Chapter 2
Robust Stakeholder-Based Group-Decision Making Framework: The Multi-Actor Multi-Criteria Analysis (MAMCA) with the Integration of Best-Worst Method (BWM)

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Abstract In recent years, there has been a growing recognition of the importance of stakeholder involvement in decision-making processes. To address this need, Multi-Actor Multi-Criteria Analysis (MAMCA) has emerged as a group decision-making framework that takes into account the preferences of key stakeholders. MAMCA provides a flexible structure that aims to capture the various points of view of stakeholders involved in the decision-making process. After the group evaluation, MAMCA encourages stakeholders to engage in discussions and negotiations to reach a consensus solution. However, sometimes it is challenging to reach a consensus solution as stakeholders normally hold conflict interests. Furthermore, during the evaluation, stakeholders may struggle to understand the weight elicitation methods, which can lead to elicitation results that do not reflect their preferences or expectations. Consequently, the Best-Worst Method (BWM) effectively addresses these challenges by simplifying the elicitation process and promoting consistency among judgments, ultimately enhancing the reliability and robustness of decision-making outcomes. This paper proposes a robust group decision-making framework based on MAMCA that incorporates BWM as the weight elicitation method. The proposed framework integrates elicited criteria weights and their consistency ratios from BWM into the consensus-reaching model to further increase the consistency of the results and identify consensual solutions that all stakeholders can accept. The effectiveness of the proposed framework is demonstrated through a logistics study.

Keywords BWM · MAMCA · Group decision making · Consensus reaching

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Introduction

Stakeholder involvement is a critical aspect of decision making in complex problems, particularly in the transportation sector where decisions must take into account the preferences of the related key interest groups, as well as a wide range of monetary and non-monetary factors such as transportation cost, travel time, environmental impact, etc. [1, 2]. It is essential to ensure that all relevant stakeholders are included in the decision-making process and that their preferences are taken into account in order to reach a consensual solution [3]. To address the decision-making problem in the aforementioned context, multi-criteria group decision making (MCGDM) [4–6] and multiattribute group decision making (MAGDM) [7] are often considered suitable frameworks. It is worth noting that MCGDM and MAGDM are essentially the same, as both involve decision-making processes that consider multiple criteria or attributes and involve multiple decision-makers [7, 8]. Multi-Actor Multi-Criteria Analysis (MAMCA) is a specific MCGDM framework that emphasizes stakeholder involvement [9].

MAMCA is a highly flexible MCGDM framework that derives its flexibility from the adaptable choice of elicitation methods and the ability to customize the evaluation structure. It provides a framework for involving multiple stakeholders in the decision-making process by considering the stakeholders' individual preferences, allowing them have different criteria sets, and taking these into account when evaluating alternatives [10–12]. This ensures that the final decision takes into account the needs and concerns of all relevant stakeholders, providing a more comprehensive evaluation. Furthermore, MAMCA allows for the integration of various weight elicitation methods and multi criteria decision-making (MCDM) methods [10]. This makes MAMCA an easy-to-understand framework that is straightforward to utilize, especially when stakeholders with different levels of expertise are involved.

In the social/public decision making, the selection of methods used in MAMCA becomes important, because the participants can have limited knowledge to understand the MCDM methods [13]. In addition, the ways of data collection can be survey filling, participants may have limited time to understand MCDM methods [12]. One MCDM method that is particularly suitable for use in MAMCA is the Best-Worst Method (BWM) [14]. BWM is ideal for use in MAMCA as it requires minimal input from participants from different stakeholders but still provides consistent results. This means that stakeholders can be involved in the decision-making process with a minimum of effort, making the process more accessible and efficient [15].

One challenge for MAMCA is the consensus reaching after the evaluation, given that MAMCA discourages assigning weights to stakeholders as it does not recommend aggregating the result that compensates the stakeholders' preferences [16]. It encourages negotiation and discussion among the participants in order to find the compromise solutions. However, arriving at a final solution without mathematical proof can be difficult. One possible solution is to conduct a sensitivity analysis to check the ranking of alternatives across all stakeholders [17]. In previous work, Huang et al. [16] proposed an optimization model based on weight sensitivity analysis to aid participants in reaching a consensus solution. Now, the integration of BWM can further enhance the robustness of the model output.

This study identifies two key challenges in stakeholder-based group decision-making: the challenge of non-expert stakeholders in eliciting criteria weights and the challenge of conflicting preferences among stakeholders in reaching a consensus. In order to address these challenges, we thus propose a robust group decision-making framework that combines BWM and MAMCA to assist stakeholder groups in finding consensus solutions. Specifically, the criteria weights elicited through BWM are incorporated into the consensus-reaching model as constraints to further increase the consistency of the results. The optimization model searches for the best solution that can be ranked highly by all stakeholders. Thanks to the integration of MAMCA and BWM, stakeholders can easier elicit criteria weights, ultimately leading to a more efficient and effective decision-making process. By reducing the potential for inconsistencies in criteria weight elicitation, the proposed framework not only produces robust results but also saves valuable time for stakeholders.

This paper first provides a brief literature review of MAMCA and BWM in Section "Literature Review: MAMCA Framework and the Possibility of Integration of BWM". We then present our proposed framework that combines MAMCA and BWM in Section "Robust MAMCA-BWM Framework". Next, we apply this framework to a real-life logistics study to demonstrate its effectiveness Section "Case Illustration". Finally, we draw the conclusion.

