Advances in Complex Decision Making

Using Machine Learning and Tools for Service-Oriented Computing

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Contents

Preface vi
Acknowledgements ix
About the Editors x
List of Contributors xii

Chapter 1 Application of Choquet–OWA Aggregation Operator to Fuse ELICIT Information 1
Wen He, Wei Liang, Álvaro Labella and Rosa M. Rodríguez

Chapter 2 GPipe: Using Adaptive Directed Acyclic Graphs to Run Data and Feature Pipelines with on-the-fly Transformations 21
José Hélio de Brum Müller, Fethi Rabhi and Zoran Milosevic

Chapter 3 Building an ESG Decision-Making System: Challenges and Research Directions 38
Fethi Rabhi, Mingqin Yu, Alan Ng, Eric Lim, Felix Tan and Alan Hsiao

Chapter 4 Analysing Trust, Security and Cost of Cloud Consumer's Reviews using RNN, LSTM and GRU 52
Muhammad Raheel Raza, Walayat Hussain and Mehdi Rajaeian

Chapter 5 Interval Type-2 Fuzzy Decision Analysis Framework Based on Online Textual Reviews 66
Xiao-Hong Pan, Shi-Fan He, Diego García-Zamora and Luis Martínez

Chapter 6 Robust Comprehensive Minimum Cost Consensus Model for Multi-criteria Group Decision Making: Application in IoT Platform Selection 88
Yefan Han, Bapi Dutta, Diego García-Zamora and Luis Martínez

Index 109

6 Robust Comprehensive Minimum Cost Consensus Model for Multi-Criteria Group Decision Making

Application in IoT Platform Selection

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6.1 INTRODUCTION

With the increasing complexity of the decision-making environment, decisions based on an alternative evaluation (one criterion) may no longer be applicable (Xu, Du, & Chen, 2015). In addition, due to the limited individuals' cognition and knowledge, many practical decision problems are often solved in a group setting, in which multiple independent experts in related fields take part (García-Zamora et al., 2022b). Therefore, multi-criteria group decision-making (MCGDM) problems have attracted a lot of attention from researchers (Ben-Arieh & Easton, 2007; Xu et al., 2015). They can be described as a process in which multiple experts evaluate feasible alternatives according to multiple criteria and then select the optimal alternative (Zhong, Xu, & Pan, 2022). Recently, MCGDM has been successfully applied to many practical decision problems in different fields, such as green supplier selection, product development, engineering project management, emergencies, etc. (Büyüközkan & Güleryüz, 2016; Fu, Chang, & Yang, 2020; Qin, Liu, & Pedrycz, 2017; Xu, Yin, & Chen, 2019).

In general, experts involved in decision making usually come from different groups of interest and differ in terms of educational background, knowledge

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structure, professional references, understanding and concerns. In such a context, the emergence of disagreements among experts is inevitable. Therefore, applying a consensus reaching process (CRP) before ranking the alternatives is indispensable (Nie et al., 2020). In a CRP, experts discuss and modify their preferences with the aim of increasing the agreement level among themselves (Palomares, Martinez, & Herrera, 2013; Xu et al., 2015). Consensus has different interpretations, ranging from the unanimous agreement within groups to a more flexible soft consensus (Fedrizzi, Fedrizzi, & Pereira, 1999; Kacprzyk, 1986; Zhang, Kou, & Peng, 2019), which is usually calculated based on two consensus measures (Tian et al., 2020; Zhong et al., 2022): (1) The distance between an individual's opinions and the collective (Nie et al., 2020) and (2) the distance between individuals' opinions (Wu & Xu, 2016).

Developing a CRP involves the adjustment of the experts' initial opinions. However, each expert wants his/her opinion to be seriously taken into account, and sometimes they may be reluctant to adjust their preferences (Rodríguez et al., 2021). Several researchers have pointed out the importance of considering the cost of modifying experts' opinions to reach consensus, which has become an attractive challenge in the CRP literature (Ben-Arieh & Easton, 2007; Labella et al., 2020; Zhang, Dong, & Xu, 2013).

Ben-Arieh and Easton (2007) first defined the concept of minimum cost consensus (6.1) models as automatic CRPs in which the cost of modifying experts' preferences is minimized subject to a consensus constraint. Dong et al. (2010) used this idea to develop a minimum adjustment model in a linguistic setting, and Zhang et al. (2011) introduced aggregation operators and built an MCC model based on a linear cost function. Subsequently, a large number of new MCC models were proposed (Gong et al., 2015; Zhang et al., 2018; Zhang, Gong & Chiclana, 2017). Labella et al. (2020) pointed out that these MCC models only considered a maximum distance between each expert's preference and the collective opinion, and neglected the classical consensus measures (Rodríguez et al., 2018). To overcome this limitation, Labella et al. (2020) introduced the comprehensive minimum cost (6.2) models. However, these models only consider cases where the preference structure is either a numerical utility value or a fuzzy preference relation, and they are not applicable to MCGDM problems with multiple evaluation criteria.

Furthermore, all the above MCC models assume that the cost of modifying experts' opinions is precisely determined. However, in real decision problems, obtaining the exact adjustment cost of each expert may be very difficult due to their uncertain nature (Han et al., 2019; Li, Zhang & Dong, 2017). In this sense, robust optimization (RO) is an emerging method for dealing with uncertain optimization problems, and it has been widely used in various fields for its ability to generate uncertainty-immune solutions (Chakrabarti, 2021; Kuhn et al., 2019; Qu et al., 2021). Compared to traditional uncertainty optimization methods, RO has the following advantages:

- RO methods take uncertainty into account in the modeling process, describe uncertain parameters in the form of an uncertainty set and limit their perturbation range (Han et al., 2019).

- RO does not require obtaining the exact distribution information or fuzzy affiliation functions of uncertain parameters in advance, which is not possible for stochastic or fuzzy programming (Kuhn et al., 2019).
- The RO model is worst-oriented, and its solution satisfies all constraints while making the value of the objective function optimal under the worst-case scenario. Therefore, the RO model has strong robustness and the optimal solution is less sensitive to parameter changes (Qu et al., 2021).

In this proposal, we build a robust CMCC model for MCGDM problems. The CMCC model is first extended to the MCGDM problem. The RO method is then introduced to place the expert's unit adjustment cost in a budget uncertainty set with the aim of obtaining the optimal solution satisfying all constraints in the worst-case scenario. Finally, we show the implementation of the proposed framework in an illustrative example related to an (Internet of Things) IoT platform selection.

The remainder of this chapter is organized as follows. Section 6.2 introduces some basics about MCGDM, CRPs and MCC models. Section 6.3 develops a CMCC model for MCGDM and a robust MCGDM model considering uncertain unit adjustment costs. An illustrative example is shown in Section 6.4. Finally, Section 6.5 gives some conclusions.

6.2 PRELIMINARIES

This section introduces some basic concepts related to MCGDM, consensus models and MCC.

6.2.1 Multi-Criteria Group Decision Making

GDM aims for multiple decision-makers to reach a common solution for a decision problem consisting of several alternatives according to their own preferences. In MCGDM problems, this collective decision must be made according to different criteria. Formally, a classical MCGDM problem consists of:

- A set of alternatives, $A = \{a_1, a_2, \ldots, a_m\}(m \geq 2)$, from which a possible solution to the problem can be selected.
- A group of experts, $E = \{e_1, e_2, \ldots, e_K\}(K \geq 2)$, who express their preference on the set of alternatives A.
- A set of evaluation criteria $Q = \{q_1, q_2, \ldots, q_n\}$ for assessing the alternatives A in different dimensions.

