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Engineering and Applied Science Research

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Published by the Faculty of Engineering, Khon Kaen University, Thailand

A comparison between subjective and objective weighting approaches for multi-criteria decision making: A case of industrial location selection

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Received 11 October 2022
Revised 29 November 2022
Accepted 9 December 2022

Abstract

Location selection is a complex decision problem, mainly caused by many considered criteria. Moreover, the criteria normally have different levels of importance or weights, and seeking a consensus among multiple decision makers regarding the weights of criteria is difficult. Since the weights are essential inputs for a logical decision-making process, this study examines the effects of varying the weights towards five weighting methods under the subjective and objective approaches. The direct rating, rank-order centroid, and rank sum represent the methods that derive the weights based on a decision maker's subjective judgement, while the entropy and standard deviation methods signify the objective approach. A case of location selection for production fragmentation of a Thai manufacturing company that ranked candidate locations by the fuzzy Technique for Order Preference by Similarity to Ideal Solution (fuzzy TOPSIS) is used as a basis for comparing the sensibility of the five weighting methods. Discussions about their methodological and practical advantages and cautions are drawn according to the three criteria, including resource requirement, potential for bias, and general complexity of each method.

Keywords: Location selection, Weighing method, Multi-criteria decision making, Fuzzy TOPSIS

1. Introduction

Industrial location selection (for a relocation, expansion, or production fragmentation) is a complex decision-making problem for business practitioners. Location describes where something is situated in association with other things. Industrial location concerns both the spatial distribution of industry and the relationships between that distribution and other phenomena [1]. When locations are chosen appropriately, this not only contributes to the economic prosperity of such a business but also avoids irreparable losses that could be caused to the environment and society [1, 2].

The location selection problem is complex due to a number of factors. First, there are a vast variety of criteria to be considered, and the criteria include not only quantitative criteria simply assessed using numerical measurement units but also qualitative criteria that are highly dependent upon decision makers' subjective judgements [3, 4]. For many criteria, furthermore, the information might be subject to frequent change or might not be readily available. In addition, the gathering of information might be time-consuming and resource-intensive. As such, incompleteness and/or uncertainty of information always cause decision makers' hesitation in the assessment [5]. Another point is that the levels of importance of those criteria are generally not equal, varying by individual concerns and the variability and complexity of the context [6, 7]. The involvement of multiple decision makers is also considered another factor that raises the complexity of the problem. It is rather difficult to receive a consensus regarding the best choice, and decision makers may conduct the assessment under different standards or interpretations of the assessment scales, or the wordings employed, particularly for qualitative criteria [8].

Multi-criteria decision making (MCDM) approaches are generally adopted to support location selection problems, mainly due to their ability to provide the best compromised choice under simultaneous consideration of a wide range of criteria [7, 9-14]. Since the problems involve many qualitative criteria that are difficult to assess precisely and quantitatively, rating scales are usually employed to handle such issues. Nevertheless, rating scales are generally built around linguistic terms, making them frequently unstandardised among decision makers and therefore rely heavily on their intuitive judgments [4]. When it comes to selecting a location for a facility, traditional MCDM techniques are usually less effective at dealing with the vagueness or lack of clarity of the linguistic assessment [15]. From the literature review, fuzzy logic is found to be a logical and reasonable approach to dealing with the ambiguity of the scales used as well as the uncertainty of information [9, 16-19]. In recent years, there has been a growing interest in applying fuzzy logic to location selection problems [15, 20-23]. Arunyanart, et al. [4] is one of the recent studies that adopted fuzzy logic with the TOPSIS method to support a location selection for production fragmentation (details are further described in the next section). For this work, up to 18 criteria were considered significant for the decision. The direct rating (DR), a simple method of subjective weighting, was adopted to determine the levels of importance of criteria (the weights) through experts' judgements. A linguistic scale (Very low, Low,

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doi: 10.14456/easr.2022.74

Medium, High, and Very high) was employed for this purpose, and the scale was then converted into a form of triangular fuzzy numbers (TFNs) to compromise the vagueness of the scale. The weights obtained, however, may be argued because of their high dependence on subjective opinions and personal bias, and the weights might be unreliable, particularly when decision makers are confused with too many criteria to consider simultaneously.