Literature Review: MAMCA Framework and the Possibility of Integration of BWM

The MAMCA framework was initially proposed to support the decision-making process in the transportation filed with the involvement of different key stakeholders [10]. It emphasizes the importance of including the perspectives and expertise of various stakeholders in process, as their support is critical for the success of the decision-making [12]. The MAMCA framework belongs to the stakeholder-based MCGDM frameworks [18, 19], as well as the participatory multi-criteria analysis (MCA) frameworks [20]. These frameworks prioritize participation and collaboration among stakeholders to achieve a common understanding and consensus. While the MAMCA framework shares many characteristics with these frameworks, it also has its unique features. One of the most significant advantages of MAMCA is its flexibility, which is reflected in its steps. The MAMCA framework is illustrated in Fig. 2.1 and the steps of MAMCA are (1) Problem identification and alternative definition; (2) Stakeholder analysis; (3) Criteria identification; (4) Criteria indicators building; (5) Stakeholder overall analyses; (6) Result discussion; (7) Implementation.

The Multi-Actor Multi-Criteria Analysis (MAMCA) framework consists of several steps that follow standard Multi-Criteria Group Decision-Making (MCGDM) frameworks [21]. However, MAMCA differs in that stakeholders are identified in the second step, so that they may be involved in subsequent steps to aid facilitators for example in identifying criteria [3]. Because MAMCA allows the stakeholders to hold different criteria, which can better help them evaluate alternatives based on their own interests and priorities. Then, criteria weights can be elicited using various methods such as SWING [22], Simos [23], or BWM [14]. In step 5, the overall analysis is conducted within stakeholders, and any MCA methods may be used to assess alternatives. Group Decision Support Methods (GDSM) [10], such as Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) [24], Analytic Hierarchy Process (AHP) [25], or BWM [14] are well-suited for this step. In the result discussion step, facilitators can aggregate scores evaluated by different stakeholders as overall preferences or encourage stakeholders to negotiate and find compromise solutions. This approach enables different robustness analyses to help reach a consensus. As mentioned above, MAMCA can be customized in different steps and adapted to suit different decision-making contexts. This flexibility is particularly beneficial in scenarios where there are diverse stakeholders with varying interests, objectives, and preferences. Additionally, permitting the utilization and combination of various criteria weight elicitation methods and MCDM methods can promote a more thorough analysis and address the constraints of methods. For example, BWM can be used to elicit criteria weights and produce consistent results, especially in situations where stakeholders have limited expertise to understand the elicitation method or limited time to elicit weights.

The Best-Worst Method (BWM) is a widely utilized pairwise-comparison approach that is favored for its efficiency and simplicity. Unlike the conventional pairwise-comparison method AHP, which can be cumbersome and time-consuming due to the large number of pairwise comparisons required, BWM only necessitates decision-makers to compare the criteria or alternatives to the most and least important/preferred ones [14]. This streamlined approach can save significant amounts of time while still providing a consistency ratio to ensure the accuracy and reliability of the elicitation process [14]. Moreover, recent research on BWM has demonstrated that it can yield results less susceptible to anchoring bias [26]. Rezaei [27] revealed that the two-vector mechanism effectively counteracts the impact of anchoring bias, which is commonly observed in single reference point approaches, such as the Simple Multi-Attribute Rating Technique (SMART) [28] and Swing [22]. To elicit criteria weights using BWM, several steps are involved. First, evaluators (i.e., stakeholders in MAMCA) need to identify the best and worst criteria. Next, they need to assess the preferences of the best criterion over all the other criteria using a scale ranging from 1 to 9, or other scales like the Likert scale [29]. Then, the preferences of all the other criteria over the worst criterion need to be determined using the same scale. Finally, the preferences will be inputted into an optimization model to obtain the optimal weights that have maximum consistency. The comparisons can be illustrated as Fig. 2.1, where only reference comparisons are conducted, and secondary comparisons based on knowledge about the reference comparisons are not conducted [14].

Like AHP, BWM also provides the consistency ratio. This helps to avoid inconsistent that could lead to unreliable decision-making. Liang et al. [30] delves deeper into the issue of consistency in BWM and provides a more comprehensive analysis of the problem. The study explores the details of the consistency issue in BWM and

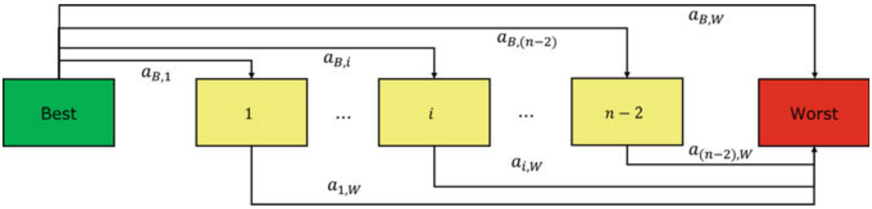

Fig. 2.1 The comparisons in the BWM [14]

provides thresholds that can be used to accept or reject inconsistency in the elicitation process. By providing such thresholds, stakeholders can have a better understanding of the consistency issue and can be confident in the reliability of the elicitation results obtained through the BWM. This further highlights the significance of BWM in ensuring consistent and reliable criteria weight elicitation for decision-making.

However, in the other side point of view, the consistency ratio in BWM also provides the possibility to help stakeholders to reach the consensus in a group decision-making context. As it is discussed previously, the consistency ratio is to check whether the stakeholders filled in consistent preference scores to different comparison. In MAMCA, when stakeholders finish the evaluation, the ranking of alternatives of stakeholders will be illustrated in step 6 [10]. Then the stakeholders need to discuss and find out compromised solutions that can be accepted by everyone. Normally, the participants and facilitators cannot identify the consensual solutions based on their rankings without any additional information [16]. Therefore, it is valuable to build a consensus reaching process (CRP) to support them [31].