Each expert expresses their assessment of the alternatives based on their own experience and knowledge. A common preference structure is the preference assessment matrix, $P = (p_{ij}) \in M([0, 1])_{m \times n}$, where $p_{ij} \in [0, 1]$ represents the evaluation value of the alternatives a_i on the criterion q_j. In order to reflect the relevance of each criterion, it is usual to consider a weighting vector $\omega = (\omega_1, \omega_2, \ldots, \omega_n)$, satisfying $\omega_j \geq 0, \sum_{j=1}^{n} \omega_j = 1$, where each ω_j represents the relative importance of the criterion q_j.

The solution to an MCGDM problem consists of two phases (Roubens, 1997):

- **Aggregation:** The collective opinion is obtained by fusing the experts' preference assessment matrices using an aggregation operator. The weight $W = (w_1, w_2, \ldots, w_K)$ of the experts is required for this process.
- **Exploitation:** The best alternative is selected as the solution to the decision problem based on collective preference.

However, this two-phase solution process does not guarantee that conflicts will not arise among the experts involved in the decision-making problem. To ensure a collective agreement, a CRP must be included in the resolution scheme before the final decision is made (Labella et al., 2020).

6.2.2 Consensus Reaching Process

A CRP is an iterative process in which experts attempt to make their preferences close to others through discussion and modification. This process usually requires a moderator, who represents the group's interest and provides guidance for the experts to properly modify their opinions. Group consensus can be achieved by scheduling various possible resources, such as manpower, material and financial resources, and persuading experts to change their preferences within a certain period through rational debate and negotiation. A classical CRP scheme usually contains four key aspects (see Figure 6.1) (Palomares et al., 2014):

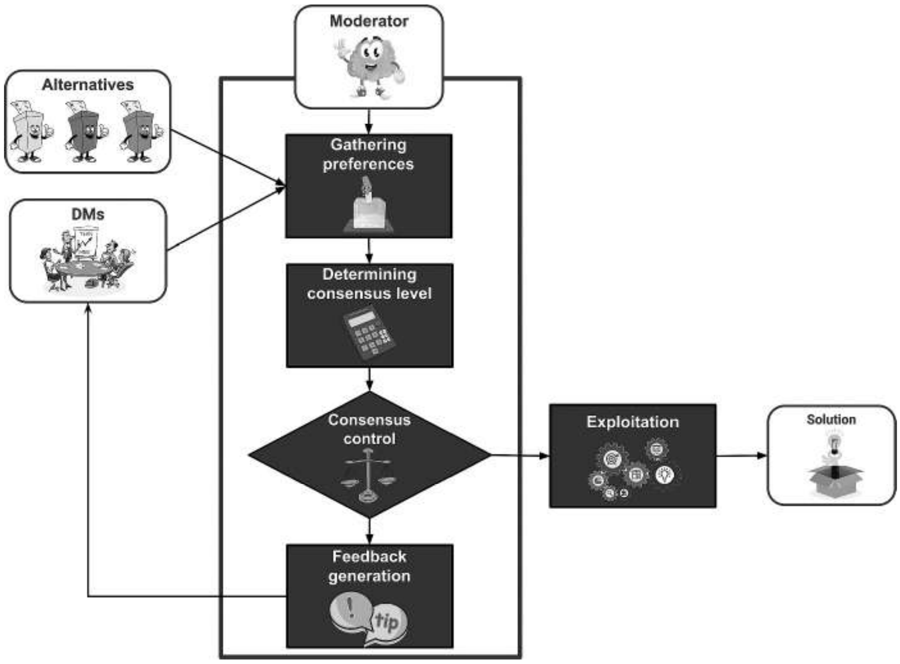

FIGURE 6.1 Scheme of a CRP.

- **Gathering preferences:** Experts' preferences are provided based on the corresponding form of preference expressions.
- **Determining consensus level:** The agreement level among experts is calculated by applying different distance measures and aggregation operators.
- **Consensus control:** The obtained agreement level is compared with a predefined consensus threshold. If the consensus level reaches the given threshold, the desired consensus has been reached and the CRP finishes; otherwise, another round of discussion process needs to be carried out.
- **Feedback generation:** A procedure to improve the consensus level through multiple rounds of discussion, in which the moderator identifies the experts causing disagreement and suggests adjustments for them. This procedure can also be performed based on automatic updates from experts.

6.2.3 Minimum Cost Consensus Models

In a CRP, certain costs, such as manpower, time, or money, inevitably occur. To reduce such costs, Ben-Arieh and Easton suggested that "a consensus is reached when the distance between experts and collective opinion is minimal" (2007). Formally, for the set of experts E, let $O = (o_1, o_2, \ldots, o_K)$ represent their initial opinions, $\bar{O} = (\bar{o}_1, \bar{o}_2, \ldots, \bar{o}_K)$ refer to the experts' adjusted opinions and $\bar{o}$ be the collective opinion. Let $C = (c_1, c_2, \ldots, c_K)$ be the unit adjustment cost of modifying experts' preferences. Then, the MCC model based on the linear cost function is as follows:

$$\begin{aligned} &\min_{\bar{O} \in \mathbb{R}^K} \sum_{k=1}^{K} c_k \left|\bar{o}_k - o_k\right| \\ &s.t. \left|\bar{o}_k - \bar{o}\right| \le \varepsilon, k = 1, 2, \ldots, K \end{aligned} \tag{6.1}$$

where ε is the maximum acceptable distance between each expert's adjusted opinion and the collective opinion. If the expert's opinion is in the interval $[\bar{o} - \varepsilon, \bar{o} + \varepsilon]$, then the expert does not need to change his/her opinion, otherwise, the expert needs to make adjustments until the distance between current opinion and $\bar{o}$ is exactly ε.

Dong et al.'s minimum adjustment consensus model provided a new perspective for the study of consensus in group decision making, which combines linguistic methods and benefits from the weighted average operator (Dong et al., 2010). Based on these investigations, Zhang et al. (2011) investigated how the aggregation operator used to fuse experts' opinions and get collective opinion that affects the calculation of the consensus level.

These models calculate the consensus degree, considering the distance between each expert and the collective opinion. However, the use of classical consensus measures to determine the consensus degree among experts was ignored. In order to ensure an acceptable consensus degree among all experts while taking into account the distance of each expert from the collective opinion, Labella et al. (2020) developed CMCC models. Such models include an additional constraint determined by a predefined consensus threshold $\alpha \in [0, 1]$ and a consensus measure $\mathbb{C} : [a, b]^K \to [0, 1]$. Therefore, the mathematical description of the CMCC model is as follows:

$$\min_{\bar{O}\in[a,b]^K} \sum_{k=1}^{K} c_k \left|\bar{o}_k - o_k\right|$$
$$s.t.\begin{cases} \left|\bar{o}_k - \bar{o}\right| \le \varepsilon, k = 1,2,\ldots,K \\ \bar{o} = F\left(\bar{o}_1, \bar{o}_2, \ldots, \bar{o}_K\right) \\ \mathbb{C}\left(\bar{o}_1, \bar{o}_2, \ldots, \bar{o}_K\right) \ge \alpha \end{cases} \tag{6.2}$$

where $F(\cdot)$ is an aggregation function.

