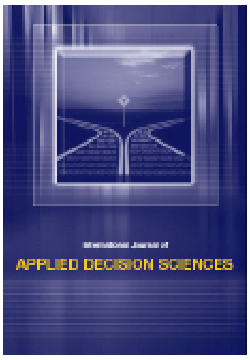

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Comparative analysis of novel fuzzy multi-criteria decision-making methods for selecting fourth-party logistics service providers: a case study in the plastic resin industry

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Comparative analysis of novel fuzzy multi-criteria decision-making methods for selecting fourth-party logistics service providers: a case study in the plastic resin industry

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Abstract: This paper proposes a systematic framework to select the best 4PLs by incorporating several MCDM methods. The aim of this paper is to conduct a comparative study to examine how different MCDM methods compare when apply for 4PLs selecting problem. First, 14 criteria of 4PLs selection are identified through literature and input from industrial experts. Second, the objective weights of criteria are derived through interval Shannon's entropy based on α-level sets. Afterward, the 4PL candidates are ranked comparatively using five novel MCDM methods reported in literature including CoCoSo, MARCOS, EDAS, MAIRCA, and CODAS. Finally, the sensitivity analysis is performed to test the robustness and reliability of the proposed framework. A case of the plastic resin industry in Thailand is used to demonstrate the application of the proposed framework. The practitioners and academics can utilise the proposed framework to select the best 4PLs.

Keywords: multi-criterion decision making; fuzzy set theory; FST; fourth-party logistics providers.

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1 Introduction

With the pressure of cost competition and rapidly emerging technological innovations, the outsourcing logistics has become an essential strategic decision of any manufacturing enterprises. Using outsource logistics service providers allows the manufactures to focus on their core business processes. Therefore, broad ranges of logistics activities such as warehouse management, transportation, distribution management and logistics information system are assigned to third-party logistics providers (referred 3PLs) (Saikouk et al., 2021). In the past few years, increasing supply chain complexity, fierce competition across industries, disruptive technologies and drastically change customer demand for speed and flexibility in the delivery of goods and service has forced manufacturers to reconsider their outsourcing logistics strategy (Huang et al., 2019). To be able to complete in such turbulent environment, manufacturers do not require only tradition outsource logistics efficiency at operational level but also require the improvement supply chain network cooperation at strategic level (Qian et al., 2021).

Table 1 Nomenclature with their definition/explanation used in this research

Nomenclature	
3PLs	Third-party logistics providers
4PLs	Fourth-party logistics providers
AAI	Anti-ideal alternative
AI	Ideal alternative
BCP	Business continuity plan
CoCoSo	Combined compromise solution
CODAS	Combinative distance-based assessment
DMs	Decision makers
E	Expert
EDAS	Evaluation based on distance from average solution
EWP	Exponentially weighted product
FST	Fuzzy set theory
IoT	Internet of things
MAIRCA	Multi-attributive ideal-real comparative analysis
MARCOS	Measurement of alternatives and ranking according to compromise solution
MCDM	Multi-criteria decision making
SAW	Simple additive weight
TFNs	Triangular fuzzy numbers
WASPAS	Weighted aggregated sum product assessment
WPM	Weighted product method

Apart from providing the logistics services, manufactures expect the 3PLs to become their strategic partners and need them to provide full range of total solutions in managing their supply chain (Mehmann and Teuteberg, 2016). However, some manufactures view that most of 3PLs remain the status quo and not capable enough to meet the changing demands. For this reason, many manufactures, especially large firms, are interested in shifting the outsource logistics activities from 3PLs to 4PLs (referred 4PLs). 4PL is an outsourced logistics services company that manages the supply chain processes on behalf of its customers (Kalkan and Aydin, 2020). Basically, 4PLs act as intermediaries in the supply chain to manage activities of multiple 3PLs, facilitate supply chain integration, manipulate at operational, tactical and strategic levels, foster relationships within the supply chain and manage global supply chain (Selviaridis and Spring, 2018). Using the right 4PLs can bring many advantages to manufactures such as optimise supply chain processes, effective supply chain costs, innovative supply chain management and sophisticated logistics technologies (Wang et al., 2018). On the other hand, using the unsuitable 4PLs can lead to negative and unsatisfactory outcomes for manufacturers (Pani et al., 2021). Hence, the selecting of 4PLs is a crucial strategic decision for manufactures aiming to outsource their logistics activities (Ekanayake et al., 2017). However, selection of the suitable 4PLs is a complex and multi-dimensional problem.

It requires an effective tool that can simultaneously handle a wide range of selected criteria. Although numerous 3PLs selection topics have been reported in the literature but few studies have focused on its application in the selection of 4PLs. This study attempts to bridge the gap by proposing a framework to select the suitable 4PLs which can be described as follows;

- Since the selection of 4PLs is a complicate decision-making problem as it relates to various criteria and some of them are contradict each other, such as quality and cost. Multi-criteria decision making (MCDM) is an effective tool for selecting and ranking the most suitable alternative by taking into account multiple conflicting criteria (Vazifehdana and Darestanib, 2019). In this study, the selection 4PLs is considered as a MCDM problem.
- There is a high degree of uncertainty and ambiguity often associated with the decision-making processes (Tao et al., 2021). Fuzzy set theory (FST) is a powerful tool for manipulating imprecise information obtained from decision makers (DMs) using fuzzy numbers (Zarei et al., 2021). There are different types of fuzzy numbers, such as monotonic, triangular, and trapezoid. Among the fuzzy numbers, triangular fuzzy numbers (TFNs) are most widely used in many MCDM applications due to their computational simplicity (Tadić, 2014). To take advantage of TFNs, it is employed to deal with imprecise information in decision making processes throughout this paper.
- Due to the criteria weights directly affect the decision making results, weight determination is an important step in MCDM procedure (Saraswat and Digalwar, 2021). Principally, there are two main approaches for determining criteria weights in MCDM as subjective weighting and objective weighting (Sitorus and Brito-Parada, 2020). Subjective weighting approaches are purely based on the experiences and judgement of the DMs. On the contrary, objective weighing approach use the structure of data to analyse the criteria weights regardless of subjective judgement of the DMs. To avoid unreliable decisions obtained by the DM, objective weighing

approach should be utilised. Among the objective weighting methods, the Shannon entropy method is one of the most commonly used for determining the criteria weights as it does not require any model assumption in mathematical calculations (Saraswat and Digalwar, 2021). In this study, the criteria weights are obtained using interval Shannon's entropy methodology.

- Regarding the alternatives ranking, there are numerous MCDM methods presented in the literatures. Each ranking method has its own uniqueness. However, using different methods may yield different ranking results when applied to the same problem that can be used for validation the robustness of decision model (Ecer, 2021). In this study, the comparative study is performed using five new MCDM ranking methods reported in literatures as combined compromise solution (CoCoSo), measurement of alternatives and ranking according to compromise solution (MARCOS), evaluation based on distance from average solution (EDAS), multi-attributive ideal-real comparative analysis (MAIRCA) and combinative distance-based assessment (CODAS) to select the best 4PL. The reasons for choosing these five ranking methods stems from
  a recent report in literatures
  b computational simplicity
  c applied to various real world problems.

In this study, the plastic resin industry in Thailand is used as a case study to validate the applicability of the proposed framework. The rest of the paper is arranged as follows. Section 2 presents the research methodologies used in this study. The proposed framework is given in Section 3. An application of the proposed framework is illustrated in Section 4. Section 5 presents a comparative analysis of rankings using different MCDM methods. Next, a sensitivity analysis is performed in Section 6. Finally, the conclusions and future research are drawn in Section 7.

2 Research methodology

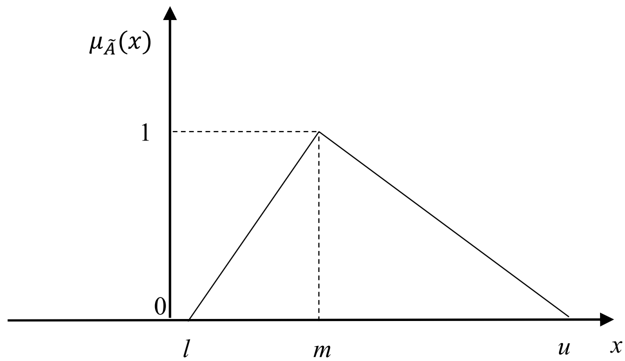
This section provides a basic concept of fuzzy sets theory. Next, the weights of each criterion are derived from interval Shannon's entropy based on α-cutting level sets. Finally, the MCDM ranking methods used in this paper are briefly reviewed as follows.