In this study, CRP based on the minimization of weight modification is a feasible solution. We argue that, unlike alternative appraisal methods, which require more objective data support, the elicitation of criteria weights is subjective and inaccurate, particularly when the imprecise weight elicitation is applied [32, 33]. In this regard, we propose to apply inverse optimization based on criteria weight sensitivity analysis [34]. The weight sensitivity analysis enables the validation of the robustness of the alternative ranking of one evaluator [35]. By applying the principles of inverse optimization theory, consensual alternatives can be identified for all stakeholders through the alteration of criteria weights. Previously, Doan and De Smet [36] developed an alternative weight sensitivity analysis based on mixed integer linear programming (MILP), and Huang et al. [16] further developed it by taking the inverse optimization point of view in the context of group decision-making framework. It can be further developed by leveraging the consistency ratio of BWM to further improve its robustness. Liang et al. [30] proposed the algorithm to determine the ordinal consistent threshold of consistency ratio for different combinations in BWM. The ordinal consistency can be validated in the optimization to ensure that the solutions obtained uphold the ordinal consistency, as we argue that the weight elicitation from the BWM should at least respect the ordinal information provided by the stakeholders. In the following section, we present our robust MAMCA-BWM framework that utilize the revised consensus-reaching model.

Robust MAMCA-BWM Framework

Without loses its generality, let us define a set of alternative $A = \{a_1, a_2, \ldots, a_M\}$ need to be appraised by stakeholders $S = \{s_1, s_2, \ldots, s_K\}$ in MAMCA. For each stakeholder group k $(k = 1, 2, \ldots, K)$ there is a set of criteria $C_k = \{c_1, c_2, \ldots, c_{N_k}\}$. The stakeholder will first elicit the criteria weights. For stakeholder k, best and worst criterion c_{B_k}, c_{W_k} are identified. Then the preferences of the best criterion over the other criteria are determined in a z-point scale (in this study, 9-point scale is used), which result in a Best-to-Others vector $A_{BO_k} = (a_{B_k1}, a_{B_k2}, \ldots, a_{B_kn_k})$, where $a_{B_kn_k}$ represents the preference of the best criterion c_{B_k} over c_{n_k} $(n_k = 1, 2, \ldots, N_k)$. Similarly, Others-to-Worst vector is determined in the same point scale $A_{OW_k} = (a_{1W_k}, a_{2W_k}, \ldots, a_{n_kW_k})$, where $a_{n_kW_k}$ represents the preference of criterion c_{n_k} over the worst criterion c_{W_k}. Then the criteria weights $(\omega_1^*, \omega_2^*, \ldots, \omega_{n_k}^*)$ for stakeholder k can be obtained by solving the linear programming problem proposed in [37]:

$$\min \xi^L, \tag{1}$$

s.t.

$$\begin{aligned}
&|\omega_{B_k} - a_{B_kn_k} \cdot \omega_{n_k}| \le \xi^L, \forall n_k \in \{1, 2, \ldots, N_k\},\\
&|\omega_{n_k} - a_{n_kW_k} \cdot \omega_{W_k}| \le \xi^L, \forall n_k \in \{1, 2, \ldots, N_k\},\\
&\sum_{n_k=1}^{N_k} \omega_{n_k} = 1.
\end{aligned} \tag{2}$$

By utilizing this model, we can obtain a unique solution for the optimal criteria weights. Consequently, these unique criteria weights can generate a single performance score through the weighted sum of the uni-criterion scores. This approach enables us to gain an initial understanding of stakeholders' preferences, proving particularly valuable when integrating the scores of various stakeholders within the later mentioned MAMCA view On the other hand, the stakeholders need to appraise the alternative performances based on their criteria. Different MCDM methods can be used in MAMCA to appraise the alternatives. In this study, we use PROMETHEE II to appraise the alternatives. Therefore, for each stakeholder, an unweighted uni-criterion net flows can be obtained. As it is not the focus of this study, and to not lose its generality, we only define the final appraised unweighted alternative performance score matrix:

$$P_k = \begin{bmatrix} p_1^1 & \cdots & p_1^M \\ \vdots & \ddots & \vdots \\ p_{N_k}^M & \cdots & p_{N_k}^M \end{bmatrix}, \tag{3}$$

where P_k is the alternative performance score matrix appraised by stakeholder k, $p_{n_k}^m$ represents the score of alternative m based on criterion n_k. We adopt the additive model, which is the conventional form in MAMCA, to aggregate the final score of alternative for one stakeholder:

$$\phi_k^m = \sum_{n_k=1}^{N_k} p_{n_k}^m \times \omega_{n_k}, \forall n_k \in \{1, 2, \ldots, N_k\}, \tag{4}$$

where ϕ_k^m represents score of alternative m for stakeholder k. In MAMCA, the matrix of the final alternative scores can be illustrated in a so-called multi-actor view. This matrix can be expressed as:

$$\Phi = \begin{bmatrix} \phi_1^1 & \cdots & \phi_1^M \\ \vdots & \ddots & \vdots \\ \phi_K^1 & \cdots & \phi_K^M \end{bmatrix}. \tag{5}$$

As aforementioned, it is difficult to identify the consensual solution solely based on matrix (5). We applied the optimization model proposed by Huang et al. [16] to search for the solutions in a context of BWM. We formulate the optimization problem as follows: 'What would be the minimum weight modifications that should be accepted by the different stakeholders such that a common alternative would get a higher position in the different rankings, where the criteria weights still respect the ordinal consistency of BWM'. As we already have the initial criteria weights elicited by BWM $(\omega_{k,1}, \omega_{k,2}, \ldots, \omega_{k,n_k})$, the modified criteria weights of stakeholder k are denoted as $(\omega'_{k,1}, \omega'_{k,2}, \ldots, \omega'_{k,n_k})$.