The weights of criteria are the critical inputs in analytical decision makings. The final results in MCDM are, many times, more sensitive to the changes in weights of the criteria than the choice of aggregation methods [7, 24]. An understanding of how different weighting methods influence the decision results allows business decision makers to gain a satisfactory and confident conclusion for their strategic planning. Methods that rely less on personal opinions also enable companies to reach a consensus and avoid conflict from the disagreement. Unfortunately, from a review of studies focusing on industrial location selection, most studies did not further analyse the effect of the change in criteria weights [3, 6, 16, 17, 25]. Furthermore, they generally determine the weights based on subjective weighting approaches, regardless of the impracticality and complexity of data elicitation processes. The problem becomes more apparent when numerous decision makers are involved in creating the criteria weights, since reaching consensus may be difficult [25]. There were also limited studies that compared how decisions turned out when switching between subjective and objective weighting techniques. This paper, therefore, aims to explore a more efficient and reliable way to aid the weighting process for Arunyanart, et al. [4] by considering other four simpler methods, including Rank sum (RS), Rank-order centroid (ROC), Entropy, and Standard deviation (SD) methods. The first two approaches, RS and ROC, are still considered subjective weighting approaches but require less effort from decision makers than the DR since only the priority of criteria is needed for determining the weights [26, 27]. Entropy and SD, on the other hand, are representatives of the objective weighting approach, which derives the weights from known data of alternatives for each criterion without the decision maker's intervention [28, 29]. The derived ranking of alternatives from Arunyanart, et al. [4] was cross-compared to those when the weights were changed according to the four proposed methods in order to investigate how these methods influence the decision-making results.

This paper is organised as follows: After the introduction, Section 2 presents a review of literature by dividing into two sub-sections. Section 2.1 provides an overview of Arunyanart, et al. [4], the baseline of this comparative study, and a review of recent studies that used MCDM techniques to solve a location selection problem. Section 2.2 then describes the four weighting methods (RS, ROC, Entropy, and SD) in terms of their theoretical concepts and computation procedures. The methodology employed for this study is explained in Section 3. Section 4 shows results and discussions. Conclusions and practical implications are drawn in Section 5.

2. A review of relevant literature

2.1 Fuzzy TOPSIS for a location selection

A selection of a facility location is very significant for manufacturing companies to minimise cost and maximise the use of resources [30]. Many researches applied MCDM techniques to determine the most suitable location. This review section provides an update on the trend of MCDM applications in this context by reviewing articles recently published during the years 2021 and 2022. Eroğlu [9] investigated suitable places to construct wind power plants by using geographic information systems (GIS). The analytic hierarchy process (AHP) was employed to elicit the weights of the criteria. Bait, et al. [6] applied AHP, TOPSIS, and cluster analysis methods to facilitate the selection of a location for a textile Italian company to settle a new plant in Africa. Ozdemir and Sahin [3] also adopted AHP to evaluate prospective locations for setting up a new solar PV power plant in Turkey. Chithambaranathan, et al. [31] applied the VIKOR method to a facility location selection problem under flexible criteria weights. In addition, MCDM methods have been applied to location selection problems in the healthcare industry. For example, Saroja, et al. [19] used fuzzy AHP to determine the weights of criteria for selecting locations to establish new COVID-19 testing centres in India, and next employed TOPSIS to rank the candidate locations. A review of recently published papers indicates that AHP, TOPSIS, and VIKOR remain prevalent approaches for site selection problems.

TOPSIS is among the most generally used methods for addressing ranking issues in real situations. The logic of TOPSIS is straightforward and simple to comprehend by computing a composite score for an alternative based on its distance from the negative ideal solution and similarity to the positive ideal solution. When all criteria are considered simultaneously, the best choice should be the one that is closest to the positive solutions and the furthest away from the negative ones [8]. Although the TOPSIS technique is prevalent, it has some constraints. For instance, decision makers frequently struggle to give an alternative a precise performance score for some criteria. Many times, some criteria are challenging to quantify, and decision makers are reluctant or unable to express their judgments in the form of single numeric values [4, 32]. Fuzzy TOPSIS technique, developed by Chen [33], was introduced to get around some constraints of the original form of the TOPSIS method afterwards. Fuzzy TOPSIS proposes evaluating alternatives and weighing criteria using a linguistic scale in the form of fuzzy numbers. It is well suited for resolving issues with group decision-making in uncertain contexts [4, 17, 34]. When compared to AHP or fuzzy AHP, which are other popular MCDM methods for ranking alternatives, fuzzy TOPSIS is also better suited to handle a complex decision problem considering a large number of criteria since AHP demands too many subjective pairwise comparisons [8, 35]. For example, according to Arunyanart, et al. [4], 18 criteria and four alternatives were considered. AHP requires up to 153 judgments from each decision maker to determine the weights for all criteria and another 108 judgments for ranking the alternatives. There is a suggestion that, for AHP, only 18 should be a realistic upper limit for the number of comparisons that can be completed in order to enable consistent judgments and avoid decision makers becoming bored and confused [36, 37].