2.1 Fuzzy sets and fuzzy numbers

Human decision-making processes often involve subjective information and uncertainty. A FST was developed by Zadeh (1965) to deal with ambiguity and imprecise information in decision-making problems. Generally, a fuzzy set can be characterised by a membership function as shown below, each element of X is assigned to a set of universe discourse X in the interval [0, 1]. There are several types of fuzzy membership functions. The triangular membership function is one of the most widely used to manipulate the fuzzy information. It is represented by TFNs as (l, m, u) as depicted in Figure 1.

$$\mu_{\tilde{A}}(x;l,m,u)=\begin{cases}\dfrac{(x-l)}{(m-l)}, l \le x \le m \\ \dfrac{(u-x)}{(u-m)}, m \le x \le u \\ 0, x > u \; or \; x < l \end{cases} \tag{1}$$

Figure 1 A triangular fuzzy number $\tilde{A}$



$\mu_{\tilde{A}}(x)=1$ when ($x = m$), l and u are the lowest and highest possible values respectively, while m is a value between l and u values. In this study, TFNs memberships of each criterion are transformed into interval data using α-cutting level sets method. The interval value of memberships can be defined as A_α where α value is a cutting level sets (confidence interval).

2.2 Constructing the initial decision matrix

The data gathered from experts can be manipulated as follows:

Step 1 The initial decision matrix of each expert k^{th} is constructed using triangular fuzzy number as:

$$X_{ij}^k = \begin{array}{c} A_1 \\ A_2 \\ \cdots \\ A_m \end{array} \begin{bmatrix} x_{11}^k & x_{12}^k & \cdots & x_{1n}^k \\ x_{21}^k & x_{22}^k & \cdots & x_{2n}^k \\ \cdots & \cdots & \ddots & \cdots \\ x_{m1}^k & x_{m1}^k & \cdots & x_{mm}^k \end{bmatrix} i=1,2\ldots,m; j=1,2\ldots,n \tag{2}$$

where $x_{ij}^k = \left(x_{ij}^{kl}, x_{ij}^{km}, x_{ij}^{ku}\right)$.

Step 2 The aggregated fuzzy initial decision matrix is calculated as:

$$\tilde{x}=\begin{bmatrix} \left(\tilde{x}_{11}^{l},\tilde{x}_{11}^{m},\tilde{x}_{11}^{u}\right) & \left(\tilde{x}_{12}^{l},\tilde{x}_{12}^{m},\tilde{x}_{12}^{u}\right) & \cdots & \left(\tilde{x}_{12n}^{l},\tilde{x}_{1n}^{m},\tilde{x}_{1n}^{u}\right) \\ \cdots & \cdots & \ddots & \cdots \\ \cdots & \cdots & \ddots & \cdots \\ \left(\tilde{x}_{m1}^{l},\tilde{x}_{m1}^{m},\tilde{x}_{m1}^{u}\right) & \left(\tilde{x}_{m2}^{l},\tilde{x}_{m2}^{m},\tilde{x}_{m2}^{u}\right) & \cdots & \left(\tilde{x}_{mn}^{l},\tilde{x}_{mn}^{m},\tilde{x}_{mn}^{u}\right) \end{bmatrix} \tag{3}$$

where

$$\tilde{x}_{ij}=\left(\tilde{x}_{ij}^{l},\tilde{x}_{ij}^{m},\tilde{x}_{ij}^{u}\right)=\left(\frac{\sum_{k=1}^{k}x_{ij}^{k}}{k},\frac{\sum_{k=1}^{k}x_{ij}^{km}}{k},\frac{\sum_{k=1}^{k}x_{ij}^{km}}{k}\right). \tag{4}$$

Step 3 The aggregated initial decision matrix is defuzzied into crisp numbers by using best non-fuzzy performance (BNP) represented by matrix Ycrisp= $[y_{ij}]_{m\times n}$ as:

$$Y^{crisp}=\begin{array}{c} \\ A_1 \\ A_2 \\ \cdots \\ A_m \end{array}\begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \end{array} \tag{5}$$

$$BNP(y_{ij})=\frac{\left(\tilde{x}_{ij}^{u}-\tilde{x}_{ij}^{l}\right)+\left(\tilde{x}_{ij}^{m}-\tilde{x}_{ij}^{l}\right)}{3}+\tilde{x}_{ij}^{l} \tag{6}$$

2.3 Interval Shannon's entropy based on α-level sets

The Shannon's entropy method was introduced by Shannon (1948). This method applies a concept of probabilistic to measure the information uncertainty. It has been broadly used to determine the objective weights for the considered criteria which can reflect realistic decision of the DMs without subjective assessment. Shannon's entropy under TFNs can be extended to the interval data cases namely 'Interval Shannon's entropy based on α-level sets' approach (Mohamadi et al., 2017). There are applications of Interval Shannon's entropy based on α-level sets used to solve MCDM problems such as analysing barriers to the implementation of continuous improvement in manufacturing (Tavana et al., 2021); assessment of contractors in electric power distribution company (Mohamadi et al., 2017). The Interval Shannon's entropy based on α-level sets is shown as follows.

Step 1 The aggregated fuzzy initial decision matrix is converted into corresponding interval data at α level as:

$$\begin{array}{lcccc} & \textit{Criterion }1 & \textit{Criterion }2 & & \textit{Criterion }3 \\ \textit{Alternative }1 & \left[\tilde{x}_{11}^{l},\tilde{x}_{11}^{u}\right] & \left[\tilde{x}_{12}^{l},\tilde{x}_{12}^{u}\right] & \cdots & \left[\tilde{x}_{1n}^{l},\tilde{x}_{1n}^{u}\right] \\ \textit{Alternative }2 & \left[\tilde{x}_{21}^{l},\tilde{x}_{21}^{u}\right] & \left[\tilde{x}_{22}^{l},\tilde{x}_{22}^{u}\right] & \cdots & \left[\tilde{x}_{2n}^{l},\tilde{x}_{2n}^{u}\right] \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \textit{Alternative }3 & \left[\tilde{x}_{m1}^{l},\tilde{x}_{m1}^{u}\right] & \left[\tilde{x}_{m2}^{l},\tilde{x}_{m2}^{u}\right] & \cdots & \left[\tilde{x}_{mn}^{l},\tilde{x}_{mn}^{u}\right] \end{array} \tag{7}$$

where the matrix represents the rating score of the alternative with respect to criterion evaluated by experts. The level set can be expressed in the following interval form as follows:

$$\left[\left(\tilde{x}_{ij}\right)_{\propto}^{i},\left(\tilde{x}_{ij}\right)_{\propto}^{u}\right]=\left[min\tilde{x}_{ij}\left\{\tilde{x}_{ij}\in R\middle|u\tilde{x}_{ij}\right\},max_{\tilde{x}ij}\left\{x_{ij}\in R\middle|u_{\tilde{x}ij}\left(\tilde{x}_{ij}\right)\geq\alpha\right\}\right] \tag{8}$$

where $0 < \alpha \leq 1$. In this paper, $\alpha = 0.5$ and 0.1, 0.7 and 0.9 values uses to perform sensitivity analysis.

Step 2 The normalised initial decision matrix is constructed as:

$$p_{ij}^{l}=\frac{x_{ij}^{l}}{\sum_{i=1}^{m}x_{ij}^{u}},\ p_{ij}^{u}=\frac{x_{ij}^{u}}{\sum_{i=1}^{m}x_{ij}^{u}}\ i=1,\ldots,m,j=1,\ldots,n \tag{9}$$

Step 3 The lower bound h_j^l and upper bound h_j^u of interval entropy are computed as:

$$h_j^l=min\left\{-h_0\sum_{i=1}^{m}p_{ij}^l.Inp_{ij}^l,-h_0\sum_{i=1}^{m}p_{ij}^u.Inp_{ij}^u\right\},j=1,\ldots,n \tag{10}$$

$$h_j^u=max\left\{-h_0\sum_{i=1}^{m}p_{ij}^l.Inp_{ij}^l,-h_0\sum_{i=1}^{m}p_{ij}^u.Inp_{ij}^u\right\},j=1,\ldots,n \tag{11}$$

where h_0 is determined by $(\ln m)^{-1}$, and $p_{ij}^i\cdot lnp_{ij}^l$ or $p_{ij}^u\cdot lnp_{ij}^u$ is equal 0 if $p_{ij}^l=0$ or $p_{ij}^u=0$.