We define the variables for the model. In order to linearize the absolute value, two other sets of variables for each stakeholder k are defined:

- $\mathcal{D}_{1,k} = \left\{d_{1,1,k}, d_{1,2,k}, \ldots, d_{1,N_k,k}\right\}$
- $\mathcal{D}_{2,k} = \left\{d_{2,1,k}, d_{2,2,k}, \ldots, d_{2,N_k,k}\right\}$

such that, $\forall k \in \{1, \ldots, K\}$; $\forall n_k \in \{1, 2, \ldots, N_k\}$:

$$\omega_{k,n_k} - \omega'_{k,n_k} = \begin{cases} d_{1,n_k,k} & \text{if } \omega_{k,n_k} - \omega'_{k,n_k} \geq 0 \\ -d_{2,n_k,k} & \text{otherwise} \end{cases}, d_{1,n_k,k}, d_{2,n_k,k} \geq 0 \tag{6}$$

$d_{1,n_k,k}$ (resp. $d_{2,n_k,k}$) is equal to $\omega_{k,n_k} - \omega'_{k,n_k}$ (resp. $-(w_{k,p} - w'_{k,p})$) if this difference is positive (resp. negative), and $d_{k,2,p}$ (resp. $d_{k,1,p}$) is equal to 0.

Then, we will solve the MILP for each stakeholder individually and for all the alternatives. For the sake of simplicity, let us consider the case of alternative a_m and stakeholder k, the MILP model can then be formalized as follows:

$$\min z_k^m = \sum_{n_k=1}^{N_k} |\omega_{k,n_k} - \omega'_{k,n_k}| = \sum_{n_k=1}^{N_k} (d_{1,n_k,k} + d_{2,n_k,k}), \tag{7}$$

s.t.

$$\sum_{n_k=1}^{N_k} \omega'_{k,n_k} = 1, \forall k = 1, 2, \ldots, K, \quad \text{(weights constraint)}, \tag{8}$$

$$\phi_k'^m = \sum_{n_k=1}^{N_k} p_{n_k}^m \times \omega'_{k,n_k}, \forall n_k \in \{1, 2, \ldots, N_k\}, \quad \text{(alternative scores computation)} \tag{9}$$

$$\phi_k'^m - \phi_k'^{m'} \leq \epsilon\, r_k^m,$$

$$\phi_k'^m - \phi_k'^{m'} \leq \epsilon\, (1 - r_k^m), \quad \text{(rank change of } a_m\text{)}$$

$$\sum_{m'=1, m' \neq m}^{M} r_k^m = M - g, \forall g = 1, 2, \ldots, M - 1, \tag{10}$$

$$\omega_{k,n_k}, d_{1,n_k,k}, d_{2,n_k,k} \geq 0, \quad \forall k \in \{1, \ldots, K\}, \forall n_k \in \{1, 2, \ldots, N_k\}. \quad \text{(domain)} \tag{11}$$

where ϵ in Eq. (10) is an arbitrary constant so that $Z \geq \frac{1}{d_{1,n_k,k}+d_{2,n_k,k}}$. r_k^m indicates whether alternative a_m has a higher net flow score, i.e., a better rank than alternative $a_{m'}$ in the modified ranking. We want to find the minimum weight modification that will lead alternative a_m to reach position g in the modified ranking for stakeholder k. We run the MILP model (7) to search alternatives for better ranking iteratively, each time we check if the modified criteria weights respect the ordinal consistency. As we utilize the linear BWM model, the minimum ξ^L obtained from Eq. (1) can be directly regarded as an indicator of comparison consistency. A lower ξ^L values indicating higher consistency [37]. And we define two different distances: weight distance and ranking distance. Weight distance $Z^m = \sum_{k=1}^{K} z_k^m$ represents the distance of modified criteria weights towards the original criteria weights elicited by BWM that lead the alternative m to the better position. And the ranking distance $O^m = \sum_{k=1}^{K} (K - r_k^m)$ represents the ranking positions of the alternative m towards the best position. Thus, when $O^m = 0$, all stakeholders rank alternative m as best solution. These two distances can construct a 2-D point $(Z^m, O^m) \in \mathbb{R}^2$ for each output of the model, where the ξ^L can be checked. If for one point where $O^m = 0$, ξ^L is within the threshold proposed in [30], we can conclude alternative m is a consensual solution that can be accepted by all stakeholders and still consistent. However, if ξ^L is rejected but $O^m = 0$, m is a compromised solution that is possible to be accepted by all stakeholders, but one or several stakeholders need to adapt their criteria weight elicitation. i.e., priorities. The final output can be illustrated in a line chart by connecting the points for a visual aid.

Case Illustration

To illustrate the benefits of robust MAMCA-BWM framework, we applied it in the same sustainable logistic case that is used in [16] as a didactic example. The main objectives of the case were to develop cost-effective strategies, measures, and tools for

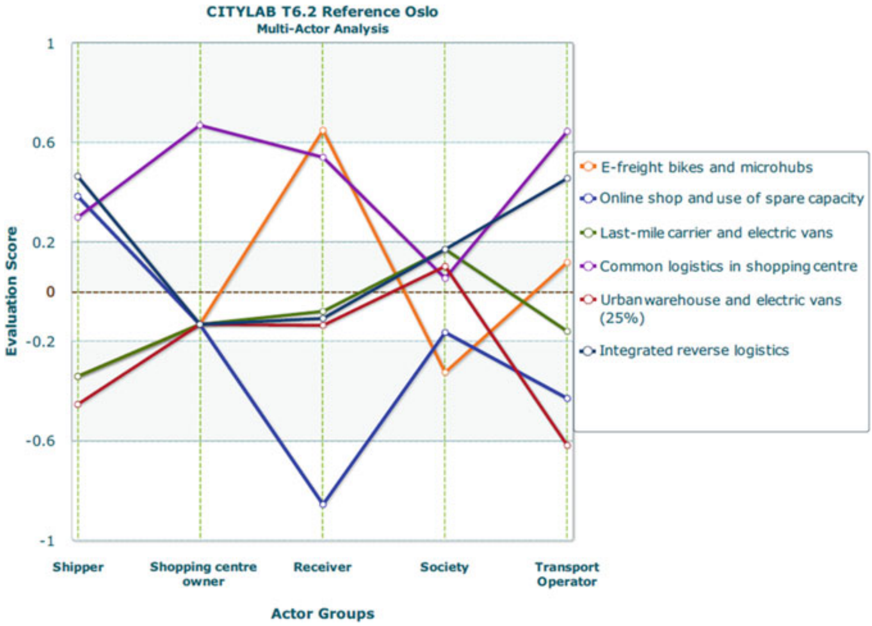

Fig. 2.2 MAMCA view of the sustainable logistic case [16]