Fuzzy TOPSIS method has been used in various fields of location selection. Erkayman, et al. [38], for example, proposed a fuzzy TOPSIS model for determining the most appropriate location for a logistics centre in the northeast region of Turkey. Kaur, et al. [39] proposed a model for selecting the most appropriate energy power plant in Turkey based on the fuzzy TOPSIS method. Alkan and Kahraman [40] identified the most suitable site for a pandemic hospital using the TOPSIS method under circular intuitionistic fuzzy members. In addition, Arunyanart, et al. [4] demonstrated the application of fuzzy TOPSIS to support the location selection for production fragmentation of an electronics company in Thailand. The candidate locations here are Thailand's neighboring countries–Cambodia, Laos, Myanmar, and Vietnam (CLMV). The criteria were gathered from a review of around 30 research articles, published from the years 1995 to 2020, that suggested a logical method to solve an industrial location selection problem. The gathered criteria were then validated in terms of their significance through expert interviews, leading to the identification of 18 criteria. As previously stated, the weights of these criteria were determined using expert judgments (the DR method) in relation to the fuzzy set theory. Table 1 shows the ranking of criteria and their aggregated fuzzy weights ($\widetilde{w}_j$), defuzzified weights (w_j), and relative weights (w_j'), for each criterion j when j = 1, 2, …, 18 criteria. The definition of each criterion can be seen in that paper. Note that the relative weights of all the criteria sum to one, or $\sum_{j=1}^{18} w'_j = 1$. In the end, their study indicated, based on the obtained closeness coefficient values (CC), that Vietnam was the most suitable location, followed by Laos, Myanmar, and Cambodia, respectively.

Table 1 The weights of criteria for industrial location selection [4].

Criteria	$\tilde{w}_j$	w_j	w'_j	Ranking
C1: Labor cost	(0.5, 0.7857, 1.0)	0.7679	0.0649	6
C2: Availability of labor force	(0.5, 0.7429, 1.0)	0.7464	0.0630	7
C3: Skill and competency level of labour	(0.5, 0.8714, 1.0)	0.8107	0.0685	1
C4: Labour laws and regulations	(0.3, 0.6714, 1.0)	0.6607	0.0558	8
C5: Foreign ownership laws	(0.5, 0.8000, 1.0)	0.7750	0.0655	4
C6: Taxation and tax incentives	(0.5, 0.8429, 1.0)	0.7964	0.0673	3
C7: Government structure and stability	(0.3, 0.5857, 0.9)	0.5929	0.0501	12
C8: Stability of government policy	(0.1, 0.5429, 0.9)	0.5214	0.0440	17
C9: Adequacy of energy and electricity	(0.5, 0.8571, 1.0)	0.8036	0.0679	2
C10: Efficiency of electrical supply systems	(0.5, 0.8000, 1.0)	0.7750	0.0655	4
C11: Price of electricity	(0.3, 0.6286, 0.9)	0.6143	0.0519	11
C12: Variety of transport modes	(0.3, 0.6286, 1.0)	0.6393	0.0540	10
C13: Efficiency of transportation systems	(0.3, 0.6571, 1.0)	0.6536	0.0552	9
C14: Availability of land	(0.3, 0.5857, 0.9)	0.5929	0.0501	12
C15: Efficiency of telecommunication and network systems	(0.3, 0.5143, 0.9)	0.5571	0.0471	15
C16: Land price	(0.3, 0.5429, 0.9)	0.5714	0.0483	14
C17: Stability of financial institutions	(0.0, 0.3714, 0.9)	0.4107	0.0347	18
C18: Risk of natural disaster	(0.1, 0.6000, 0.9)	0.5500	0.0465	16