Step 4 The interval of diversification of lower and upper bound is defined as $[d_j^l,d_j^u]$ is calculated by:

$$d_j^l=1-h_j^u,d_j^u=1-h_j^l,j=1,\ldots,n \tag{12}$$

Step 5 The interval weight is defined by lower and upper bound $[w_j^l,w_j^u]$ can be obtained by:

$$w_j^l=\frac{\left(d_{ij}^l\right)}{\sum_{s=1}^{n}d_s^u},w_j^u=\frac{d_i^u}{\sum_{s=1}^{n}d_s^l},j=1,\ldots,n \tag{13}$$

Step 6 The final weights are determined by:

$$w_j'=\frac{w_j^l+w_j^u}{2} \tag{14}$$

$$w_j=\frac{w_j'}{\sum_{i=1}^{N}w_j'} \tag{15}$$

2.4 CoCoSo

The CoCoSo is a recent MCDM ranking method developed by Yazdani et al. (2019). The principle of this method is a combination of three ranking approaches including simple additive weighting (SAW), weighted aggregated sum product assessment (WASPAS), and exponentially weighted product (EWP) to produce a stable and reliable ranking. Recently, CoCoSo was employed to rank various MCDM problems such as analyse IoT adoption barriers (Cui et al., 2021); assessment of social sustainability performance (Torkayesh et al., 2021); assessment of battery electric vehicles (Ecer, 2021); risk evaluation of occupational health and safety (Chen et al., 2022); assessment of the European container ports (Pamucar and Görçün, 2022); evaluation of circular supply chains barriers (Shang et al., 2022); analysing the impact of COVID-19 on the financial performance of the hospitality and tourism industries (Ghosh and Bhattacharya, 2022). CoCoSo's procedure is presented as follows:

Step 1 The aggregated initial decision matrix equation (3) is normalised as:

$$\tilde{Z}_{ij} = \begin{array}{c} \\ A_1 \\ A_2 \\ \cdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} \overset{=}{z}_{11} & \overset{=}{z}_{12} & \cdots & \overset{=}{z}_{1n} \\ \overset{=}{z}_{21} & \overset{=}{z}_{22} & \cdots & \overset{=}{z}_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ \overset{=}{z}_{m1} & \overset{=}{z}_{m2} & \cdots & \overset{=}{z}_{1n} \end{bmatrix} \end{array} \tag{16}$$

The benefit and cost criteria are normalised by equation (16) and equation (17), respectively.

$$\overset{=}{z}_{ij} = \frac{y_{ij} - y_{ij}^{-}}{y_{ij}^{+} - y_{ij}^{-}}, \text{ if } j \text{ is a benefit criterion} \tag{17}$$

$$\overset{=}{z}_{ij} = \frac{y_{ij}^{+} - y_{ij}}{y_{ij}^{+} - y_{ij}^{-}}, \text{ if } j \text{ is a cost criterion} \tag{18}$$

Step 2 The S_i and P_i values are obtained by:

$$S_i = \sum_{j=1}^{n} w_j \overset{=}{z}_{ij} \tag{19}$$

$$P_i = \sum_{j=1}^{n} \left(\overset{=}{z}_{ij}\right)^{w_j} \tag{20}$$

where w_j is the criteria weight of j^{th} criterion obtained by interval Shannon's entropy at α level.

Step 3 The appraisal score strategies for each alternative are computed by:

$$\xi_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m}(P_i + S_i)} \tag{21}$$

$$\xi_{ib} = \frac{S_i}{\underset{i}{min} S_i} + \frac{P_i}{\underset{i}{min} P_i} \tag{22}$$

$$\xi_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{\lambda \underset{i}{min} S_i + (1-\lambda) \underset{i}{max} P_i}; 0 \leq \lambda \leq 1 \tag{23}$$

Basically, $\lambda = 0.5$ is assigned.

Step 4 The performance scores of alternatives is computed by:

$$\xi_i = (\xi_{iao} \cdot \xi_{ib} \cdot \xi_{ic})^{1/3} + \frac{1}{3}(\xi_{ia} \cdot \xi_{ib} \cdot \xi_{ic}) \tag{24}$$

Step 5 The alternatives are ranked in descending order of their performance score (ξ_i).

2.5 MARCOS

MARCOS is one of the recent MCDM ranking method, was proposed by Stević et al. (2020). This approach overcomes some weaknesses of other MCDM techniques such as ignoring the relative importance of distance and complex calculations. This method was applied in many fields such as risk assessment of dam construction (Celik and Gul, 2021); assessment of alternative fuel vehicles (Pamucar et al., 2021); assessment of battery electric vehicles (Ecer, 2021); prioritising the alternatives of the natural gas grid conversion to hydrogen (Iordache et al., 2022); overcoming sustainable vaccine supply chain challenges (Yadav and Kumar, 2022). MARCOS's procedure is summarised as follows:

Step 1 The extend initial matrix X^G is formulated by adding an ideal alternative (AI) and an anti-ideal alternative (AAI) as:

$$Y^G = \begin{array}{c} A_1 \\ A_2 \\ \cdots \\ A_3 \\ AAI \\ AI \end{array} \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \\ y_{aa1} & y_{aa2} & \cdots & y_{aan} \\ y_{ai1} & y_{ai2} & \cdots & y_{ain} \end{bmatrix} \tag{25}$$

where AI and AAI are obtained by:

$$\begin{cases} AAI = \underset{i}{min}\{y_{ij}\} i, \text{ if } j \text{ is a benefit criterion } (B) \\ AI = \underset{i}{max}\{y_{ij}\} i, \text{ if } j \text{ is a benefit criterion } (B) \end{cases} \tag{26}$$

$$\begin{cases} AAI = \underset{i}{min}\{y_{ij}\} i, \text{ if } j \text{ is a benefit criterion } (B) \\ AI = \underset{i}{max}\{y_{ij}\} i, \text{ if } j \text{ is a benefit criterion } (B) \end{cases} \tag{27}$$

Step 2 The extended initial decision matrix is normalised as:

$$n_{ij} = \frac{y_{ai}}{y_{ij}},\ if\ j\ is\ a\ cost\ criterion\ (C) \tag{28}$$

$$n_{ij} = \frac{y_{ij}}{y_{ai}},\ if\ j\ is\ a\ benefit\ criterion(B) \tag{29}$$

where $y_{ij} \in Y^G$ and $y_{ai} \in Y^G$

$$v_{ij} = n_{ij} \cdot w_j \tag{30}$$

where w_j is the criteria weight of j^{th} criterion obtained by interval Shannon's entropy at α level.

Step 3 The utility degree of each alternative is computed by:

$$K_i^- = \frac{S_i}{S_{aai}} \tag{31}$$

$$K_i^+ = \frac{S_i}{S_{ai}} \tag{32}$$

where S_i can be obtained by equation (33).

$$S_i = \sum_{i=1}^{n} v_{ij} \tag{33}$$

Step 4 The utility function of each alternative $f(K_i)$ is computed as:

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \tag{34}$$

where $f(K_i^-)$ is stand for the utility function as per the anti-ideal solution, while $f(K_i^+)$ is stand for the utility function as per the ideal solution. $f(K_i^-)$ and $f(K_i^+)$ can be calculates by equations (35)–(36), respectively.

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{35}$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{36}$$

Step 5 The alternatives are ranked in descending order of their utility function values ($f(K_i)$).

2.6 EDAS

EDAS method was proposed by Ghorabaee et al. (2015). It is one of the MCDM distance-based ranking methods. The concept of this method is that the alternatives ranking are based on the distance of each alternative from the mean solution on each criterion. Compared to other distance-based ranking methods, this method is simpler and the calculation process is lower. EDAS applications were reported in many academic papers such as evaluation of sustainable hydrogen production options (Abdel-Basset et al., 2021); renewable energy investments (Karatop et al., 2021); assessment of renewable energy resources (Yazdani et al., 2020); prioritisation of sustainable mobility sharing systems (Pamucar et al., 2022). EDAS's method is illustrated as follows:

Step 1 The average value matrix $AV = [AV_j]_{1\times n}$ is constructed as:

$$AV_j = \frac{\sum_{i=1}^{n} y_{ij}}{n} \tag{37}$$

Step 2 The positive distance from average ($PDA = [PDA_{ij}]_{m\times n}$) matrix and the negative distance from the average ($NDA = [NDA_{ij}]_{m\times n}$) are computed in accordance with the type of criteria (cost or benefit) as:

If a type of criterion is cost

$$PDA_{ij} = \frac{max\left(0, \left(AV_j - y_{ij}\right)\right)}{AV_j}; NDA_{ij} = \frac{max\left(0, \left(y_{ij} - AV_j\right)\right)}{AV_j} \tag{38}$$

If a type of criterion is benefit

$$PDA_{ij} = \frac{max\left(0, \left(K_{ij} - AV_j\right)\right)}{AV_j}; NDA_{ij} = \frac{max\left(0, \left(AV_j - K_{ij}\right)\right)}{AV_j} \tag{39}$$

Step 3 The weighted total positive value (SP_i) and the weighted negative value (SN_i) of each alternative are computed as:

$$SP_i = \sum_{j=1}^{n} w_j \times PDA_{ij} \tag{40}$$

$$SN_i = \sum_{j=1}^{n} w_j \times NDA_{ij} \tag{41}$$

where w_j is the criteria weight of j^{th} criterion obtained by interval Shannon's entropy at α level.

