0.1, 0.1)
A_{12}	(0.028, 0.043, 0.05)	(0.006, 0.013, 0.028)	(0.006, 0.024, 0.039)	(0.028, 0.046, 0.05)
A_{13}	(0.011, 0.048, 0.078)	(0.011, 0.026, 0.056)	(0.033, 0.063, 0.1)	(0.056, 0.093, 0.1)

In this example, we have

$$A^+ = \left(\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_{13}^+\right) = ((0.078, 0.1, 0.), (0.056, 0.085, 0.1), (0.056, 0.078, 0.1), (0.056, 0.085, 0.1), (0.014, 0.019, 0.025), (0.078, 0.1, 0.1), (0.039, 0.05, 0.05), (0.014, 0.023, 0.025), (0.028, 0.046, 0.05), (0.078, 0.1, 0.1), (0.078, 0.1, 0.1), (0.028, 0.046, 0.05), (0.056, 0.093, 0.1)),$$

$$A^- = \left(\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_{13}^-\right) = ((0.011, 0.018, 0.056), (0.011, 0.056, 0.078), (0.011, 0.026, 0.056), (0.033, 0.056, 0.078), (0.008, 0.016, 0.025), (0.011, 0.018, 0.056), (0.006, 0.013, 0.028), (0.003, 0.010, 0.019), (0.006, 0.020, 0.039), (0.011, 0.026, 0.056), (0.011, 0.026, 0.056), (0.006, 0.013, 0.028), (0.011, 0.026, 0.056)).$$

Step 5: Calculate the distance of each potential CLC location from FPIS and FNIS, i.e.,

$$d_i^+ = \sum_{j=1}^{13} d\left(\tilde{v}_{ij}, \tilde{v}_j^+\right), \quad i = 1, 2, 3, 4.$$

$$d_i^- = \sum_{j=1}^{13} d\left(\tilde{v}_{ij}, \tilde{v}_j^-\right), \quad i = 1, 2, 3, 4.$$

where $d(\cdot)$ is the distance measurement between two triangular fuzzy numbers. For example, if $\tilde{a} = (a_1, a_2, a_3)$, $\tilde{b} = (b_1, b_2, b_3)$, then the distance between $\tilde{a}$ and $\tilde{b}$ is

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}\left[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2\right]}.$$

So we have

$$d_1^+ = 0.138, \quad d_2^+ = 0.279, \quad d_3^+ = 0.173, \quad d_4^+ = 0.035.$$
$$d_1^- = 0.161, \quad d_2^- = 0.020, \quad d_3^- = 0.126, \quad d_4^- = 0.263.$$

Step 6: Calculate the closeness coefficient (CC_i) of each alternative.

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}, \quad i = 1, 2, 3, 4.$$

Then we obtain $CC_1 = 0.538$, $CC_2 = 0.066$, $CC_3 = 0.421$, $CC_4 = 0.882$.

Step 7: Rank the alternatives according to the values of $CC_i,\ i = 1, 2, 3, 4$. The greater the value of CC_i, the better is alternative B_i.

From step 6, we have $CC_4 > CC_1 > CC_3 > CC_2$, therefore $B_4 \succ B_1 \succ B_3 \succ B_2$.

It can be seen that the ranking result obtained by using fuzzy TOPSIS is the same as that obtained by this paper. While these two methods demonstrate the validity of the decision-making results with each other, there are differences between them.

First, in fuzzy TOPSIS, all the linguistic assessment values are transformed into triangular fuzzy numbers and the experts' decision information is aggregated by the weighted averaging operator, or the operation of taking the bigger or smaller in fuzzy mathematics. The transformations are only approximate forms to express the initial linguistic assessment values, which may be lost and distort the original information and hence may bring about a lack of precision. However, in our method, the decision information is expressed by the linguistic values based on a linguistic 2-tuple. Thus, our method can effectively avoid the loss and distortion of information in the process of information gathering.

Second, in our method, the evaluation results of the CLC locations have definite and specific meanings. For example, the collective overall evaluation values of the four alternatives locations are $(s_3, -0.395)$, $(s_1, 0.236)$, $(s_2, 0.460)$ and $(s_3, 0.227)$ respectively, which means that the comprehensive evaluation level of B_1 is superior to the rating "Medium" but inferior to "Good", the comprehensive evaluation level of B_2 is superior to "Poor" but inferior to "Medium", the comprehensive evaluation level of B_3 is superior to "Medium" but inferior to "Good", and the comprehensive evaluation level of B_4 is superior to "Good" but inferior to "Very good". Although B_1 and B_3 belong to the same rating, the values 0.460 and -0.395 can reflect the deviation degree. That is, our method cannot only rank the order of the four potential CLC locations by using the linguistic comparison rules but can also give the specific comprehensive evaluation ratings. However, in fuzzy TOPSIS, the comprehensive evaluation results of CLC locations are expressed by the closeness coefficient $CC_1 = 0.538$, $CC_2 = 0.066$, $CC_3 = 0.421$ and $CC_4 = 0.882$. These numbers can only show the optimal solution and the worst order of four potential CLC locations, but these have no definite and specific meanings on the evaluation rating.

Finally, while the *THOWA* operator may mitigate the adverse effects of irrationality in the decision-making process, and can make the decision results fairer and more reasonable by assigning low weights to the biased arguments, these advantages are not reflected if we use fuzzy TOPSIS.

Conclusion

This paper presents a new evaluation system for the location selection of a CLC by integrating the three dimensions of sustainability, namely, economic, environmental, and social, and proposes a fuzzy multi-attribute group decision making method based on the linguistic 2-tuple to evaluate all potential CLC locations under a fuzzy uncertainty information environment. We present a new *THOWA* operator to aggregate the evaluation values given by the experts into a collective overall evaluation value for each alternative. We also proved that this *THOWA* operator has the properties of idempotency, commutativity, monotonicity and boundedness. To demonstrate the practicality and effectiveness of our decision method based on the *THOWA* operator, we provide an application example and compare our method with fuzzy TOPSIS. The comparison results show that (i) our method can effectively avoid the loss and distortion of information in the process of information gathering; (ii) in our method, the evaluation results of CLC locations have definite and specific meanings; and (iii) our method can reduce the adverse effects of emotional factors in the decision-making process, thus making the decision results fair and reasonable through assigning low weights to those "biased" arguments. This is impactful as it offers a more objective based decision making process. In this paper, our contribution is to provide a theoretical basis and decision-making reference to help business select optimal CLC locations under sustainability. As in all methods, however, our approach has its limitations, i.e., it is largely suitable for multi-attribute group decision making with the criteria values in the form of fuzzy linguistic variables, albeit it is not suitable for multi-attribute group decision making with hybrid criteria values, i.e., where real numbers, interval numbers and linguistic fuzzy variables coexist. In reality, there are situations which use hybrid criteria values. In future, we will focus on the hybrid criteria values in a sustainable CLC locations selection problem under an uncertain information environment.

Acknowledgements

This work is supported by the National Natural Science Foundation of China (Nos. 71201064, 61273206, 71371147), the Postdoctoral Science Foundation of China (No. 2012M521432), the Special Fund of Postdoctoral Science Foundation of China (No. 2013T60724), the Natural Science Foundation of Hubei Province, China (No. 2014CFC1096), and the 2014 Key Project of Hubei provincial Department of Education, China (No. D20142903).

Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.trd.2015.02.008.

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