2.2 Weighting methods (RS, ROC, Entropy, and SD)

In the majority of MCDM models, criteria weighting must be thoroughly considered since it has a direct impact on the decision-making outcome. Some experts specified weights directly, whereas the majority considered mathematical weighing procedures essential [41]. This section briefly describes the four weighting methods adopted for this comparative study, including RS, ROC, Entropy, and SD. The first two methods, RS and ROC, are accounted for in rank-based or rank-ordering weighting methods [26, 27]. Based on these, ordinal data can be converted into the relative weights through specified mathematical formulations. The basic principle is that criteria in the better positions receive higher weights. Equations (1) and (2) show mathematical formulations to determine the weights for RS and ROC, where n is the total number of criteria (n = 18 for this study), r_j is the rank of criterion j, (j = 1, 2, …, n). For example, if criterion j is the most important one, it is ranked first (r_j = 1). The least important one has $r_j = n$.

$$w'_j(RS) = \frac{n-r_j+1}{\sum_{k=1}^{n} n-r_k+1} \tag{1}$$

$$w'_j(ROC) = \frac{1}{n} \cdot \sum_{k=j}^{n} \frac{1}{r_k} \tag{2}$$

Entropy and SD methods are used to represent the objective weighting approach, which determines the weights of criteria based only on known data about the problem without considering subjective opinions. For the Entropy method, criteria with performance ratings that are extremely diverse from one another receive higher weights since they have a greater impact on differentiating and ranking alternatives. At the same time, if the alternatives have similar performance ratings for a criterion, then that one has less important weight [29]. The Entropy weights can be computed following these steps [42].

From the normalised decision matrix, $R = [r_{ij}]_{mxn}$, for m alternatives and n criteria, r_{ij} denotes the normalised assessment data of alternative i on criterion j, as shown in Table 2. The first step is to calculate the entropy, E_j, of criterion j using Equation (3). Next, the relative weight of criterion j, or w'_j, can be computed through Equation (4).

Table 2 Normalised decision matrix m x n.

Alternative *i*	**Criterion *j* (*j* = 1, …, *n*)**			
(*i* = 1, …, *m*)	**1**	**2**	**…**	***n***
1	r_{11}	r_{12}	…	r_{1n}
2	r_{21}	r_{22}	…	r_{2n}
…	…	…	…	…
…	…	…	…	…
m	r_{m1}	r_{m2}	…	r_{mn}

$$E_j = \frac{-(\sum_{i=1}^{m} r_{ij}\, ln(r_{ij}))}{ln(m)} \tag{3}$$

$$w'_j = \frac{1-E_j}{\sum_{k=1}^{n}(1-E_k)} \tag{4}$$

The SD method is analogous to the Entropy approach in that it gives a criterion a small weight if its values across alternatives are comparable, while giving a high weight if the alternatives' data is massively diverse. The SD method calculates the weight of criterion j based on its standard deviations (σ_j), following Equations (5) and (6).

$$w_j' = \frac{\sigma_j}{\sum_{j=1}^{n}\sigma_j} \tag{5}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}(r_{ij}-\bar{r}_j)^2}{m}} \tag{6}$$

3. Methods

This section explains steps to investigate the influence of changing the weighting approaches on a location selection problem. This study employed secondary data from Arunyanart, et al. [4] in terms of the assessment data of the CLMV countries in each criterion. The data was gathered from 14 experts who were asked to assess the four potential nations for production fragmentation in light of the 18 criteria using a linguistic scale, which was next transformed into TFNs. The assessment data from all experts was aggregated and then normalised. Their normalised fuzzy decision matrix, $\tilde{R} = \left[\tilde{r}_{ij}\right]_{mxn}$ and $\tilde{r}_{ij} = (r_{ij1}, r_{ij2}, r_{ij3})$, is shown in Table 3.

Table 3 The normalised fuzzy decision matrix from the assessment of the CLMV countries [4].