Step 4 The normalised weighted total positive value (NSP_i) and the normalised weighted total negative value (NSN_i) for each alternative are obtained by:

$$NSP_i = \frac{SP_i}{maxi(SP_i)} \tag{42}$$

$$NSN_i = 1 - \frac{SN_i}{max_i(SN_i)} \tag{43}$$

Step 5 The final evaluation score (AS_i) for each alternative is calculated by:

$$AS_i = \frac{1}{2} \times (NSP_i + NSN_i) \tag{44}$$

Step 6 The alternatives are ranked in descending order of their AS_i values.

2.7 MAIRCA

MAIRCA technique was recently introduced by Pamucar et al. (2020), The basic idea of this approach is to define the gap between theoretical and real assessment. The total gap for every alternative is determined by the summation the gaps for each criterion. The best ranked alternative is the one with the smallest value of the total gap. MAIRCA were applied to solve many MCDM problems such as assessment of battery electric vehicles (Ecer, 2021); prioritising the energy storage technologies (Pamucar et al., 2020); healthcare waste treatment technology selection (Adar and Delice, 2019); outranking of geospatial data (Riahi et al., 2022); assessment flood susceptibility (Hadian et al., 2022). MAIRCA's method is presented as follows:

Step 1 The preferences for the choice of options (P_{Ai}) is determined by:

$$P_{A_i} = \frac{1}{m}; \sum_{j=1}^{m} P_{A_i} = 1, i = 1, 2, \ldots, m \tag{45}$$

where m is the number of alternative under consideration. All alternatives have the same preference for selection as:

$$P_{A_i} = P_{A_2} = \ldots = P_{A_m} \tag{46}$$

Step 2 The theoretical rating matrix $T_P = [t_{Pij}]_{m \times n}$ is formulated by:

$$T_P = \begin{array}{c} \\ P_{A_1} \\ P_{A_2} \\ \cdots \\ P_{A_m} \end{array} \begin{array}{c} \begin{array}{cccc} w_1 & w_2 & \ldots & w_n \end{array} \\ \begin{bmatrix} t_{p11} & t_{p12} & \cdots & t_{pn} \\ t_{p21} & t_{p22} & \cdots & t_{p2n} \\ \cdots & \cdots & \cdots & \cdots \\ t_{pm1} & t_{pm2} & \cdots & t_{pmn} \end{bmatrix} \end{array} = \begin{array}{c} \\ P_{A_1} \\ P_{A_2} \\ \cdots \\ P_{A_m} \end{array} \begin{array}{c} \begin{array}{cccc} w_1 & w_2 & \ldots & w_n \end{array} \\ \begin{bmatrix} P_{A_1} w_1 & P_{A_1} w_2 & \cdots & P_{A_1} w_n \\ P_{A_2} w_1 & P_{A_2} w_2 & \cdots & P_{A_2} w_n \\ \cdots & \cdots & \cdots & \cdots \\ P_{A_m} w_1 & P_{A_m} w_2 & \cdots & P_{A_{1m}} w_n \end{bmatrix} \end{array} \tag{47}$$

where w_j is the criteria weight of j^{th} criterion obtained by interval Shannon's entropy at α level.

Step 3 The real rating matrix (T_r) is determined by multiply the elements in matrix T_P with the element in matrix Y^{crisp} as:

For the benefit criteria,

$$t_{rij} = t_{pij} \cdot \left(\frac{y_{ij} - y_i^-}{y_i^+ - y_i^-} \right) \tag{48}$$

For the cost criteria,

$$t_{rij} = t_{pij} \cdot \left(\frac{y_{ij} - y_i^+}{y_i^- - y_i^+} \right) \tag{49}$$

where $y_i^+ = \max(y_1, y_2, \ldots, y_m)$ and $y_i^- = min(y_1, y_2, \ldots, y_m)$.

Step 4 The total gap matrix $G = [g_{ij}]_{m \times n}$ is constructed by a different between T_P and T_r as:

$$G = T_P - T_r = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ g_{m1} & g_{m2} & \cdots & g_{mn} \end{bmatrix} = \begin{bmatrix} t_{p11} - t_{r11} & t_{p12} - t_{r12} & \cdots & t_{p1n} - t_{r1n} \\ t_{p21} - t_{r21} & t_{p22} - t_{r22} & \cdots & t_{p2n} - t_{r2n} \\ \cdots & \cdots & \cdots & \cdots \\ t_{pm1} - t_{rm1} & t_{pm2} - t_{rm2} & \cdots & t_{pmn} - t_{rmn} \end{bmatrix} \tag{50}$$

where g_{ij} stands for the gap for i^{th} alternative as per j^{th} criterion.

Step 5 The final values of the criteria functions Q_i are computed as:

$$Q_i = \sum\nolimits_{j=1}^{n} g_{ij}, i = 1, 2, \ldots, m \tag{51}$$

Step 6 The alternatives are ranked in ascending order of their Q_i values.

2.8 CODAS

CODAS was pioneered by Ghorabaee et al. (2016). This approach combines the concept of two different ranking methods as SAW and weighted product method (WPM). CODAS use two measurement distances including Euclidean distance and Euclidean distance. Euclidean distance is considered the primary measurement and Taxicab distance is a secondary measure. CODAS was applied to solve many real world and academic problems such as vehicle shredding facility location analysis (Simic et al., 2021); workforce attributes for Industry 4.0 (Vinodh and Wankhede, 2021); supplier selection (Bolturk, 2018); evaluation of worst polluted cities (Raheja et al., 2022). CODAS's procedure is demonstrated as follow:

Step 1 The aggregated initial decision matrix is constructed as.

$$Y^{crisp} = \begin{array}{c} \\ A_1 \\ A_2 \\ \cdots \\ A_3 \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \end{array} \tag{52}$$

Step 2 The aggregated initial decision matrix is normalised by:

$$n_{ij} = \begin{cases} \dfrac{y_{ij}}{max_i\{y_{ij}\}} & if\ j \in N_b \\ \dfrac{min_i\{y_{ij}\}}{y_{ij}} & if\ j \in N_c \end{cases} \tag{53}$$

where N_b is the benefit criterion and N_c is the cost criterion.

Step 3 The weighted normalised decision matrix is calculated by:

$$r_{ij} = w_j n_{ij} \tag{54}$$

where w_j is the criteria weight of j^{th} criterion obtained by interval Shannon's entropy at α level.

Step 4 The negative-ideal solution is computed by:

$$ns_j = [ns_j]_{1\times m} \tag{55}$$

where $ns_j = \min_i nr_{ij}$.

Step 5 The Euclidean distance (E_i) and Taxicab distance (T_i) of alternatives from negative-ideal solution can be obtained by:

$$E_i = \sqrt{\sum_{j=1}^{m} \left(r_{ij} - ns_j\right)^2} \tag{56}$$

$$T_i = \sum_{j=1}^{m} \left|r_{ij} - ns_j\right| \tag{57}$$

Step 6 The relative assessment matrix $H_a = [h_{ik}]_{n \times n}$ is calculated as:

$$h_{ik} = (E_i - E_k) + \left(\psi(E_i - E_k) \times (T_i - T_k)\right),\ \psi(x) \tag{58}$$

where $k = \{1, 2, \ldots, n\}$ and ψ stands for a function to realise the equality of the Euclidean.

$$\psi(x) = \begin{cases} 1 \ if \ |x| \geq \tau \\ 0 \ if \ |x| < \tau \end{cases} \tag{59}$$

τ is the threshold parameter at a value [0.01, 0.05].

Step 7 The assessment score for each alternative can be obtained as:

$$H_i = \sum_{k=1}^{n} h_{ik} \tag{60}$$

Step 8 The alternatives are ranked in descending order of their H_i values.