For instance, if the consensus measure is defined as $\mathbb{C}\left(\bar{o}_1, \bar{o}_2, \ldots, \bar{o}_K\right) = 1 - \sum_{k=1}^{K} w_k \left|\bar{o}_k - o_k\right|$, where $w_1, w_2, \ldots, w_K \ge 0$, $\sum_{k=1}^{K} w_k = 1$, stand for the experts' relative importance, the aforementioned model is as follows:

$$\min_{\bar{O}\in[a,b]^K} \sum_{k=1}^{K} c_k \left|\bar{o}_k - o_k\right|$$
$$s.t.\begin{cases} \left|\bar{o}_k - \bar{o}\right| \le \varepsilon, k = 1,2,\ldots,K \\ \bar{o} = \sum_{k=1}^{K} w_k \bar{o}_k \\ 1 - \sum_{k=1}^{K} w_k \left|\bar{o}_k - o_k\right| \ge \alpha \end{cases}.$$

6.2.4 Robust Optimization

RO method is an effective and popular tool for dealing with data uncertainty in mathematical programming models. They have received a great deal of attention because of their ability to generate uncertainty-immune solutions. The basic idea of RO is to establish a suitable uncertainty set to limit the perturbation range of uncertain parameters and generate solutions that satisfy all the constraints.

Consider the general linear programming problem:

$$\min_{x\in\mathbb{R}^{n\times 1}} c^T x$$
$$s.t. Ax \ge b \tag{6.3}$$

where $x \in \mathbb{R}^{n \times 1}$ is the vector of the decision variable and $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^{m \times 1}$ are the coefficient matrix and vector, respectively. In RO, the aim is to minimize an objective function subject to some constraints defined via uncertain parameters. For instance,

$$\min_{x\in\mathbb{R}^{n\times 1}} c^T x$$
$$s.t. Ax \geq b, \ \forall \ A, b \in \mathcal{U} \qquad (LP_{\mathcal{U}})$$

where A, b are uncertain and belong to the uncertainty set $\mathcal{U}$, which is supposed to be parameterized by a perturbation vector ξ varying in a certain perturbation set $\mathcal{Z}$.

If x is a feasible robust solution to the robust problem ($LP_{\mathcal{U}}$), it satisfies all realizations of the constraint of the uncertainty set $\mathcal{U}$. Note that the robust problem is worst-oriented, that is, the solution to $LP_{\mathcal{U}}$ is given as:

$$\min_{x\in\mathbb{R}^{n\times 1}} \left\{ \sup_{(A,b)\in\mathcal{U}} c^T x : Ax \geq b \ \forall \ A, b \in \mathcal{U} \right\}$$

which is the best robust goal value for all feasible solutions.

6.3 ROBUST COMPREHENSIVE MINIMUM COST CONSENSUS FOR MULTI-CRITERIA DECISION MAKING

This section establishes a deterministic CMCC model for the MCGDM problem. Then, a robust CMCC model for MCGDM is developed, considering the uncertainty regarding experts' unit adjustment costs.

The decision matrix is one of the most widely used preference structures in MCGDM (García-Zamora et al., 2022b). Therefore, we first need to extend the (6.2) model to manage decision matrices.

Given the decision matrices $P_k = \left(p_{ij}^k\right) \in \mathcal{M}\left([0,1]\right)_{m\times n}, k = 1,\ldots,K,$ where $p_{ij}^k \in [0,1]$ represents expert e_k's evaluation for the alternative a_i with respect to the criteria q_j, let $\overline{P}_k = \left(\overline{p}_{ij}^k\right) \in \mathcal{M}\left([0,1]\right)_{m\times n}, k = 1,2,\ldots,K$ denote the experts' adjusted preference decision matrices. The collective opinion $\overline{P} \in \mathcal{M}\left([0,1]\right)_{m\times n}$ may be computed using the weighted average (WA) operator as follows:

$$\overline{p}_{ij} = \sum_{k=1}^{K} w_k \overline{p}_{ij}^k, i = 1,\ldots,m, j = 1,\ldots,n,$$

where w_1, …, w_K stand for experts' weights. On the basis of this collective decision matrix, the consensus measure $\mathbb{C} : \mathcal{M}\left([0,1]\right)_{m\times n}^K \to [0,1]$ can be defined as follows:

$$\mathbb{C}\left(\overline{P}^1, \overline{P}^2, \ldots, \overline{P}^K\right) = 1 - \frac{1}{mn} \sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n} w_k \left|\overline{p}_{ij}^k - \overline{p}_{ij}\right|$$

Since we also aim to control the degree of consensus of the selected alternative after taking into account the weights of the criteria $\omega_1, \ldots, \omega_n \geq 0, \sum_{j=1}^{n} \omega_j = 1$, we need to introduce the following additional constraints:

$$\overline{p}_i^k = \sum_{j=1}^{n} \omega_j \overline{p}_{ij}^k, i = 1,\ldots,m, k = 1,\ldots,K$$

$$\overline{p}_i = \sum_{k=1}^{K} w_k \overline{p}_i^k, i = 1,\ldots,m$$

$$\beta \geq \left|\overline{p}_i^k - \overline{p}_i\right|, i = 1,\ldots,m, k = 1,\ldots,K$$

where $\overline{p}_i^k$ represents the score provided by the expert e_k about alternative a_i after considering all criteria, $\overline{p}_i$ is the collective score for alternative a_i and β is a threshold to control the distance between them. Therefore, the deterministic CMCC model (6.4) for MCGDM can be formulated as follows:

$$\min_{\left(\overline{p}_{ij}^k\right) \in \mathcal{M}([0,1])_{m\times n}} \sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n} c_k \left|\overline{p}_{ij}^k - p_{ij}^k\right|$$

$$s.t.\begin{cases} \overline{p}_{ij} = \sum_{k=1}^{K} w_k \overline{p}_{ij}^k, i = 1,\ldots,m, j = 1,\ldots,n \\ \left|\overline{p}_{ij}^k - \overline{p}_{ij}\right| \leq \varepsilon, k = 1,\ldots,K, i = 1,\ldots,m, j = 1,\ldots,n \\ 1 - \frac{1}{mn}\sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n} w_k \left|\overline{p}_{ij}^k - \overline{p}_{ij}\right| \geq \alpha \\ \overline{p}_i^k = \sum_{j=1}^{n} \omega_j \overline{p}_{ij}^k, i = 1,\ldots,m, k = 1,\ldots,K \\ \overline{p}_i = \sum_{k=1}^{K} w_k \overline{p}_i^k, i = 1,\ldots,m \\ \left|\overline{p}_i^k - \overline{p}_i\right| \leq \beta, i = 1,\ldots,m, k = 1,\ldots,K \end{cases} \tag{6.4}$$

The existence of absolute value operation increases the difficulty of solving the nonlinear model (6.4). Therefore, we transform it into an equivalent linear programming model to improve the efficiency of obtaining optimal solutions in decision-making scenarios.