emission-free city logistics and implement them on a larger scale. In the original case, there are six alternatives, and the MAMCA view is depicted in Fig. 2.2. The lines represent different alternatives, illustrating the aggregated performance scores for various stakeholders. It is evident that significant conflicts exist among stakeholders. To effectively demonstrate the benefits of the framework without delving too deeply into the original case, we have chosen three alternatives: (1) E-freight bikes and micro-hubs, (2) common logistics in shopping centers, and (3) integrated reverse logistics, as well as three stakeholders: shipper, receiver, and transport operator. These three alternatives exhibit relatively high scores for the three stakeholders but generate three distinct rankings (see Table 2.4). In fact, a previous study found that these three alternatives required the minimum weight distance to be ranked in the top position for all stakeholders in [16]. In other words, these alternatives are most likely to be accepted by all stakeholders as a solution. Conversely, the other three alternatives are less competitive, typically displaying negative unweighted uni-criterion net flows. Thus, we invited three researchers/experts in transport and logistics to role-play the three original stakeholders and evaluate the selected alternatives. They are asked to re-elicit the criteria weights by applying BWM. The criteria of the stakeholders are illustrated in Table 2.1.

The original BWM weights, output-based consistency ratios, unweighted PROMETHEE uni-criterion net flows, aggregated performance scores and rankings of alternatives for stakeholders are presented in Table 2.4. All numerical values

Table 2.1 Criteria of different stakeholders

Stakeholders	Criteria
Shipper	Positive effect on society, high quality deliveries, low cost for transport, high quality pick-ups
Receiver	Positive effect on society, low cost for receiving goods, high quality deliveries, attractive shopping environment
Transport operator	Viable investment, positive effect on society, satisfied employees, profitable operations, high quality service

Table 2.2 Threshold of ξ^L for different combinations using output-based consistency measurement

Number of criteria	Scale						
	3	4	5	6	7	8	9
4	0.0612	0.0820	0.1003	0.1167	0.1299	0.1420	0.1542
5	0.0497	0.0686	0.0851	0.1000	0.1129	0.1244	0.1351

are maintained to three decimal places. The scores are aggregated based on (4). It is important to note that the net flows of alternatives for each criterion do not sum to zero. This is because we have only "hided" the net flows of the other three unused alternatives, rather than deleting them. By doing so, we preserve the original outranking information of the alternatives. The pairwise comparison vectors for stakeholders' criteria can be found in the appendix for readers' reference. In the original criteria weights, the ξ^L values are validated to determine if they exhibit ordinal consistency. We employed the same method as presented in [30] to identify the approximate thresholds for the output-based consistency ratio in the linear BWM model. The corresponding thresholds of ξ^L for 4 and 5 criteria are provided in Table 2.2.

Since the linear model aims to find a unique solution instead of allowing for multi-optimality, it leads to relatively strict consistency thresholds for the ξ^L. Adjusting the weights can easily result in exceeding the approximated thresholds. Therefore, in this study, we will not only verify whether the optimized ξ^Ls fall within the threshold, but also ensure that the optimized weights preserve the same rank as the original rank, in order to provide a broader insight.

It is evident that the original rankings for stakeholders differ, highlighting the value of applying the consensus-reaching model to identify a consensus among the various stakeholder preferences. We then applied the consensus-reaching model to search for better rankings for alternatives. For example, the MILP output of alternative 'E-freight bikes and micro-hubs' are illustrated in Table 2.3.

Table 2.3 MILP model result of alternative 'E-freight bikes and micro-hubs'

MILP	z_1	z_2	z_3	o_1	o_2	o_3	Z	O	ξ^L within threshold	Preserving same rank
1	0	0	0	3	1	3	0	4	Yes	Yes
2	0	0	0.324	3	1	2	0.324	3	No	No
3	0	0	0.569	3	1	1	0.569	2	No	No
4	0.619	0	0.569	2	1	1	1.188	1	No	No
5	0.943	0	0.569	1	1	1	1.512	0	No	No

Table 2.4 Original criteria weights and uni-criterion net flows

Stakeholders	Criteria	Weight	Score of (1) E-freight bikes and micro-hubs	Score of (2) common logistics in shopping center	Score of (3) integrated reverse logistics	ξ^L	Ranking
Shipper	Positive effect on society	0.0799	0	0	1	0.090	(3) > (2) > (1)
	Low cost for receiving goods	0.0511	0.8	0	0		
	High quality deliveries	0.550	−0.6	0.6	0.2		
	Attractive shopping environment	0.319	−0.2	−0.2	1		
	Weighted sum performance score	/	−0.353	0.266	0.509		
Receiver	Positive effect on society	0.091	0	−1	0	0.076	(1) > (2)> (3)
	Low cost for receiving goods	0.066	0.8	0	0		
	High quality deliveries	0.184	−0.6	1	0.2		
	Attractive shopping environment	0.660	1	0.6	−0.2		
	Overall performance score	/	0.601	0.487	−0.095		
Transport operator	Viable investment	0.197	−0.6	0.6	0.6	0.062	(2) > (3) > (1)
	Positive effect on society	0.073	0.8	0.8	0		
	Satisfied employees	0.148	−0.6	−0.6	0.8		
	Profitable operations	0.052	0.8	0	0		
	High quality service	0.530	0.4	1	0.4		
	Overall performance score	/	0.105	0.618	0.448		