3 Proposed framework

The present paper proposes three basis stages framework methodologies including:

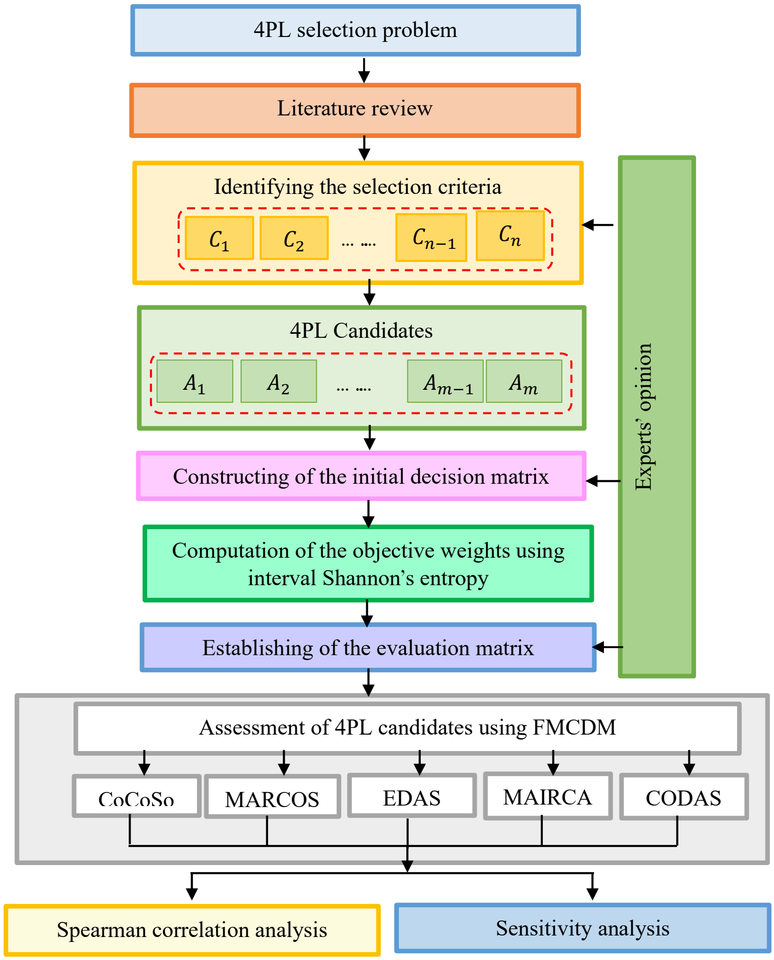
1 identification of 4PL selection criteria to be used in the framework through extensive literature review and then final validated by experts

2 determination the objective weights of selected criteria using interval Shannon's entropy based on α-level sets

3 selection the best 4PL among five candidates (A_1, A_2, A_3, A_4, A_5) using CoCoSo, MARCOS, EDAS, MAIRCA and CODAS under fuzzy condition.

The schematic diagram of the proposed framework for the selection of 4PL is depicted in Figure 2.

Figure 2 Proposed framework for the selection of 4PL (see online version for colours)



4 An application of the proposed framework

The proposed framework is applied to solve a 4PL selection problem in the plastic resin industry located at eastern part of the Thailand. Due to intense competition in both domestic and global markets, Thai plastic resin producers face the challenge of reducing their logistics costs in more innovative ways. In this regard, managing logistics outsourcing by 3PLs is one of key areas to be focused. The using 3PLs needs to be reconsidered as they provide the logistics services in a traditional way that fails to meet the expectations of the plastic resin industry. As a result, Thai plastic resin producers have a growing trend to shift their logistics outsourcing services from 3PLs to 4PLs. Using 4PLs allows manufacturers to expand their supply chain management boundaries by integrating various 3PLs and optimising all logistics processes to accomplish high operational efficiency. In this study, a case company is one of the largest plastic resin manufactures in Thailand, located in Rayong province. This manufacturer plans to change its outsourcing contracts for transportation and distribution of finished products from current 3PLs to 4PLs. This is because the selection of 4PLs is a complex decision making problem and involves a number of selection criteria. The logistics managers of the case manufacturing have no experiences in selecting 4PLs. Hence, they require a systematic framework to select the best 4PL from five candidates: i.e., A_1, A_2, A_3, A_4 and A_5. In doing this, ten industrial experts are formed (as shown in Table 2) to make the decision to select the best one.

Table 2 Details of ten industrial experts

Expert (E)	*Experience (years)*	*Position*	*Organisation*	*Area of expertise*
E1	10	Logistics analyst system	Plastics resin company	Logistics management
E2	10	Logistics analyst	Plastics resin and compound company	Logistics management
E3	12	Delivery manager	Plastics resin company	Transportation management
E4	12	Logistics safety engineer	Plastics resin company	Transportation safety management
E5	15	Warehouse and delivery department manager	Plastics products company	Warehousing and Transportation management
E6	23	Delivery department manager	Plastics resin and chemicals products company	Transportation management
E7	26	Logistics support division manager	Plastics resin company	Logistics management
E8	27	Logistics support manager	Plastics resin company	Logistics management
E9	32	Assistant manager director	Plastics resin company	Transportation partners management
E10	33	Logistics division manager	Plastics resin company	Logistics management

4.1 Criteria for selecting 4PLs

In this paper, the eleven criteria are identified through a review of the extant literature and three more criteria are added by experts Table 1. The selection criteria consist of one cost criterion and 13 benefit criteria. Table 2 shows the final selection criteria confirmed by experts.

Table 3 The list of 4PLs selection criteria

Code	*Selection criteria*	*Description*	*Type of criteria*	*Reference*
C1	Costs of service	The costs of services charged by 4PL applicant compared to service value offerings in fleet transportation management.	Cost	Balezentis and Balezentis (2011)
C2	Past service performance	The 4PL applicant has good references for past service performance in fleet transportation management.	Benefit	Kalkan and Aydin (2020)
C3	New process design capability	The 4PL applicant has the ability to design a new process for fleet transportation management such as intermodal transport design.	Benefit	Mehmann and Teuteberg (2016)
C4	3PLs network management capability	The 4PL applicant has the ability to manage the 3PLs network in fleet transportation such as optimise transport network planning, enhance punctuality.	Benefit	Huang et al. (2019)
C5	Green freight transportation management capability	The 4PL candidate has the ability to set up a green freight transportation management system to reduce carbon dioxide emissions such as decarbonising transportation program.	Benefit	Meyer (2020), Qian et al. (2021), Pani et al. (2021)
C6	Ready-to-use IT platforms for fleet transportation management	The 4PL candidate has ready-to-use IT platforms to manage fleet transportation such as a transportation management system (TMS), truck tracking system.	Benefit	Kayikci (2018)
C7	Communication channels management	The 4PL applicant can establish effective communication channels connecting between contractors and 3PLs such as a single contact channel.	Benefit	Kolinski et al. (2019)
C8	Developing advanced IT systems capability	The 4PL applicant has the ability to develop advanced IT systems for fleet transportation management such as the internet of things (IoT), blockchain.	Benefit	Giustia et al. (2019)
C9	Fleet transport safety management capability	The 4PL applicant has the ability to set up effective fleet transport safety management guidelines such as transportation risk assessment, safety driver development, safe driving incentive awards program, and fleet safety management practices.	Benefit	Huang et al. (2019)

Table 3 The list of 4PLs selection criteria (continued)

Code	*Selection criteria*	*Description*	*Type of criteria*	*Reference*
C10	Fleet transport network integration	The 4PL applicant has the ability to integrate fleet truck operations in the 3PLs' transport network such as freight transport exchanges.	Benefit	Kalkan and Aydin (2020)
C11	Coordination mechanism	The 4PL applicant can establish an effective coordination mechanism to manage entire freight transport operations.	Benefit	Subramanian et al. (2016), Puangsombat and Singdong (2019)
C12	Risk management of transporting hazardous materials	The 4PL applicant has the ability to perform risk analysis and route of hazardous materials.	Benefit	Experts' input
C13	Occupational safety and health for transportation	The 4PL applicant has the ability to improve occupational safety and health for truck drivers such as fatigue management for long haul transport.	Benefit	Experts' input
C14	Emergency management	The 4PL applicant has emergency procedures to manage unexpected events in fleet transport operations such business continuity plan (BCP).	Benefit	Experts' input

Table 4 The fuzzy linguistic scales of the selection criteria

Linguistic terms	*Symbol*	*Fuzzy score*
Very high	VH	(0.75, 1.0, 1.0)
High	H	(0.5, 0.75, 1.0)
Moderate	M	(0.25, 0.5, 0.75)
Low	L	(0.0, 0.25, 0.50)
Very low	VL	(0.0, 0.0, 0.25)

4.2 Constructing the initial decision matrix

Each expert provides the rating score of 4PL candidates (A_1, A_2, A_3, A_4 and A_5) with respect to the selection criteria by using linguistic terms in Table 3. Thereafter, the linguistic terms are converted into corresponding fuzzy scores. As a result, the initial decision matrix for each expert is constructed using equation (2). By using equations (3)–(4), the initial decision matrices for all experts are aggregated as shown in Table 4. The aggregated initial decision matrix is defuzzied into crisp numbers by using BNP using equations (5)–(6) and the results shown in Table 5.