Criteria	Cambodia (A1)	Laos (A2)	Myanmar (A3)	Vietnam (A4)
C1	(0.5, 0.7, 0.9)	(0, 0.1, 0.3)	(0.7, 0.9, 1)	(0, 0.1, 0.3)
C2	(0, 0.1, 0.3)	(0, 0.1, 0.3)	(0, 0.1, 0.3)	(0.7, 0.9, 1)
C3	(0.1, 0.457, 0.7)	(0.1, 0.429, 0.7)	(0.5, 0.614, 0.9)	(0.5, 0.814, 1)
C4	(0.1, 0.457, 0.7)	(0.3, 0.571, 0.9)	(0.1, 0.414, 0.7)	(0.5, 0.771, 1)
C5	(0.1, 0.471, 0.7)	(0.3, 0.557, 0.9)	(0.1, 0.471, 0.7)	(0.5, 0.743, 1)
C6	(0.111, 0.476, 0.778)	(0.111, 0.524, 0.778)	(0.556, 0.762, 1)	(0.333, 0.682, 1)
C7	(0.3, 0.6, 0.9)	(0.3, 0.743, 1)	(0.1, 0.4, 0.7)	(0.5, 0.771, 1)
C8	(0.3, 0.643, 0.9)	(0.5, 0.829, 1)	(0.1 ,0.443, 0.7)	(0.5, 0.786, 1)
C9	(0, 0.1, 0.3)	(0.7, 0.9, 1)	(0.3, 0.5, 0.7)	(0, 0.1, 0.3)
C10	(0, 0.1, 0.3)	(0.3, 0.5, 0.7)	(0, 0.1, 0.3)	(0.7, 0.9, 1)
C11	(0, 0.1, 0.3)	(0.7, 0.9, 1)	(0.5, 0.7, 0.9)	(0.7, 0.9, 1)
C12	(0.3, 0.6, 0.9)	(0.1, 0.4, 0.7)	(0.3, 0.657, 0.9)	(0.5, 0.814, 1)
C13	(0.1, 0.486, 0.7)	(0.1, 0.314, 0.5)	(0.3, 0.614, 0.9)	(0.5, 0.829, 1)
C14	(0, 0.1, 0.3)	(0, 0.1, 0.3)	(0, 0.1, 0.3)	(0.7, 0.9, 1)
C15	(0.1, 0.457, 0.9)	(0.3, 0.571, 0.9)	(0.1, 0.343, 0.7)	(0.5, 0.771, 1)
C16	(0.5, 0.7, 0.9)	(0.7, 0.9, 1)	(0, 0.1, 0.3)	(0.1, 0.3, 0.5)
C17	(0.1, 0.514, 0.9)	(0.1, 0.543, 0.9)	(0.1, 0.357, 0.7)	(0.5, 0.743, 1)
C18	(0.333, 0.667, 1)	(0.333, 0.698, 1)	(0.111, 0.333, 0.556)	(0.111, 0.508, 0.778)

First, the RS and ROC weights were simply computed using Equations (1) and (2) towards the ranking order of criteria shown in Table 1. Second, the Entropy and SD weights were calculated using the data in Table 3. Before adopting Equations (3) – (6), every $\tilde{r}_{ij}$ must be defuzzified, using Equation (7), to convert them back to crip values (r_{ij}), as shown in Table 2.

$$r_{ij} = \frac{r_{ij1}+2r_{ij2}+r_{ij3}}{4} \tag{7}$$

From all the weighting processes mentioned previously, the new sets of weights for the 18 criteria are presented in Table 4. The new weights were then applied to the decision-making process towards the fuzzy TOPSIS method as demonstrated in Arunyanart, et al. [4] in order to generate the ranking orders of the CLMV countries. The results obtained from the four sets of weights were cross-compared to the reference one.

Table 4 Criteria weights from the RS, ROC, Entropy, and SD methods.

Criteria	RS	ROC	Entropy	SD
C1: Labor cost	0.0760	0.0673	0.1200	0.0901
C2: Availability of labor force	0.0702	0.0581	0.1790	0.1268
C3: Skill and competency level of labour	0.1053	0.1942	0.0148	0.0333
C4: Labour laws and regulations	0.0643	0.0501	0.0132	0.0318
C5: Foreign ownership laws	0.0848	0.0854	0.0106	0.0285
C6: Taxation and tax incentives	0.0936	0.1108	0.0094	0.0264
C7: Government structure and stability	0.0380	0.0241	0.0105	0.0270
C8: Stability of government policy	0.0117	0.0064	0.0109	0.0276
C9: Adequacy of energy and electricity	0.0994	0.1386	0.1187	0.0934
C10: Efficiency of electrical supply systems	0.0848	0.0854	0.1187	0.0934
C11: Price of electricity	0.0468	0.0315	0.0609	0.0584
C12: Variety of transport modes	0.0526	0.0370	0.0106	0.0275
C13: Efficiency of transportation systems	0.0585	0.0432	0.0231	0.0411
C14: Availability of land	0.0380	0.0241	0.1790	0.1268
C15: Efficiency of telecommunication and network systems	0.0234	0.0135	0.0136	0.0319
C16: Land price	0.0292	0.0175	0.0800	0.0733
C17: Stability of financial institutions	0.0058	0.0031	0.0119	0.0300
C18: Risk of natural disaster	0.0175	0.0098	0.0151	0.0326