Where z_k, o_k represents the weight distance and ranking distance for stakeholder k, the MILP always search the minimum weight modification to rank alternative 'E-freight bikes and micro-hubs' to a higher position for any stakeholder. For example, from MILP 1 (original criteria weights) to MILP 2, it finds the minimum

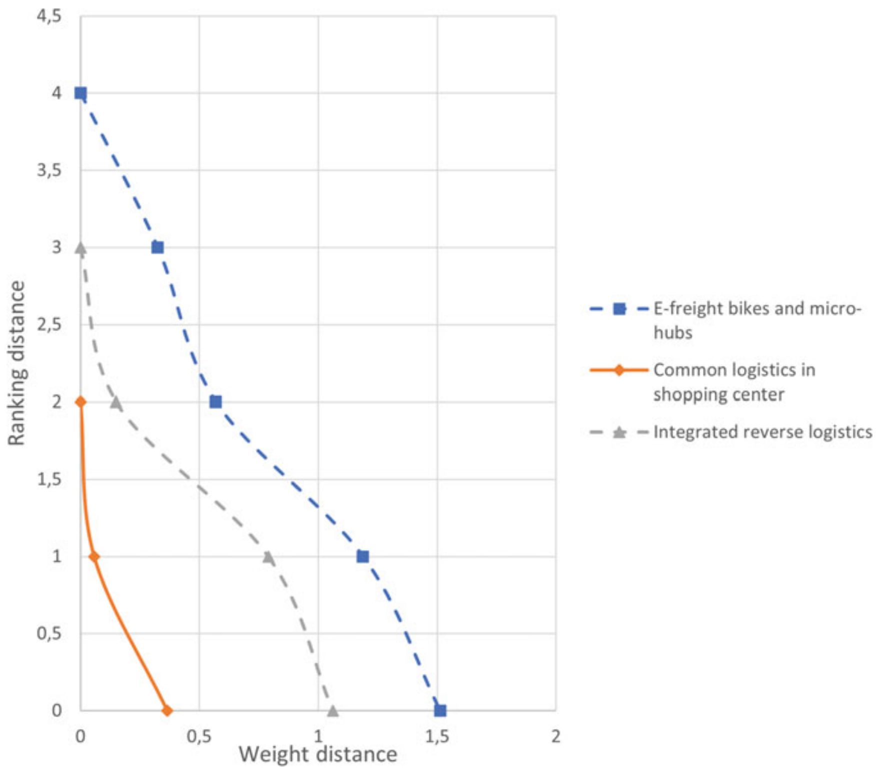

Fig. 2.3 MILP outputs

weight modification (0.324) that can help stakeholder 'transport operator' to rank 'E-freight bikes and micro-hubs' from worst position (3rd position) to a better position (2nd position). Thus, weight distance Z increases to 0.324, and ranking distance decreases to 3. However, this weight modification already results in a change of criteria rank compared to the original criteria rank information provided by the 'transport operator' stakeholder. Upon closer investigation, the first optimization alters the weight set elicited by 'transport operator' from $\{0.197, 0.073, 0.148, 0.051, 0.530\}$ to $\{0.188, 0.007, 0, 0.212, 0.53\}$. In this case, the ranks of the criteria "positive effect on society", "low cost for receiving goods", and "high quality deliveries" have changed. While we can still use the MILP to search for a better position, the further weight modification will always violate the ordinal consistency as illustrated in Table 2.3. Therefore, if the decision-makers want to choose the alternative 'E-freight bikes and micro-hubs' as the solution, they need to make a significant effort to persuade the stakeholders to reach a compromise (Table 2.4).

After conducting the MILP on all the alternatives, we can present the results in the form of a line chart, which connects the scattered points (Z^m, O^m). This visualization can provide a clear visualization of the performance of each alternative (see Fig. 2.3).

Where the Y-axis represents the ranking distances of all the alternatives; And the X-axis represents the weight distances. The lines with markers illustrate the rank changes of the alternatives with the weight modification. The dashed lines on the chart represent alternatives with weight modifications that violate rank order. It is important to note that all the ξ^Ls obtained after optimization surpass the approximated thresholds. Based on the result, we can find out 'common logistics in shopping center' is the only solution that can reach a consensus by all stakeholders, which the weight modification still preserves the same rank as the original rank. Although the alternative 'integrated reverse logistics' initially requires only a minor weight modification to improve its rank, the rank order of the criteria weights already differs from the original weights. The first optimization occurs in the stakeholder 'transport operator' by adjusting the weight of the third most important criterion, 'positive effect on society,' from 0.073 to 0, which turns it into the least important criterion. If decision-makers would like to adopt this alternative as solution, stakeholders need to make compromise. Although it is a simplified version of the decision-making process compared to the case study in [16], and the results of these two case studies are not comparable, it still addresses the limitation in the previous study. By validating ordinal consistency, the output of the MILP becomes more robust, allowing MAMCA to effectively identify both "consensual" and "compromise" alternatives in the decision-making process.