Theorem 1

Model (6.4) is equivalent to the linear programming model (6.5).

$$\min_{\left(\bar{p}_{ij}^{k}\right)\in\mathcal{M}([0,1])_{m\times n}} B$$

$$s.t.\begin{cases}\sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n}c_k z_{ij}^{k}\le B\\ \bar{p}_{ij}=\sum_{k=1}^{K}w_k\bar{p}_{ij}^{k}, i=1,\ldots,m, j=1,\ldots,n\\ 1-\frac{1}{mn}\sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n}w_k t_{ij}^{k}\ge\alpha\\ t_{ij}^{k}\le\varepsilon, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n\\ \bar{p}_{i}^{k}=\sum_{j=1}^{n}\omega_j\bar{p}_{ij}^{k}, i=1,\ldots,m, k=1,\ldots,K\\ \bar{p}_{i}=\sum_{k=1}^{K}w_k\bar{p}_{i}^{k}, i=1,\ldots,m\\ \bar{p}_{ij}^{k}-p_{ij}^{k}=y_{ij}^{k}, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n\\ y_{ij}^{k}\le z_{ij}^{k}, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n\\ -y_{ij}^{k}\le z_{ij}^{k}, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n\\ \bar{p}_{ij}^{k}-\bar{p}_{ij}=s_{ij}^{k}, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n\\ s_{ij}^{k}\le t_{ij}^{k}, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n\\ -s_{ij}^{k}\le t_{ij}^{k}, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n\\ \bar{p}_{i}^{k}-\bar{p}_{i}\le\beta, i=1,\ldots,m, k=1,\ldots,K\\ -\bar{p}_{i}^{k}+\bar{p}_{i}\le\beta, i=1,\ldots,m, k=1,\ldots,K\end{cases} \quad (6.5)$$

Proof: Consider the transformation $\bar{p}_{ij}^{k}-p_{ij}^{k}=y_{ij}^{k}, \left|\bar{p}_{ij}^{k}-p_{ij}^{k}\right|=z_{ij}^{k}$. Based on the property of the absolute value $|a|$ = max $\{a, -a\}$, we obtain $y_{ij}^{k}\le z_{ij}^{k}, -y_{ij}^{k}\le z_{ij}^{k}$. Similarly, the transformation $\bar{p}_{ij}^{k}-\bar{p}_{ij}=s_{ij}^{k}, \left|\bar{p}_{ij}^{k}-\bar{p}_{ij}\right|=t_{ij}^{k}$ yields $s_{ij}^{k}\le t_{ij}^{k}, -s_{ij}^{k}\le t_{ij}^{k}$. Using the above transformations, the last six constraints of the model (6.5) can be linearized. Subsequently, we replace the absolute value constraints as per above transformations to convert the nonlinear programming model (6.4) into an equivalent linear programming model (6.5). Furthermore, by solving the linear model (6.5), we can obtain optimal solution for the CMCC model (6.4).

For most existing MCC models, the unit adjustment cost of each expert is usually assumed to be precisely known. However, in practical decision-making problems, it is very difficult for the moderator to determine the exact values for such costs. Furthermore, since experts involved in GDM usually come from various social groups, they have different social experiences and represent distinct interests, which implies that the corresponding unit adjustment cost may be uncertain. Therefore, below we developed a robust CMCC model for MCGDM with uncertain costs, which allows for minimizing the worst-case total compensation cost and enhancing the stability of the model solution.

Classical MCC models assume that the costs of modifying experts' opinions are fixed crisp values. However, in the robust consensus problem, the only information available regarding the uncertain unit adjustment costs c_k is that they belong to an uncertainty set $\mathcal{U}$. So, the cost function in the robust form of the model (6.4) is given as:

$$\sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n} c_k \left|\overline{p}_{ij}^k - p_{ij}^k\right|, c_k \in \mathcal{U}$$

Without any loss of generality, we can assume that each $c_k \in \mathcal{U}$ may be expressed as

$$c_k = c_k^0 + \xi_k \hat{c}_k, k = 1, 2, \ldots, K,$$

where c_k^0 is the nominal unit adjustment cost and $\hat{c}_k$ is the corresponding perturbation value. The uncertain parameter $\xi = (\xi_1, \ldots, \xi_K)$ belongs to a perturbation set $\mathcal{Z}$, which must be convex and closed, and controls the perturbation range of the uncertainty. Here, we will assume that the perturbation set is a budget uncertainty set, which is defined based on the maximum norm and the 1-norm. It can be mathematically expressed as:

$$\mathcal{Z}_\Gamma = \left\{\xi \in \mathbb{R}^K : \|\xi\|_\infty \le 1, \|\xi\|_1 \le \Gamma\right\}$$

where $\Gamma \in [1, K]$ is known as the "uncertainty budget". The budget uncertainty set is essentially the intersection of two polytopes, and each point in the intersection may be related to a possible value of the uncertain unit cost. The next result determines the robust counterpart of the MC-CMCC models under the budget uncertainty set $\mathcal{Z}_\Gamma$. In other words, a robust version of model MC-CMCC can be defined as:

$$\min_{\left(\overline{p}_{ij}^k\right) \in \mathcal{M}([0,1])_{m\times n}} \sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n} c_k^0 \left|\overline{p}_{ij}^k - p_{ij}^k\right| + \sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n} \xi_k \hat{c}_k \left|\overline{p}_{ij}^k - p_{ij}^k\right|$$

$$s.t.\begin{cases} \xi_k \in \mathcal{Z}_\Gamma \\ \overline{p}_{ij} = \sum_{k=1}^{K} w_k \overline{p}_{ij}^k, i = 1,\ldots,m, j = 1,\ldots,n \\ \left|\overline{p}_{ij}^k - \overline{p}_{ij}\right| \le \varepsilon, k = 1,\ldots,K, i = 1,\ldots,m, j = 1,\ldots,n \\ 1 - \dfrac{1}{mn}\sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n} w_k \left|\overline{p}_{ij}^k - \overline{p}_{ij}\right| \ge \alpha \\ \overline{p}_i^k = \sum_{j=1}^{n} \omega_j \overline{p}_{ij}^k, i = 1,\ldots,m, k = 1,\ldots,K \\ \overline{p}_i = \sum_{k=1}^{K} w_k \overline{p}_i^k, i = 1,\ldots,m \\ \left|\overline{p}_i^k - \overline{p}_i\right| \le \beta, i = 1,\ldots,m, k = 1,\ldots,K \end{cases} \tag{6.6}$$

The next result provides an equivalent version of the previous model that facilitates its resolution:

Theorem 2

Model (6.7) is a robust counterpart of model (6.4).

$$\min_{(\bar{p}_{ij}^k)\in\mathcal{M}([0,1])_{m\times n}} \sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n} c_k^0 \left|\bar{p}_{ij}^k - p_{ij}^k\right| + \sum_{k=1}^{K}\left|u_k\right| + \tilde{\text{A}}\cdot \max_{k\in[1,K]\cap\mathbb{N}}\left|v_k\right|$$

$$s.t.\begin{cases} \sum_{i=1}^{m}\sum_{j=1}^{n}\hat{c}_k\left|\bar{p}_{ij}^k - p_{ij}^k\right| = -u_k - v_k, k=1,\ldots,K \\ \bar{p}_{ij} = \sum_{k=1}^{K} w_k\bar{p}_{ij}^k, i=1,\ldots,m, j=1,\ldots,n \\ \left|\bar{p}_{ij}^k - \bar{p}_{ij}\right| \le \varepsilon, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n \\ 1-\frac{1}{mn}\sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n} w_k\left|\bar{p}_{ij}^k - \bar{p}_{ij}\right| \ge \alpha \\ \bar{p}_i^k = \sum_{j=1}^{n}\omega_j\bar{p}_{ij}^k, i=1,\ldots,m, k=1,\ldots,K \\ \bar{p}_i = \sum_{k=1}^{K} w_k\bar{p}_i^k, i=1,\ldots,m \\ \left|\bar{p}_i^k - \bar{p}_i\right| \le \beta, i=1,\ldots,m, k=1,\ldots,K \end{cases} \tag{6.7}$$