Table 5 The aggregated initial decision matrix

Criteria	*A1*	*A2*	*A3*	*A4*	*A5*
C1	(0.130,0.330,0.450)	(0.330,0.500.0.600)	(0.330,0.550,0.600)	(0.180,0.400,0.530)	(0.250,0.400,0.530)
C2	(0.280,0.530,0.730)	(0.530,0.750,0.850)	(0.150,0.280,0.480)	(0.350,0.600,0.800)	(0.330,0.580,0.800)
C3	(0.680,0.930,0.930)	(0.200,0.043,0.650)	(0.080,0.180,0.700)	(0.300,0.550,0.780)	(0.100,0.200,0.450)
…	…	…	…	…	…
C12	(0.280,0.530,0.730)	(0.280,0.530,0.730)	(0.280,0.530,0.730)	(0.330,0.580,0.750)	(0.280,0.530,0.730)
C13	(0.400,0.650,0.830)	(0.330,0.500.0.600)	(0.350,0.600,0.080)	(0.400,0.650,0.830)	(0.400,0.650,0.830)
C14	(0.480,0.730,0.830)	(0.500,0.750,0.880)	(0.480,0.730,0.830)	(0.550,0.800,0.900)	(0.550,0.800,0.900)

Table 6 The crisp aggregated initial decision matrix

Criteria	A_1	A_2	A_3	A_4	A_5
C1	0.303	0.387	0.403	0.403	0.393
C2	0.513	0.603	0.193	0.700	0.570
C3	0.847	0.148	0.113	0.643	0.250
⋮	⋮	⋮	⋮	⋮	⋮
C12	0.513	0.363	0.363	0.663	0.513
C13	0.627	0.403	0.433	0.760	0.627
C14	0.680	0.583	0.563	0.933	0.750

Table 7 The aggregated initial decision matrix in interval data $\alpha = 0.05$ level

Criteria	A_1	A_2	A_3	A_4	A_5
C_1	[0.230,0.390]	[0.415,0.550]	[0.440,0.575]	[0.290,0.465]	[0.325,0.465]
C_2	[0.405,0.630]	[0.640,0.800]	[0.215,0.380]	[0.475,0.700]	[0.455,0.690]
C_3	[0.805,0.930]	[0.122,0.347]	[0.130,0.290]	[0.425,0.665]	[0.150,0.325]
⋮	⋮	⋮	⋮	⋮	⋮
C_{12}	[0.405,0.630]	[0.405,0.630]	[0.405,0.630]	[0.445,0.665]	[0.405,0.630]
C_{13}	[0.525,0.740]	[0.440,0.650]	[0.475,0.340]	[0.525,0.740]	[0.525,0.740]
C_{14}	[0.605,0.780]	[0.625,0.815]	[0.605,0.780]	[0.675,0.850]	[0.675,0.850]

Table 8 The normalised decision matrix at $\alpha = 0.5$ level

Criteria	A_1	A_2	A_3	A_4	A_5
C_1	[0.022,0.038]	[0.047,0.062]	[0.059,0.077]	[0.028,0.045]	[0.038,0.054]
C_2	[0.039,0.061]	[0.072,0.091]	[0.029,0.051]	[0.046,0.068]	[0.053,0.080]
C_3	[0.078,0.090]	[0.014,0.039]	[0.017,0.039]	[0.041,0.065]	[0.017,0.038]
⋮	⋮	⋮	⋮	⋮	⋮
C_{12}	[0.039,0.061]	[0.046,0.072]	[0.054,0.084]	[0.044,0.065]	[0.047,0.073]
C_{13}	[0.051,0.071]	[0.050,0.074]	[0.063,0.045]	[0.051,0.072]	[0.061,0.086]
C_{14}	[0.058,0.075]	[0.071,0.092]	[0.081,0.140]	[0.066,0.083]	[0.078,0.099]

4.3 Determination the objective weights of criteria

In this study, interval Shannon's entropy based on α-level sets is applied to determine the objective weights of criteria. First, each element in the aggregated initial decision matrix Table 4 is converted into corresponding interval data at α level using equations (7)–(8). In this study $\alpha = 0.5$, the results are shown in Table 6. Second, the normalised initial decision matrix is constructed using equation (9) as shown in Table 7. Third, the lower bound (h_j^l) and upper bound (h_j^u) of interval entropy are computed using equations (10)–(11), respectively. Fourth, the interval of diversification degree of the lower bound values (d_j^l) and upper bound values (d_j^u) are calculated using equation (12). Next, the interval weights of lower bound (w_j^l) and upper bound (w_j^u) are obtained using Eq. (13).

Finally, the final weights are determined using equations (14)–(15), as shown in Table 8. According to Table 8, the objective weights of the 14 criteria in descending order can be concluded as C_7, C_8 (0.094) > C_3(0.088) > C_1(0.083) > C_6(0.079) > C_{10}(0.078) > C_2(0.073) > C_{12}(0.072) > C_{13}(0.069) > C_4(0.068) > C_{14}(0.055) > C_9(0.053) > C_5(0.050) > C_{11}(0.046).

Table 9 Final weights for interval Shannon's entropy based on $\alpha = 0.5$ level

Criteria	$\left[h_j^l, h_j^u\right]$	$\left[d_j^l, d_j^u\right]$	$\left[w_j^l, w_j^u\right]$	w'_j	w_j	*Rank*
C_1	[0.384,0.491]	[0.509,0.616]	[0.067,0.103]	0.085	0.083	3
C_2	[0.445,0.574]	[0.426,0.555]	[0.056,0.093]	0.075	0.073	6
C_3	[0.329,0.478]	[0.522,0.671]	[0.069,0.112]	0.091	0.088	2
C_4	[0.475,0.607]	[0.393,0.525]	[0.052,0.088]	0.070	0.068	9
C_5	[0.620,0.704]	[0.296,0.380]	[0.039,0.063]	0.051	0.050	12
C_6	[0.406,0.529]	[0.471,0.594]	[0.062,0.099]	0.081	0.079	4
C_7	[0.299,0.429]	[0.571,0.701]	[0.075,0.117]	0.096	0.094	1
C_8	[0.302,0.426]	[0.574,0.698]	[0.076,0.117]	0.096	0.094	1
C_9	[0.598,0.686]	[0.314,0.402]	[0.041,0.067]	0.054	0.053	11
C_{10}	[0.404,0.540]	[0.460,0.596]	[0.061,0.100]	0.080	0.078	5
C_{11}	[0.652,0.721]	[0.279,0.348]	[0.037,0.058]	0.047	0.046	13
C_{12}	[0.439,0.582]	[0.418,0.561]	[0.055,0.094]	0.074	0.072	7
C_{13}	[0.495,0.572]	[0.428,0.505]	[0.057,0.084]	0.070	0.069	8
C_{14}	[0.580,0.673]	[0.327,0.420]	[0.043,0.070]	0.057	0.055	10

4.4 CoCoSo method computation

The CoCoSo method is proposed for the selection the best 4PL candidates. Based on the crisp aggregated initial decision matrix in Table 5, the elements are normalised using equations (16)–(18). By using the criteria weights obtained by interval Shannon's entropy at $\alpha = 0.5$ level in Table 8, the sum of weighted comparability (S_i) and power weighted comparability sequences (P_i) for each 4PL candidate are computed using equations (19)–(20), respectively. Next, the three evaluation scores (ξ_{ia}, ξ_{ib}, ξ_{ic}) of each 4PL candidate are calculated using equations (21)–(23) by taking λ=0.5. The performance score of each 4PL candidate (ξ_i) is obtained using equation (24) as shown in Table 9. According to Table 9, the 4PL candidates are ranked in descending order of the performance score as A_4 (19.207) > A_1 (16.121) >A_5 (12.820) > A_2 (6.422) > A_3 (1.623).

Table 10 The ranking of 4PL candidate by CoCoSo

4PL candidates	S_i	P_i	ξ_{ia}	ξ_{ib}	ξ_{ic}	ξ_i	*Rank*
A_1	0.640	13.451	0.271	29.914	6.770	16.121	2
A_2	0.176	7.788	0.153	9.796	3.906	6.422	4
A_3	0.026	2.588	0.050	2.000	1.296	1.623	5
A_4	0.087	12.949	0.266	38.623	6.535	19.207	1
A_5	0.432	13.003	0.259	21.702	6.532	12.820	3

4.5 MARCOS method computation

The MARCOS method is employed for the selection of the best 4PL candidates. According to the crisp aggregated initial decision matrix in Table 5, the extend initial matrix is formulated by adding an ideal alternative (AI) and an anti-ideal alternative (AAI) based on equations (25)–(27). Then, the elements in extend initial matrix are normalised using equation (28) for cost criterion, whereas equation (29) for benefit criterion. By using the criteria weights obtained by interval Shannon's entropy at $\alpha = 0.5$ level in Table 8, the weight matrix (v_{ij}) is computed by equation (30). The utility degrees of each 4PL candidate are computed using equations (31)–(33) respectively. Next, the utility function ($f(K_i)$) of each 4PL candidate is calculated using equations (34)–(36). According to Table 10, the 4PL candidates are ranked in descending order of $f(K_i)$ values as $A_5(0.954) > A_2, A_4(0.632) > A_1(0.514) > A_3(0.415)$.