4. Results and discussion

According to Figure 1, the ranking orders of the candidate locations generated by DR, RS, Entropy, and SD weights are exactly the same (the *CC* scores for Vietnam > Laos > Myanmar > Cambodia). For DR and RS, their weight functions for all criteria are rather similar. Both are close to the linear function, but the RS weight is just steeper. Entropy and SD weights, on the other hand, are noticeably different from those of the subjective ones. For Entropy and SD, the range of criteria values is incorporated into the weighting procedure. The logic behind them is to capture a discrepancy between a group of alternatives based on each criterion, and then the weight of each criterion reflects the degree to which it contributes to discriminating the alternatives. From this concept, as seen in Figure 2, C2, C14, C9, C10, and C1 turn out to be the five most important criteria. However, as stated, the changes in weights towards the objective approach still do not influence the robustness of the ranking order.

ROC yields a different ranking order to the others in terms of the second- and third-ranked locations (Laos and Myanmar), while Vietnam is still the best location and Cambodia holds the least position in all sets of the weights adopted. This difference is partly caused by the fact that ROC provides the largest gaps between the weights of the most important criterion and the second-most important, and between the most and the least important ones. Furthermore, the least important criterion receives the lowest weight compared to that obtained by other methods, as shown in Figure 2, where the ROC weight function is very steep and non-linear. From this, Myanmar, which is ranked third by other weighting methods, moves to the second place by ROC. The main reasons are that Myanmar performs much better than Laos and Cambodia in terms of labour skills and competency (C3), which receives an outstanding weight from ROC. At the same time, its worst performances in terms of the stability of financial institutions (C17) and government policy (C8) do not significantly drop its ranking position since the ROC weights of these two criteria are very small.

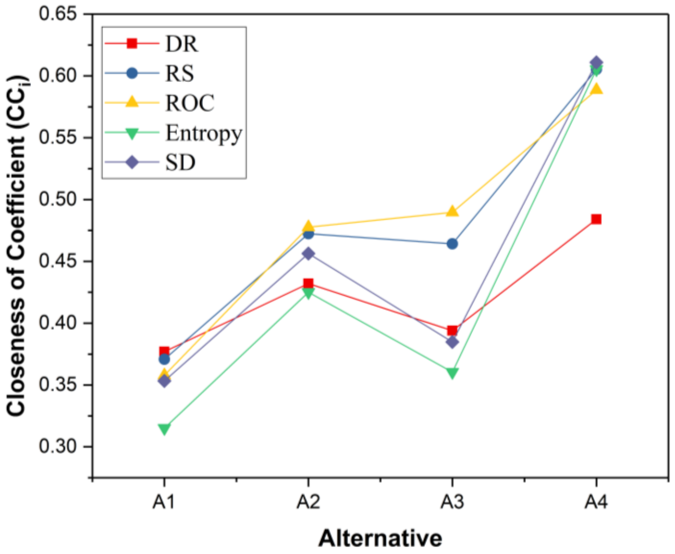

Figure 1 Ranking orders of alternatives derived by the five weighting methods.

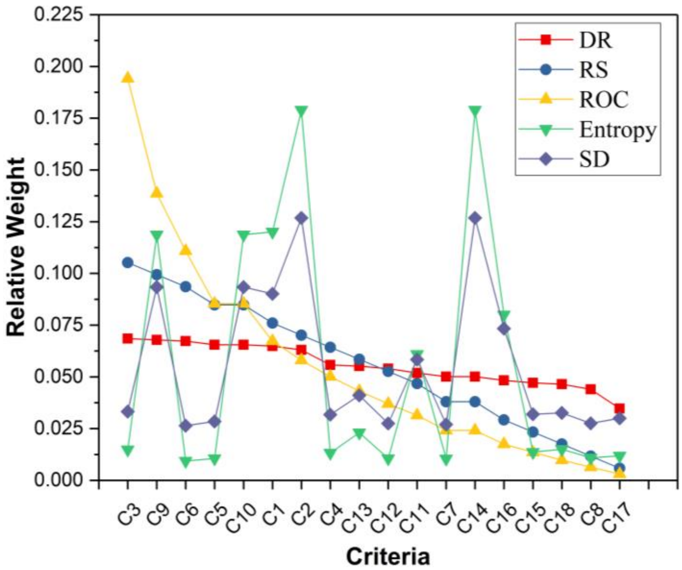

Figure 2 The relative weights of the 18 criteria from the five weighting methods.