Proof: Note that the perturbation set may be expressed as the intersection of two cones:

$$\mathcal{Z} = \left\{\xi \in \mathbb{R}^K : G_1\xi + g_1 \in \mathcal{K}^1, G_2\xi + g_2 \in \mathcal{K}^2\right\},$$

where

$$G_1\xi := (\xi, 0), g_1 := (0_{K\times 1}, 1) \in \mathbb{R}^{K+1}, G_2\xi := (\xi, 0), g_2 := (0_{K\times 1}, \Gamma) \in \mathbb{R}^{K+1},$$
$$\mathcal{K}^1 = \left\{(h_1, h_2) \in \mathbb{R}^K \times \mathbb{R} : \| h_1 \|_\infty \le h_2\right\}, \mathcal{K}^2 = \left\{(h_1, h_2) \in \mathbb{R}^K \times \mathbb{R} : \| h_1 \|_1 \le h_2\right\}.$$

Let us define $r_1 := (u, \tau_1) \in \mathcal{K}^2, r_2 := (v, \tau_2) \in \mathcal{K}^1$, where τ_1, τ_2 are non-negative numbers and u, $v \in \mathbb{R}^K$. Since $\mathcal{K}^1$ and $\mathcal{K}^2$ are dual cones, that is, $\mathcal{K}_*^1 = \mathcal{K}^2, \mathcal{K}_*^2 = \mathcal{K}^1$, according to the cone duality theory by Ben-Tal et al. (2009), the model R-MC-CMCC:1 is equivalent to:

$$\min_{\left(\bar{p}_{ij}^{k}\right)\in\mathcal{M}([0,1])_{m\times n}} B$$

$$s.t.\begin{cases}\sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n}c_k^0\left|\bar{p}_{ij}^k-p_{ij}^k\right|+\tau_1+\Gamma\cdot\tau_2\le B\\ \sum_{i=1}^{m}\sum_{j=1}^{n}\hat{c}_k\left|\bar{p}_{ij}^k-p_{ij}^k\right|=-u_k-v_k, k=1,\ldots,K\\ \| u \|_1\le\tau_1\\ \| v \|_\infty\le\tau_2\\ \bar{p}_{ij}=\sum_{k=1}^{K}w_k\bar{p}_{ij}^k, i=1,\ldots,m, j=1,\ldots,n\\ \left|\bar{p}_{ij}^k-\bar{p}_{ij}\right|\le\varepsilon, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n\\ 1-\frac{1}{mn}\sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n}w_k\left|\bar{p}_{ij}^k-\bar{p}_{ij}\right|\ge\alpha\\ \bar{p}_i^k=\sum_{j=1}^{n}\omega_j\bar{p}_{ij}^k, i=1,\ldots,m, k=1,\ldots,K\\ \bar{p}_i=\sum_{k=1}^{K}w_k\bar{p}_i^k, i=1,\ldots,m\\ \left|\bar{p}_i^k-\bar{p}_i\right|\le\beta, i=1,\ldots,m, k=1,\ldots,K\end{cases}$$

which is equivalent to (6.7).

Compared to model (6.4), the robust model (6.7) considers all possible values of unit adjustment cost in the uncertainty set and minimizes the minimum cost under worst-case scenarios, ensuring that the solution of the model is feasible for all uncertain scenarios. In contrast, model (6.4) only considers the compensation costs of the nominal scenario. Although it requires fewer compensation costs, it cannot handle data perturbations caused by external factors. This can lead to catastrophic losses in some practical decisions. For example, in some emergency decision-making problems, over-optimistic decisions that do not consider uncertainty may even threaten people's lives (Chakrabarti, 2021).

Theorem 3

Model (6.7) is equivalent to the linear robust model (6.8).

$$\min_{\left(\overline{p}_{ij}^{k}\right)\in\mathcal{M}([0,1])_{m\times n}} \sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n} c_k^0 z_{ij}^k + \sum_{k=1}^{K}\hat{u}_k + \Gamma\cdot V$$

$$s.t.\begin{cases}
\sum_{i=1}^{m}\sum_{j=1}^{n}\hat{c}_k z_{ij}^k = -u_k - v_k, k=1,\ldots,K\\
u_k \le \hat{u}_k, k=1,\ldots,K\\
-u_k \le \hat{u}_k, k=1,\ldots,K\\
v_k \le \hat{v}_k, k=1,\ldots,K\\
-v_k \le \hat{v}_k, k=1,\ldots,K\\
\hat{v}_k \le V, k=1,\ldots,K\\
V \ge 0\\
\overline{p}_{ij} = \sum_{k=1}^{K} w_k \overline{p}_{ij}^k, i=1,\ldots,m, j=1,\ldots,n\\
1-\frac{1}{mn}\sum_{k=1}^{K}\sum_{i=1}^{m}\sum_{j=1}^{n} w_k t_{ij}^k \ge \alpha\\
t_{ij}^k \le \varepsilon, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n\\
\overline{p}_i^k = \sum_{j=1}^{n}\omega_j \overline{p}_{ij}^k, i=1,\ldots,m, k=1,\ldots,K\\
\overline{p}_i = \sum_{k=1}^{K} w_k \overline{p}_i^k, i=1,\ldots,m\\
\overline{p}_{ij}^k - p_{ij}^k = y_{ij}^k, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n\\
y_{ij}^k \le z_{ij}^k, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n\\
-y_{ij}^k \le z_{ij}^k, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n\\
\overline{p}_{ij}^k - \overline{p}_{ij} = s_{ij}^k, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n\\
s_{ij}^k \le t_{ij}^k, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n\\
-s_{ij}^k \le t_{ij}^k, k=1,\ldots,K, i=1,\ldots,m, j=1,\ldots,n\\
\overline{p}_i^k - \overline{p}_i \le \beta, i=1,\ldots,m, k=1,\ldots,K\\
-\overline{p}_i^k + \overline{p}_i \le \beta, i=1,\ldots,m, k=1,\ldots,K
\end{cases} \tag{6.8}$$

The proof process is similar to Theorem 1, and we will not describe it in detail for the sake of the brevity of this chapter. By solving the model (6.7), the optimal consensus preference $\overline{P}^1,\ldots,\overline{P}^K$ and the total compensation cost can be obtained.

6.4 CASE STUDY

This section provides an illustrative example of IoT platform selection to demonstrate the implementation process of the proposed approach. Then, a sensitivity analysis considering different parameters of the model (6.7) and consensus thresholds is performed.

6.4.1 Numerical Experiment

The cognitive Internet enables the intelligence of home appliances (Pramanik, Pal, & Choudhury, 2018). In this direction, commercial companies are working to update their devices and make them smarter to enhance market competitiveness. For example, Whirlpool is manufacturing smart washing machines that can be controlled by mobile devices (Kim & Moon, 2022). Xiaomi has launched an air purifier that can be operated remotely from a mobile phone and developed a smart module that can be integrated into all home appliances (Abdullah, Roobashini, & Alkawaz, 2021). With the development of IoT, smart home appliances will have greater cognition to assist users by detecting their intentions and usage patterns.