Table 11 The ranking of 4PL candidate by MARCOS

4PL candidates	S_i	K_i^-	K_i^+	$f(K_i^-)$	$f(K_i^+)$	$f(K_i)$	*Rank*
A_1	4.804	11.667	0.516	0.042	0.924	0.514	3
A_2	5.894	14.315	0.633	0.042	0.937	0.632	2
A_3	3.878	9.419	0.417	0.042	0.908	0.415	4
A_4	5.898	14.324	0.634	0.042	0.937	0.632	2
A_5	8.899	21.612	0.956	0.042	0.958	0.954	1

4.6 EDAS method computation

The EDAS method is utilised for the selection the best 4PL candidates. According to the crisp aggregated initial decision matrix in Table 5, the average value matrix (AV) is constructed by equation (37). Next, the positive distance from average alternative matrix (PDA) and the negative distance from average alternative matrix (NDA) are obtained using equation (38) for cost criterion, whereas equation (39) for benefit criterion. By using the criteria weights obtained by interval Shannon's entropy at $\alpha = 0.5$ level in Table 8, the weighted total positive value (SP_i) and the weighted negative value (SN_i) of each 4PL candidate are computed using equations (40)–(41), respectively. Then, the normalised weighted total positive value (NSP_i) and the normalised weighted total negative value (NSN_i) for each 4PL candidate are obtained using equations (42)–(43), respectively. Next, the final evaluation score (AS_i) for each 4PL candidate is calculated using equation (44). Table 11 shows the 4PL candidates are ranked in descending order of the AS_i values as $A_4(1.000) > A_1(0.587) > A_5(0.515) > A_2(0.148) > A_3(0.016)$.

Table 12 The ranking of 4PL candidate by EDAS

4PL candidates	SP_i	SN_i	NSP_i	NSN_i	AS_i	*Rank*
A_1	0.573	0.215	0.414	0.760	0.587	2
A_2	0.057	0.667	0.041	0.256	0.148	4
A_3	0.044	0.896	0.032	0.000	0.016	5
A_4	1.384	0.000	1.000	1.000	1.000	1
A_5	0.365	0.209	0.264	0.766	0.515	3

4.7 MAIRCA method computation

The MAIRCA method is deployed for the selection the best 4PL candidates. According to the crisp aggregated initial decision matrix in Table 5, the preferences for the choice of options (P_{A_i}) is determined using equations (45)–(46). Then, the theoretical rating matrix (T_P) is formulated as equation (47). The real rating matrix (T_r) is determined by equation (48) for benefit criteria and equation (49) for the cost criteria. The total gap matrix (G) is formulated regarding the different between T_P and T_r as equation (50). Next, the final value of criterion function for each 4PL candidate (Q_i) is computed using equation (51). Table 12 shows the 4PL candidates are ranked in ascending order of the Q_i values as $A_4(0.026) > A_1(0.072) > A_5(0.114) > A_2(0.165) > A_3(0.195)$.

Table 13 The ranking of 4PL candidate by MAIRCA

4PL candidates	Q_i	*Rank*
A_1	0.072	2
A_2	0.165	4
A_3	0.195	5
A_4	0.026	1
A_5	0.114	3

4.8 CODAS method computation

The CODAS method is used for the selection the best 4PL candidates. According to the crisp aggregated initial decision matrix in Table 5, the elements are normalised using equations (52)–(53). By using the criteria weights obtained by interval Shannon's entropy at α = 0.5 level in Table 8, the weighted normalised performance matrix (r_{ij}) is formulated using equation (54). The negative-ideal solution matrix (ns_j) is computed using equation (55). Next, the Euclidean and Taxicab distances of 4PL candidates (E_i and T_i) from the negative-ideal solution can be obtained by equations (56)–(57), respectively. The relative assessment matrix (H_a) is constructed using equations (58)–(59) by taking $\psi = 0.02$. Thereafter, the assessment score of each 4PL candidate (H_i) is calculated using equation (60). Table 13 shows the 4PL candidates are ranked in descending order of H_i values as $A_4(0.581) > A_1(0.238) > A_5(0.018) > A_2(-0.231) > A_3(-0.314)$.

Table 14 The ranking of 4PL candidate by CODAS

4PL candidates	E_i	T_i	h_{ik}	H_i	*Rank*
A1	0.179	0.516	0.924	0.238	2
A2	0.081	0.633	0.937	–0.231	4
A3	0.019	0.417	0.908	–0.314	5
A4	0.042	0.634	0.247	0.581	1
A5	0.042	0.956	0.135	0.018	3

5 Comparative analysis of rankings using different MCDM methods

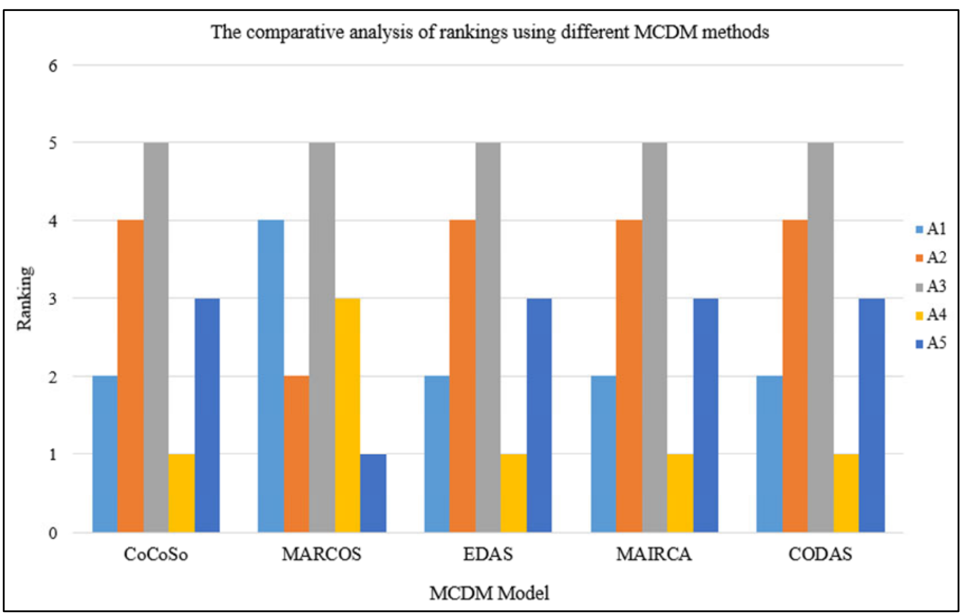
In this section, the comparative analysis of rankings using different MCDM methods is carried out. The first comparative analysis is the ranking results from five MCDM methods. From Table 14 and Figure 3, it can be seen that CoCoSo, EDAS, MAIRCA, and CODAS give the same ranking results as A4>A1>A5>A2>A3 except the MARCOS method ranking as A5 > A2, A4 > A1 > A3. This is because MARCOS uses different ranking concepts from others by,

1 an ideal alternative (AI) and an anti-ideal alternative (AAI) are included in normalisation process, while the other four methods do not use this step

2 the compromise ranking alternatives is based on the basis of utility functions that determines the best alternative is the one closest to the ideal and at the same time furthest from the anti-ideal reference point.

Since MARCOS gives the different result from other four methods. This study recommends that the decision-makers should suitably use the majority votes from all methods as a guide for problem solving. This is fairly supported by Mulliner et al. (2016) who stated that one of the most important criteria in selecting a MCDM method is its compatibility with the objective of the problem.

Figure 3 The comparative analysis of rankings using different MCDM methods (see online version for colours)



The second comparative analysis is the correlation of ranking results between different MCDM methods. The relationship of 4PL candidates ranking results obtained from five MCDM methods is examined by using Spearman correlation coefficient calculated as follows:

$$\rho = \frac{1-6\sum_{a=1}^{n} D_a^2}{n(n^2-1)} \tag{61}$$

where D_a = Ranks difference obtained by two ranking methods, and n = number of attributes.