Conclusion

In the context of group decision-making framework MAMCA, stakeholders may encounter two main challenges during the decision-making process. The first challenge is related to the complexity and time-consuming nature of weight elicitation methods or MCDM methods. Stakeholders may find it difficult to comprehend the methods used for weight elicitation, resulting in elicitation results that do not reflect their preferences or expectations. Alternatively, they may not have enough time to understand and undertake the time-consuming elicitation process. The Best-Worst Method (BWM) is a possible solution to address this challenge due to its easy-to-understand and easy-to-implement process. By allowing stakeholders to compare the criteria or alternatives pairwise based on their best and worst, BWM saves time and cognitive resources compared to other complex elicitation methods. Moreover, the consistency ratio provided by BWM ensures that the elicited criteria weights are reliable and consistent, further strengthening the decision-making process.

On the other hand, due to the flexibility that MAMCA provides, allowing stakeholders to express their preferences during the decision-making process, arriving at a consensual solution can often be difficult due to conflicting interests among stakeholders. This can create significant challenges at the end of the evaluation process, leaving stakeholders struggling to find common ground. In this study, we propose a robust stakeholder-based group decision-making framework that utilizes BWM as a weight elicitation method in MAMCA to address both challenges. At the end of the evaluation, an optimization model was applied to help stakeholders find consensual solutions that could be accepted by all stakeholders while respecting the consistency in BWM. The consensus-reaching model built on top of BWM facilitates the identification of 'consensual' and 'compromise' alternatives. By allowing stakeholders to negotiate and modify the criteria weights, it fosters a collaborative decision-making process that takes into account the perspectives and preferences of all stakeholder groups involved. This promotes greater transparency, accountability, and legitimacy in the decision-making process and helps ensure that the final outcome aligns with the objectives and priorities of the stakeholder groups.

In this study, we have solely utilized the robust MAMCA-BWM framework on a didactic case, which has its inherent limitations due to the relatively simplistic nature of the problem. However, it is crucial to test its feasibility in more complex real-life decision-making problems. Therefore, in future research, we plan to apply the MAMCA-BWM framework on real-life cases to evaluate its practicality and effectiveness in addressing complex decision-making challenges faced by stakeholders in various fields. This will enable us to assess the generalizability and scalability of the proposed approach, and potentially identify opportunities for further improvements and refinements.

In conclusion, we would like to remind that the robust MAMCA-BWM framework is not the only MCGDM approach that can benefits from the advantage of BWM. In MAMCA-BWM, the linear BWM method is initially employed to quickly capture stakeholders' preferences. In contrast to the multi-stakeholder BWM presented by Liang et al. [38], which offers a range of criteria weights for stakeholders. MAMCA-BWM first attempts to identify a consensual solution. However, if a consensual solution is not found, an optimization model is applied as a post-hoc analysis. Rather than functioning as a decision-making framework, MAMCA-BWM operates more like as a decision-support framework. Its primary aim is to uncover stakeholders' perspectives and facilitate empathy-sharing during the decision-making process. The optimization model for consensus reaching serves as a mathematical proof for stakeholders to identify possible consensual solutions but is not a definitive result. Stakeholders have the autonomy to refuse to modify criteria weights, reject the proposed solution, or suggest reevaluation. The ultimate consensus should be reached through negotiation and discussion among stakeholders, with the model providing valuable support.

Appendix

The pairwise comparison vectors of stakeholders are shown in Table 2.5.

Table 2.5 Best-to-others (BO) and others-to-worst (OW) pairwise comparison vectors for three stakeholders

Shipper					
BO		Positive effect on society	Low cost for receiving goods	High quality deliveries	Attractive shopping environment
Best criterion: high quality deliveries		8	9	1	2
OW		Worst criterion: low cost for receiving goods			
Positive effect on society					2
Low cost for receiving goods					1
High quality deliveries					9
Attractive shopping environment					8
Receiver					
BO		Positive effect on society	Low cost for receiving goods	High quality deliveries	Attractive shopping environment
Best criterion: low cost for receiving goods		8	9	4	1
OW		Worst criterion: attractive shopping environment			
Positive effect on society					2
Low cost for receiving goods					1
High quality deliveries					4
Attractive shopping environment					9
Receiver					
BO	Viable investment	Positive effect on society	Satisfied employees	Profitable operations	High quality service
Best criterion: high quality service	5	8	4	9	1
OW		Worst criterion: profitable operations			
Viable investment					5
Positive effect on society					2
Satisfied employees					4
Profitable operations					1
High quality service					9