To improve market competitiveness, the company EasyTV wants to develop a new smart appliance that could perfectly cater to market demand. Therefore, EasyTV's CEOs need to choose which one of the most widely used IoT Platforms (Chakraborty et al., 2021; Kondratenko, Kondratenko, & Sidenko, 2018), namely Amazon Web Services (AWS), Google Cloud Platform, Microsoft Azure, Digital Ocean and IBM Watson IoT Platform, is the most suitable for the company. The evaluation criteria include device management, integration level, security and reliability levels, data collection protocols, variety of data analytics and database functionality (Kondratenko et al., 2018). To select the best IoT platform, EasyTV's CEOs will apply the proposed framework to make the final decision by asking the seven members of the advisory council. Table 6.1 shows the preference matrices provided by the seven experts, and the relevant parameter settings are shown in Table 6.2.

If no CRP is developed and the WA operator is directly used to fuse experts' preferences, the collective opinion is as follows:

$$P = \begin{bmatrix} 0.62 & 0.41 & 0.52 & 0.34 & 0.52 & 0.58 \\ 0.42 & 0.55 & 0.71 & 0.64 & 0.41 & 0.4 \\ 0.4 & 0.21 & 0.5 & 0.37 & 0.16 & 0.4 \\ 0.48 & 0.53 & 0.58 & 0.5 & 0.5 & 0.44 \\ 0.35 & 0.53 & 0.4 & 0.59 & 0.52 & 0.52 \end{bmatrix}$$

For this collective opinion, the consensus degree is $\mathbb{C}\left(P^1, P^2, \ldots, P^K\right) = 1 - \sum_{k=1}^{K} w_k \left|P_k - P\right| = 0.765 \le \alpha = 0.8$. And the maximum distance between experts' preferences and collective opinion for each alternative is $\left|p_3^2 - p_3\right| = 0.355$. Since the experts are required to reach an agreed decision for a consensus degree greater than $\alpha = 0.8$ and the distance of the alternative's score need to be lower than $\beta = 0.1$, it is necessary to apply a robust CMCC model to adjust the experts' preferences, so as to improve the consensus degree. Taking the preferences in Table 6.1 and the parameters in Table 6.2 as input to the model (6.7), the optimal adjusted collective preference is

TABLE 6.1
Experts' Initial Preference Matrix

$$P^1 = \begin{bmatrix} 0.63 & 0.55 & 0.16 & 0.01 & 0.33 & 0.9 \\ 0.71 & 0.77 & 0.95 & 0.85 & 0.71 & 0.52 \\ 0.42 & 0.18 & 0.87 & 0.16 & 0.19 & 0.94 \\ 0.36 & 0.13 & 0.16 & 0.18 & 0.5 & 0.16 \\ 0.49 & 0.69 & 0.49 & 0.46 & 0.78 & 0.87 \end{bmatrix} P^2 = \begin{bmatrix} 0.45 & 0.77 & 0.05 & 0.57 & 0.94 & 0.1 \\ 0.76 & 0.53 & 0.77 & 0.91 & 0.54 & 0.55 \\ 0.91 & 0.6 & 0.95 & 0.69 & 0.19 & 0.65 \\ 0.3 & 0.58 & 0.4 & 0.06 & 0.69 & 0.95 \\ 0.04 & 0.04 & 0.72 & 0.82 & 0.21 & 0.45 \end{bmatrix}$$

$$P^3 = \begin{bmatrix} 0.28 & 0.23 & 0.18 & 0.04 & 0.46 & 0.62 \\ 0.79 & 0.93 & 0.86 & 0.03 & 0.4 & 0.17 \\ 0.27 & 0.43 & 0.65 & 0.27 & 0.31 & 0.46 \\ 0.67 & 0.56 & 0.91 & 0.96 & 0.45 & 0.26 \\ 0.23 & 0.54 & 0.01 & 0.76 & 0.68 & 0.41 \end{bmatrix} P^4 = \begin{bmatrix} 0.76 & 0.05 & 0.76 & 0.28 & 0.82 & 0.81 \\ 0.22 & 0.99 & 0.14 & 0.44 & 0.29 & 0.62 \\ 0.54 & 0.06 & 0.42 & 0.25 & 0.01 & 0.14 \\ 0.19 & 0.76 & 0.88 & 0.6 & 0.24 & 0.81 \\ 0.73 & 0.05 & 0.06 & 0.67 & 0.05 & 0.34 \end{bmatrix}$$

$$P^5 = \begin{bmatrix} 0.64 & 0.43 & 0.9 & 0.94 & 0.59 & 0.59 \\ 0.06 & 0.09 & 0.89 & 0.97 & 0.22 & 0.06 \\ 0.16 & 0.07 & 0.39 & 0.57 & 0.06 & 0.15 \\ 0.87 & 0.91 & 0.54 & 0.4 & 0.83 & 0.15 \\ 0.23 & 0.76 & 0.83 & 0.63 & 0.99 & 0.65 \end{bmatrix} P^6 = \begin{bmatrix} 0.88 & 0.21 & 0.54 & 0.0 & 0.39 & 0.64 \\ 0.21 & 0.3 & 0.48 & 0.06 & 0.6 & 0.71 \\ 0.23 & 0.27 & 0.25 & 0.45 & 0.12 & 0.62 \\ 0.84 & 0.19 & 0.8 & 0.94 & 0.33 & 0.07 \\ 0.56 & 0.97 & 0.48 & 0.81 & 0.85 & 0.18 \end{bmatrix}$$

$$P^7 = \begin{bmatrix} 0.74 & 0.86 & 0.65 & 0.19 & 0.03 & 0.03 \\ 0.45 & 0.01 & 0.92 & 0.99 & 0.43 & 0.55 \\ 0.47 & 0.19 & 0.03 & 0.32 & 0.36 & 0.26 \\ 0.09 & 0.11 & 0.26 & 0.34 & 0.38 & 0.74 \\ 0.04 & 0.76 & 0.32 & 0.06 & 0.01 & 0.48 \end{bmatrix}$$

TABLE 6.2
Parameter Settings

c^0	$\hat{c}$	Experts' Weights	Criteria' Weights	ε	α	β	Γ
$(c_1^0,\ldots,c_7^0) = (2,2,1,3,2,3,1)$	$(\hat{c}_1,\ldots,\hat{c}_7) =$ (0.75, 0.17, 0.28, 0.84, 0.52, 0.44, 0.16)	$(w_1, \ldots, w_7) =$ (0.15, 0.08,0.16, 0.20, 0.22, 0.06, 0.13)	$(\omega_1, \ldots, \omega_6) =$ (0.24, 0.1, 0.17, 0.28, 0.12, 0.09)	0.3	0.8	0.1	3

$$\bar{P} = \begin{bmatrix} 0.64 & 0.35 & 0.42 & 0.44 & 0.35 & 0.43 \\ 0.53 & 0.18 & 0.56 & 0.53 & 0.55 & 0.73 \\ 0.47 & 0.54 & 0.47 & 0.28 & 0.6 & 0.37 \\ 0.44 & 0.63 & 0.53 & 0.41 & 0.13 & 0.5 \\ 0.55 & 0.6 & 0.45 & 0.37 & 0.45 & 0.52 \end{bmatrix}$$

which implies a minimum total cost (TC) for reaching the consensus equal to TC = 31.53. Then the optimal overall evaluation value of each IoT platform is: $\overline{p}_1 = 0.46, \overline{p}_2 = 0.52, \overline{p}_3 = 0.43, \overline{p}_4 = 0.43, \overline{p}_5 = 0.47$.

Thus the ranking of the five IoT platforms can be obtained: $a_2 \succ a_5 \succ a_1 \succ a_3 = a_4$. Therefore, the Google Cloud Platform is the best choice.