Even though, overall, the ranking order of the four locations for this case is considerably robust and not susceptible to the change of weights, this does not mean that the five weighting methods will always give the same ranking of alternatives for every case. Selection of a weighting method can be based on several specific considerations. Next, the five weighting methods were compared, based on their methodological and practical viewpoints, towards three criteria, adapted from Németh, et al. [36], including resource requirement, chance of bias, and general complexity. All of them are considered within the cost criteria (the lower the better). The resource requirement means time and money spent on data collection and weight elicitation. The chance of bias refers to the potential for personal bias regarding the weights obtained from each method, which possibly leads to unreliable outcomes as well as conflict or disagreement among multiple decision makers. Here, reliability means the extent to which the method produces the same result after several trials [43, 44]. General complexity is assessed based on the complexity of mathematical computation. The comparison shown in Table 5 is based on the theoretical advantages and drawbacks of each method, as well as the authors' viewpoints.

Table 5 A comparison of subjective and objective weighting methods.

Weighting approaches	Weighting methods	Resource requirement	Chance of bias	General complexity
Subjective weighting	DR	Moderate	High	Low
	RS	Low	Moderate	Moderate
	ROC	Low	Moderate	Moderate
Objective weighting	Entropy	High	Low	High
	SD	High	Low	High

When simplicity or resource constraints are important, the three subjective weighting methods appear to be superior to the Entropy and SD methods, especially when a large number of criteria are considered. The DR, RS, and ROC only require a decision maker's subjective judgement to determine the weights, while the analyst needs to complete the assessment of all alternatives on all criteria before the weights can be computed through the Entropy and SD methods. This implies that the objective methods tend to consume more time and resources for data collection. The rank-based methods are awarded the first for this criterion due to the fact that, while DR calls for a decision maker to straightforwardly assign scores to reflect degrees of criteria importance, focusing only on the priority of the criteria (as seen for the cases of RS and ROC) is much easier and quicker. The literature also affirms that the rank-based weighting is appropriate when there is a time constraint and when decision makers lack the knowledge or information necessary to undertake a complicated elicitation process [26, 27, 43, 45-48].

The appropriate choice of weighting method might be changed when considering the potential for personal bias and unreliable outcomes. According to this criterion, objective methods are the best because the weights are determined by quantitative data rather than personal judgments, avoiding conflict among the peer group. The reliability of the weights determined by the objective methods can be confirmed, unless the evaluation results of the alternatives are still uncertain. The literature also praises the rationality of incorporating the range of feasible values into the weighting procedure, and many researchers support that a criterion should receive a higher weight as its range of alternative data increases [49-53]. Among the subjective methods, the rank-based approach is still superior to DR in terms of the potential for personal bias and unreliable outcomes. As previously stated, when decision makers feel more confident in solely prioritising the criteria, the weights obtained should be more dependable accordingly. On the other hand, decision makers generally find it more difficult to assign accurate weights, so their decisions are frequently ambiguous or superficial. Furthermore, in group decision making, agreement on the precise weights of many criteria seems to be an impractical demand; it is more likely that participants will agree on a ranking order [26, 27, 45-48, 54]. DR is also claimed to lack a scientific basis for weight elicitation [36]. In terms of general complexity, however, DR has a big advantage in the ease of computation [36], while the rank-based and objective methods both use more complicated mathematical formulas.

The five methods considered here also have some limitations that practitioners should be aware of. The rank-based methods may only be useful when an accurate weight of a criterion is not a key issue for consideration since ordinal information communicates just one aspect of its relative importance and the strength of the decision maker's preference is not expressed [52, 55]. Regarding the objective methods, the generalisability of the weights depends on the completeness of the choices investigated as well as the availability and reliability of the data [42]. Generally speaking, if the assessment data from the alternatives being considered is uncertain, incomplete, and does not cover the entire range of feasible values, the weights generated might be misleading. The DR method is claimed that its process of weight elicitation is not rational as it does not consider the range of alternatives' performances [51, 56, 57]. To get around this restriction, it is suggested here to add one more step before beginning the weighting procedure. A debate discussing the range of values for each criterion, or the best and worst situations for that criterion, may be held. This allows for the implicit assimilation of the feasible discrepancy within the alternatives into the decision maker's cognitive learning.