References

1. Lindenau, M., & Böhler-Baedeker, S. (2014). Citizen and stakeholder involvement: A precondition for sustainable urban mobility. *Transportation Research Procedia, 4*, 347–360.
2. Barfod, M. B. (2018). Supporting sustainable transport appraisals using stakeholder involvement and MCDA. *Transport, 33*(4), 1052–1066.
3. Macharis, C. (2005). The importance of stakeholder analysis in freight transport.
4. Hwang, C.-L., & Lin, M.-J. (2012). *Group decision making under multiple criteria: Methods and applications* (Vol. 281). Springer.
5. Yager, R. R. (1993). Non-numeric multi-criteria multi-person decision making. *Group Decision and Negotiation, 2*(1), 81–93.
6. Liu, W., Dong, Y., Chiclana, F., Cabrerizo, F. J., & Herrera-Viedma, E. (2017). Group decision-making based on heterogeneous preference relations with self-confidence. *Fuzzy Optimization and Decision Making, 16*, 429–447.
7. Kabak, Ö., & Ervural, B. (2017). Multiple attribute group decision making: A generic conceptual framework and a classification scheme. *Knowledge-Based Systems, 123*, 13–30.
8. Kilgour, D. M., Chen, Y., & Hipel, K. W. (2010). Multiple criteria approaches to group decision and negotiation. In *Trends in multiple criteria decision analysis* (pp. 317–338).
9. Macharis, C., & Bernardini, A. (2015). Reviewing the use of multi-criteria decision analysis for the evaluation of transport projects: Time for a multi-actor approach. *Transport Policy, 37*, 177–186.
10. Macharis, C., De Witte, A., & Ampe, J. (2009). The multi-actor, multi-criteria analysis methodology (MAMCA) for the evaluation of transport projects: Theory and practice. *Journal of Advanced Transportation, 43*(2), 183–202.
11. Macharis, C. (2007). Multi-criteria analysis as a tool to include stakeholders in project evaluation: The MAMCA method. In *Transport project evaluation: Extending the social cost-benefit approach* (pp. 115–131). Edward Elgar.
12. Huang, H., Mommens, K., Lebeau, P., & Macharis, C. (2021). The multi-actor multi-criteria analysis (MAMCA) for mass-participation decision making. In *Decision Support Systems XI: Decision Support Systems, Analytics and Technologies in Response to Global Crisis Management: 7th International Conference on Decision Support System Technology, ICDSST 2021, Proceedings*, Loughborough, UK, May 26–28, 2021 (pp. 3–17). Springer
13. Huang, H., Lebeau, P., & Macharis, C. (2020). The multi-actor multi-criteria analysis (MAMCA): New software and new visualizations. In *Decision Support Systems X: Cognitive Decision Support Systems and Technologies: 6th International Conference on Decision Support System Technology, ICDSST 2020, Proceedings*, Zaragoza, Spain, May 27–29, 2020 (Vol. 6, pp. 43–56). Springer.
14. Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega, 53*, 49–57.
15. Mohammadi, M., & Rezaei, J. (2020). Bayesian best-worst method: A probabilistic group decision making model. *Omega, 96*, 102075.
16. Huang, H., De Smet, Y., Macharis, C., & Doan, N. A. V. (2021). Collaborative decision-making in sustainable mobility: Identifying possible consensuses in the multi-actor multi-criteria analysis based on inverse mixed-integer linear optimization. *International Journal of Sustainable Development & World Ecology, 28*(1), 64–74.
17. Macharis, C., Turcksin, L., & Lebeau, K. (2012). Multi actor multi criteria analysis (MAMCA) as a tool to support sustainable decisions: State of use. *Decision Support Systems, 54*(1), 610–620.
18. Chakhar, S., & Saad, I. (2014). Incorporating stakeholders' knowledge in group decision-making. *Journal of Decision Systems, 23*(1), 113–126.
19. Pahl-Wostl, C. (2002). Participative and stakeholder-based policy design, evaluation and modeling processes. *Integrated Assessment, 3*(1), 3–14.
20. Dean, M. (2021). Participatory multi-criteria analysis methods: Comprehensive, inclusive, transparent and user-friendly? An application to the case of the london gateway port. *Research in Transportation Economics, 88*, 100887.

21. Huang, H., Canoy, R., Brusselaers, N., & Te Boveldt, G. (2023). Criteria preprocessing in multi-actor multi-criteria analysis. *Journal of Multi-Criteria Decision Analysis*.
22. Von Winterfeldt, D., & Edwards, W. (1993). Decision analysis and behavioral research.
23. Simos, J. (1989). *L'évaluation environnementale*. Technical report, EPFL.
24. Brans, J.-P., & De Smet, Y. (2016). Promethee methods. In *Multiple criteria decision analysis: State of the art surveys* (pp. 187–219).
25. Saaty, T. L. (1989). Group decision making and the AHP. In *The analytic hierarchy process: Applications and studies* (pp. 59–67).
26. Rezaei, J., Arab, A., & Mehregan, M. (2022). Analyzing anchoring bias in attribute weight elicitation of smart, swing, and best-worst method. *International Transactions in Operational Research*.
27. Rezaei, J. (2022). The balancing role of best and worst in best-worst method. In *Advances in Best-Worst Method: Proceedings of the Second International Workshop on Best-Worst Method (BWM2021)* (pp. 1–15). Springer.
28. Edwards, W. (1977). How to use multiattribute utility measurement for social decision making. *IEEE Transactions on Systems, Man, and Cybernetics, 7*(5), 326–340.
29. Barua, A. (2013). Methods for decision-making in survey questionnaires based on Likert scale. *Journal of Asian Scientific Research, 3*(1), 35–38.
30. Liang, F., Brunelli, M., & Rezaei, J. (2020). Consistency issues in the best worst method: Measurements and thresholds. *Omega, 96*, 102175.
31. Zhang, H., Dong, Y., Chiclana, F., & Yu, S. (2019). Consensus efficiency in group decision making: A comprehensive comparative study and its optimal design. *European Journal of Operational Research, 275*(2), 580–598.
32. Jia, J., Fischer, G. W., & Dyer, J. S. (1998). Attribute weighting methods and decision quality in the presence of response error: A simulation study. *Journal of Behavioral Decision Making, 11*(2), 85–105.
33. Barron, F. H., & Barrett, B. E. (1996). The efficacy of smarter-simple multi-attribute rating technique extended to ranking. *Acta Psychologica, 93*(1–3), 23–36.
34. Roland, J., Figueira, J. R., & De Smet, Y. (2016). Finding compromise solutions in project portfolio selection with multiple experts by inverse optimization. *Computers & Operations Research, 66*, 12–19.
35. Insua, D. R., & French, S. (1991). A framework for sensitivity analysis in discrete multi-objective decision-making. *European Journal of Operational Research, 54*(2), 176–190.
36. Doan, N. A. V., & De Smet, Y. (2018). An alternative weight sensitivity analysis for PROMETHEE II rankings. *Omega, 80*, 166–174.
37. Rezaei, J. (2016). Best-worst multi-criteria decision-making method: Some properties and a linear model. *Omega, 64*, 126–130.
38. Liang, F., Verhoeven, K., Brunelli, M., & Rezaei, J. (2021). Inland terminal location selection using the multi-stakeholder best-worst method. *International Journal of Logistics Research and Applications*, 1–23.