Table 15 The comparative analysis of rankings using different MCDM methods

MCDM ranking methods	*Ranking results*
CoCoSo	$A_4 > A_1 > A_5 > A_2 > A_3$
MARCOS	$A_5 > A_2 > A_4 > A_1 > A_3$
EDAS	$A_4 > A_1 > A_5 > A_2 > A_3$
MAIRCA	$A_4 > A_1 > A_5 > A_2 > A_3$
CODAS	$A_4 > A_1 > A_5 > A_2 > A_3$

The correlation analysis results are shown in Table 15 where each element represents the Spearman correlation coefficient between the rankings calculated from pair of MCDM methods. it can be seen that the correlation coefficients between CoCoSo, EDAS, MAIRCA, and CODAS of '1' indicates the highest conformity raking of the four MCDM methods. While, the Pearson correlation coefficients between MARCOS and the aforementioned four methods equal to '0.416' indicates the weakest concordance raking.

Table 16 Summary of Spearman rank correlation analysis between MCDM methods

MCDM methods	*CoCoSo*	*MARCOS*	*EDAS*	*MAIRCA*	*CODAS*
CoCoSo	1	0.416	1	1	1
MARCOS	0.416	1	0.416	0.416	0.416
EDAS	1	0.416	1	1	1
MAIRCA	1	0.416	1	1	1
CODAS	1	0.416	1	1	1

6 Sensitivity analysis

In this section, a sensitivity analysis is carried out to confirm the robustness and reliability of the five MCDM ranking methods by altering the objective weights of criteria obtained from interval Shannon's entropy at α = 0.1,0.3,0.7, and 0.9 respectively as shown in Table 16. This aims to investigate whether the ranking of 4PL candidates has changed. The final ranking of 4PL candidates related to the different values of objective weights are shown in Table 17. It can be seen that the ranking of all MCDM methods remain unchanged for all α levels; $A_4 > A_1 > A_5 > A_2 > A_3$ ranked by CoCoSo, EDAS, MAIRCA, and CODAS and $A_5 > A_2$, $A_4 > A_1 > A_3$ ranked by MARCOS. On the other word, 4PL candidates ranking are insensitive to all objective weight variations. This means that the proposed framework in this paper is robustness.

7 Conclusions and future research

The selection of the best 4PLs problem is characterised by various criteria and these criteria are inherently contradiction. In general, the MCDM is an effective tool for solving such problems. This paper proposes a MCDM framework to select the 4PLs for fleet transportation management. The plastic resin industry in Thailand is used as a case study. To deal with the uncertainty and imprecise input data from experts, TFNs are applied to evaluate and rank in decision-making processes. First, 14 4PLs selection criteria were identified through extensive literature review and input from industry experts. Shannon's entropy based on α-level sets method is used to determine the objective weights of the selection criteria. The results of the analysis indicated that the criteria namely 'communication channels management' (C_1), 'developing advanced IT systems capability' (C_8) followed by 'ready-to-use IT platforms for fleet transportation management' (C_6) are three most important criteria for 4PLs selection in a case of plastic resin industry in Thailand. Second, five novel MCDM methods as CoCoSo, MARCOS, EDAS, MAIRCA, and CODAS are deployed to select and rank the five 4PL candidates (A_1, A_2, A_3, A_4, and A_5). The comparative analysis shows that CoCoSo, EDAS, MAIRCA, and CODAS provide the same ranking as $A_4 > A_1 > A_5 > A_2 > A_3$ but different from MARCOS which has $A_5 > A_2$, $A_4 > A_1 > A_3$.

Spearman statistical correlation analysis showed the highest consistent correlation of the ranking results between the four MCDM methods (CoCoSo, EDAS, MAIRCA, and CODAS) and the weakest correlation of the ranking results between the four MCDM methods and MARCOS. Through, the sensitivity analysis indicates the robustness and stability of the five MCDM ranking methods. The findings in this study are consistent with Ecer (2021), stated that although MCDM methods demonstrate their robustness and effectiveness but the different MCDM methods can produce different ranking results.

Apart from the aforementioned conclusions, this paper makes following three-fold contributions. Firstly, most of existing research have made notable contributions for the selection of 3PLs in several aspects but no studies have been done on the selection of 4PLs. To the best of the knowledge of the authors, this paper is the first attempt to propose a comprehensive framework for selecting 4PLs in the literature. Secondly, this study employs several a combination MCDM approaches under a fuzzy environment for the comparison and validation of the findings. Until now, there have been no published studies comparing MCDM rating methods, including CoCoSo, MARCOS, EDAS, MAIRCA, and CODAS. Finally, the proposed framework is applied on the real case study of 4PLs selection in plastic resin practitioners to make a rational decision in selecting 4PLs. In addition, the proposed framework can be applied to other similar industries that plan to outsource their logistics services to 4PLs. Regarding future work extended from this study, it is interesting to address the interaction between among selection criteria. The combination between objective and subjective weights should be examined for the effect of 4PLs ranking results. Lastly, 4PL selection should be further investigated under other fuzzy environments such as intuitionistic fuzzy, hesitant fuzzy, Pythagorean fuzzy.

Table 17 The objective weights of criteria obtained from interval Shannon's entropy at $\alpha = 0.1$, 0.3, 0.7, and 0.9

Criteria	$\alpha = 0.1$		$\alpha = 0.3$		$\alpha = 0.7$		$\alpha = 0.9$	
	$[w_j^l, w_j^u]$	w_j	$[w_j^l, w_j^u]$	w_j	$[w_j^l, w_j^u]$	w_j	$[w_j^l, w_j^u]$	w_j
C1	[0.059,0.118]	0.820	[0.063,0.110]	0.083	[0.073,0.095]	0.083	[0.073,0.095]	0.083
C2	[0.048,0.108]	0.073	[0.052,0.101]	0.073	[0.062,0.085]	0.072	[0.062,0.085]	0.072
C3	[0.055,0.121]	0.082	[0.061,0.116]	0.085	[0.079,0.108]	0.092	[0.079,0.108]	0.092
…	…	…	…	…	…	…	…	…
C12	[0.047,0.111]	0.074	[0.051,0.102]	0.073	[0.061,0.085]	0.072	[0.061,0.085]	0.072
C13	[0.054,0.100]	0.072	[0.055,0.092]	0.070	[0.059,0.076]	0.067	[0.059,0.076]	0.067
C14	[0.039,0.085]	0.058	[0.041,0.078]	0.057	[0.046,0.062]	0.053	[0.046,0.062]	0.053

Table 18 The final ranking of 4PL candidates related to the different values of objective weights

4PL candidates	CoCoSo		MARCOS		EDAS		MAIRCA		CODAS	
	ξ_i	*Rank*	$f(K_i)$	*Rank*	AS_i	*Rank*	Q_i	*Rank*	H_i	*Rank*
					$\alpha = 0.1$					
A_1	15.865	2	0.514	3	0.576	2	0.074	2	0.205	2
A_2	6.413	4	0.632	2	0.147	4	0.165	4	–0.199	4
A_3	1.618	5	0.415	4	0.016	5	0.195	5	–0.308	5
A_4	19.116	1	0.632	2	1.00	1	0.035	1	0.583	1
A_5	12.843	3	0.954	1	0.520	3	0.113	3	0.031	3
					$\alpha = 0.3$					
A_1	15.964	2	*0.514*	*3*	0.581	2	*0.073*	*2*	0.220	2
A_2	6.409	4	*0.632*	*2*	0.147	4	*0.165*	*4*	–0.214	4
A_3	1.620	5	*0.415*	*4*	0.016	5	*0.195*	*5*	–0.310	5
A_4	19.131	1	*0.632*	*2*	1.000	1	*0.026*	*1*	0.582	1
A_5	12.818	3	*0.954*	*1*	0.518	3	*0.113*	*3*	0.025	3
					$\alpha = 0.7$					
A_1	16.310	2	0.514	3	0.595	2	0.071	2	0.258	2
A_2	6.440	4	0.632	2	0.150	4	0.165	4	–0.251	4
A_3	1.625	5	0.415	4	0.016	5	0.195	5	–0.318	5
A_4	19.304	1	0.632	2	1.000	1	0.026	1	0.580	1
A_5	12.828	3	0.954	1	0.512	3	0.114	3	0.010	3
					$\alpha = 0.9$					
A_1	16.546	2	0.514	3	0.604	2	0.069	2	0.281	2
A_2	6.466	4	0.632	2	0.151	4	0.165	4	–0.274	4
A_3	1.629	5	0.415	4	0.016	5	0.195	5	–0.323	5
A_4	19.435	1	0.632	2	1.000	1	0.026	1	0.580	1
A_5	12.846	3	0.954	1	0.508	3	0.115	3	0.001	3

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