6.4.2 Sensitivity Analysis

This section analyzes the impact of changes in different parameters on the consensus cost in the model (6.7).

Figure 6.2 shows the variation of the TC with respect to the uncertainty level parameter Γ. Since the number of experts is 7, according to the definition of the budget uncertainty set, we vary Γ from 0 to 7 with a stepsize of 0.5 assuming that the unit adjustment costs of all experts are uncertain. As shown in Figure 6.2, the TC increases as Γ increases. This is because the uncertainty level parameter Γ controls the size of the uncertainty set. When Γ increases, the perturbation range of uncertain parameters expands. Therefore, to ensure that all possible scenarios are considered, the TC of the worst-oriented R-MC-CMCC model also increases with the expansion of the uncertainty set. Furthermore, $\Gamma = 0$, dictates that the model does not take into account uncertainty, and in this scenario the result is more optimistic than the robust cost.

Next, we analyze the impact of the consensus thresholds at the criteria level (ε), alternatives level (β) and group level (α) on the TC. For different configurations of these parameters, we solve the model (6.7) to compute the TC, and the results are reported. Figure 6.3 shows the impact of the three thresholds on the TC. Figure 6.3 (a) illustrates the variation of the TC with thresholds ε and β for a fixed group consensus level $\alpha = 0.8$. We observe that when ε or β decreases, more experts are needed

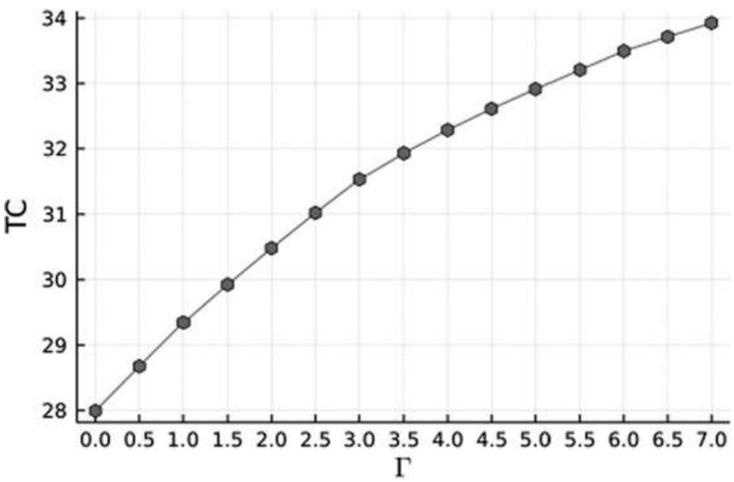

FIGURE 6.2 Variation of the total cost with respect to Γ.

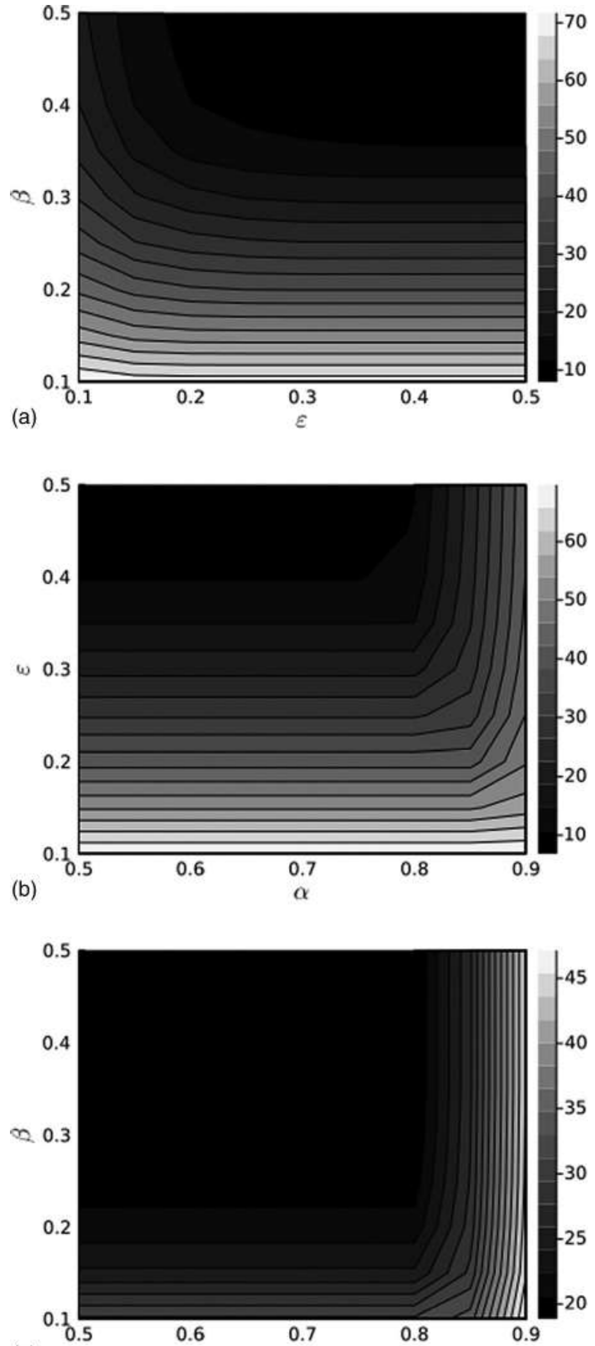

FIGURE 6.3 Total cost under different pairs of threshold. (a) Fixed α=0.8; (b) Fixed β=0.2; (c) Fixed ε=0.3.

to make changes, and the TC increases accordingly. When $\varepsilon < \beta$, alternative consensus level β does not have any effect on the model. Figure 6.3 (b) shows the variation of TC with criteria thresholds ε and consensus threshold α for $\beta = 0.2$. In this case, the TC decreases with an increasing ε and increases with an increasing α. This means that a higher consensus threshold drives more experts to make adjustments, resulting in higher consensus costs. And for larger ε, the consensus threshold α will have a stronger binding force on the consensus, thus increasing the consensus cost. Figure 6.3 (c) shows the variation of TC with the alternative level threshold β and consensus level α for a fixed $\varepsilon = 0.3$. A similar result to Figure 6.3 (b) can be obtained, where TC decreases with increasing alternative level threshold and increases with increasing consensus threshold. When $\beta > \varepsilon = 0.3$, the change of β will no longer affect the consensus cost, which further confirms the result of Figure 6.3 (a).

6.5 CONCLUSIONS

Nowadays, consensus decisions are increasingly important in MCGDM problems. To obtain a consensus solution agreed by the majority of experts, CRP is used to soften the disagreements among experts. Considering the calculation of consensus through different consensus measures, the CMCC model preserves as much as possible the experts' initial opinions while ensuring a desired group consensus degree. However, these CMCC models focus on single-criteria decision-making problems, and they may not be efficient for dealing with MCGDM problems. Furthermore, they do not take into account the uncertainty of the expert's unit adjustment cost, which is very common in real-world decision-making problems.

This chapter develops a new CMCC model for the MCGDM problem, which allows experts to express their preferences for alternatives based on multiple evaluation criteria, expressed in the form of a decision matrix. In addition to the classic constraints considered in CMCC models, the linear model (6.5) includes an additional restriction to guarantee consensus on the final decision that is made according to the weights of the criteria. Furthermore, in the model (6.4), in order to solve the uncertainty of the unit adjustment cost of experts, this chapter establishes the model (6.4) based on robust optimization, which increases the stability of the model. Finally, to demonstrate the usability and advantages of the proposed model (6.7), an illustrative example of the selection of an IoT platform and the corresponding sensitivity analysis was performed.