Instead of choosing only one approach to generate criteria weights for MCDM problems, a number of recent studies have shifted to combining both approaches to utilise information from different angles. Wu, et al. [58], for example, determined the aggregated weights of criteria by combining subjective weights with objective weights using a linear weight vector with a parameter to control the proportion between them. Their case study of a hotel selection based on the TOPSIS method demonstrated that the overall ranking of hotel alternatives began to significantly change as the proportion of objective weights reached 0.7 and above. Their study extracted the objective weights of criteria from the textual online reviews of the hotels (relying on counting wording frequencies), while the subjective weights are determined by the best worst method. Şahin [59] and Nuriyev [60] used similar ideas when weighing criteria in a location selection problem. The first one, Şahin [59], evaluated potential locations in Turkey for an automotive manufacturing plant by integrating rankings of candidate locations derived by various objective and subjective weighting methods to determine the optimal location. The four objective methods considered in this study included Entropy, SD, criteria importance through inter-criteria correlation (CRITIC), and equal weighting, while AHP was the only subjective weighting method used. Six common MCDM methods (including TOPSIS) were used to rank alternative locations. Their results revealed a significantly high correlation between each pair of the three objective methods (Entropy, SD, and CRITIC) on the criteria weights. In general, they proved that the criteria weights prominently affected the ranking outcomes for most MCDM methods. Some scenarios in this study showed that the rank of an alternative could be changed from the first to the seventh when changing weighting methods, particularly when switching between objective and subjective approaches (except for PROMETHEE, which suggested the same best locations regardless of the changes in weighting methods). Nuriyev [60] also proposed a combination of subjective and objective weights in the selection of power plant locations using the fuzzy TOPSIS method. Entropy represented the objective approach in this study, while the DR and fuzzy AHP with linguistic scales denoted the subjective approach. Similar to Wu, et al. [58], the combined weights of criteria were generated using a linear vector with a parameter to control the proportions of the two approaches. However, the sensitivity of the rankings of candidate locations to the changes in criteria weighting methods was only at a mild level for this study (the change in each location's rank did not exceed one point). In general, these studies illustrate the reasonableness and applicability of the combined approaches, which utilise both existing useful information about alternatives and the decision maker's opinions to elicit the weights of criteria for a logical decision. Nuriyev [60] also claims that such a combination could increase the reliability and consistency of the decision outcomes.

5. Conclusions

From the selection of the most appropriate locations among the CLMV countries using the fuzzy TOPSIS method as the basis for computing the composite index and for ranking the alternatives, Vietnam shows up as the best compromise location in all weighting scenarios. Although this study does not discover massive differences in the rankings of alternatives across different weighting methods, it provides insightful discussions about the methodological and practical points of view of the five methods under the subjective and objective weighting approaches, which are generic and can be applied to other cases of MCDM problems. The practical implications provided by this paper are summarised below.

- This study illustrates that considering a more efficient and reliable way to aid the weighting process is worthwhile. It suggests that decision makers choose a method based on their personal logic, considering the availability of time and financial resources, the potential for bias and conflict in group decision making, as well as the complexity of each method.
- The three subjective weighting methods appear to be preferable to the Entropy and SD methods when simplicity or resource limitations are crucial. For this concern, the rank-based methods are first suggested, particularly when a lot of criteria are being considered.
- When addressing the potential for personal bias and unreliable results, it turns out that objective methods are the most appropriate choice.
- In terms of computational complexity, DR appears to utilise the simplest procedure, while the rank-based and objective methods need more involved mathematical formulations.

Suggestions for future studies are that other MCDM methods commonly used for alternative ranking, such as VIKOR, may be adopted. VIKOR is like TOPSIS in that they consider the closeness to the ideal solution of each alternative. The end result of VIKOR can be a set of the best compromise options that are not significantly different from each other. TOPSIS, on the other hand, does not examine whether or not the composite scores of the alternatives are significantly different. Furthermore, increasing the number of alternatives can also be considered when comparing outcomes from several weighting methods since the difference tends to become more apparent with a greater number of alternatives. The approach that uses both subjective and objective methods together, as mentioned at the end of the previous section, should also be considered in further research.

6. Acknowledgements

This work was supported by Research and Graduate Studies, and Supply Chain and Logistics System Research Unit, Khon Kaen University.

7. References

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