In future research, we will investigate the applicability and performance of different uncertainty sets (Han, Ji & Qu, 2021), extend the proposed multi-criteria CMCC models to large-scale MCGDM problems (García-Zamora, Labella, Ding, Rodríguez & Martínez, 2022b) and deeper analyze the relation between the parameters involved in the model (García-Zamora, Dutta, Massanet, Riera & Martínez, 2022a).

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REFERENCES

Abdullah, M.I., Roobashini, D., & Alkawaz, M.H. (2021). Active monitoring of energy utilization in smart home appliances. *2021 IEEE 11th IEEE symposium on computer applications & industrial electronics (ISCAIE)* (pp. 245–249). doi: 10.1109/ISCAIE51753.2021.9431776

Ben-Arieh, D., & Easton, T. (2007). Multi-criteria group consensus under linear cost opinion elasticity. *Decision Support Systems*, *43* (3), 713–721.

Ben-Tal, A., El Ghaoui, L., & Nemirovski, A. (2009). *Robust optimization* (Vol. 28). Princeton, New Jersey: Princeton University Press.

Büyüközkan, G., & Güleryüz, S. (2016). A new integrated intuitionistic fuzzy group decision making approach for product development partner selection. *Computers & Industrial Engineering*, *102*, 383–395.

Chakrabarti, D. (2021). Parameter-free robust optimization for the maximum-sharpe portfolio problem. *European Journal of Operational Research*, *293* (1), 388–399.

Chakraborty, A., Jindal, M., Khosravi, M.R., Singh, P., Shankar, A., & Diwakar, M. (2021). A secure IoT-based cloud platform selection using entropy distance approach and fuzzy set theory. *Wireless Communications and Mobile Computing*, *2021*, 1–11.

Dong, Y., Xu, Y., Li, H., & Feng, B. (2010). The OWA-based consensus operator under linguistic representation models using position indexes. *European Journal of Operational Research*, *203* (2), 455–463.

Fedrizzi, M., Fedrizzi, M., & Pereira, R.A.M. (1999). Soft consensus and network dynamics in group decision making. *International Journal of Intelligent Systems*, *14* (1), 63–77.

Fu, C., Chang, W., & Yang, S. (2020). Multiple criteria group decision making based on group satisfaction. *Information Sciences*, *518*, 309–329.

García-Zamora, D., Dutta, B., Massanet, S., Riera, J.V., Martínez, L. (2022a). Relationship between the distance consensus and the consensus degree in comprehensive minimum cost consensus models: A polytope-based analysis. *European Journal of Operational Research*. doi: 10.1016/j.ejor.2022.08.015

García-Zamora, D., Labella, Á., Ding, W., Rodríguez, R.M., & Martínez, L. (2022b, Jun). Large-scale group decision making: A systematic review and a critical analysis. *IEEE/CAA Journal of Automatica Sinica*, *9* (6), 949–966.

Gong, Z., Zhang, H., Forrest, J., Li, L., Xu, X. (2015). Two consensus models based on the minimum cost and maximum return regarding either all individuals or one individual. *European Journal of Operational Research*, *240* (1), 183–192.

Han, Y., Ji, Y., Qu, S. (2021). A robust minimum-cost consensus model with uncertain aggregation weights based on data-driven method. *IEEE Transactions on Computational Social Systems*, *9* (4), 1167–1184.

Han, Y., Qu, S., Wu, Z., Huang, R. (2019). Robust consensus models based on minimum cost with an application to marketing plan. *Journal of Intelligent & Fuzzy Systems*, *37* (4), 5655–5668.

Kacprzyk, J. (1986). Group decision making with a fuzzy linguistic majority. *Fuzzy Sets and Systems*, *18* (2), 105–118.

Kim, S., & Moon, H. (2022). Understanding consumer acceptance of smart washing machines: How do female consumers' occupations affect the acceptance process? *International Journal of Human–Computer Interaction*, 1–22. doi: 10.1080/10447318.2022.2049135

Kondratenko, Y., & Kondratenko, G., Sidenko, I. (2018). Multi-criteria decision making for selecting a rational IoT platform. *2018 IEEE 9th international conference on dependable systems, services and technologies (dessert)* (pp. 147–152). doi: 10.1109/DESSERT.2018.8409117

Kuhn, D., Esfahani, P.M., Nguyen, V.A., & Shafieezadeh-Abadeh, S. (2019). Wasserstein distributionally robust optimization: Theory and applications in machine learning. In *Operations research & management science in the age of analytics* (pp. 130–166). Washington: Informs.

Labella, Á., Liu, H., & Rodríguez, R.M., Martínez, L. (2020). A cost consensus metric for consensus reaching processes based on a comprehensive minimum cost model. *European Journal of Operational Research*, *281* (2), 316–331.

Li, Y., Zhang, H., & Dong, Y. (2017). The interactive consensus reaching process with the minimum and uncertain cost in group decision making. *Applied Soft Computing*, *60*, 202–212.

Nie, R.-X., Tian, Z.-P., & Wang, J.-Q., Luo, H.-Y. (2020). An objective and interactive-information-based feedback mechanism for the consensus-reaching process considering a non-support degree for minority opinions. *Expert Systems*, *37* (5), e12543.

Palomares, I., Estrella, F.J., Martínez, L., & Herrera, F. (2014). Consensus under a fuzzy context: Taxonomy, analysis framework AFRYCA and experimental case of study. *Information Fusion*, *20*, 252–271.

Palomares, I., Martinez, L., & Herrera, F. (2013). A consensus model to detect and manage noncooperative behaviors in large-scale group decision making. *IEEE Transactions on Fuzzy Systems*, *22* (3), 516–530.

Pramanik, P.K.D., Pal, S., & Choudhury, P. (2018). Beyond automation: The cognitive IoT. Artificial intelligence brings sense to the internet of things. *Cognitive computing for big data systems over IoT* (pp. 1–37). Cham: Springer.

Qin, J., Liu, X., & Pedrycz, W. (2017). An extended TODIM multi-criteria group decision making method for green supplier selection in interval type-2 fuzzy environment. *European Journal of Operational Research*, *258* (2), 626–638.

Qu, S., Han, Y., Wu, Z., & Raza, H. (2021). Consensus modeling with asymmetric cost based on data-driven robust optimization. *Group Decision and Negotiation*, *30* (6), 1395–1432.

Rodríguez, R.M., Labella, Á., & De Tré, G., Martínez, L. (2018). A large scale consensus reaching process managing group hesitation. *Knowledge-Based Systems*, *159*, 86–97.

Rodríguez, R.M., Labella, Á., & Dutta, B., Martínez, L. (2021). Comprehensive minimum cost models for large scale group decision making with consistent fuzzy preference relations. *Knowledge-Based Systems*, *215*, 106780.

Roubens, M. (1997). Fuzzy sets and decision analysis. *Fuzzy sets and systems*, *90* (2), 199–206.

Tian, Z.-P., Nie, R.-X., Wang, J.-Q., Long, R.-Y. (2020). Adaptive consensus-based model for heterogeneous large-scale group decision-making: detecting and managing noncooperative behaviors. *IEEE Transactions on Fuzzy Systems*, *29* (8), 2209–2223.

Wu, Z., & Xu, J. (2016). Managing consistency and consensus in group decision making with hesitant fuzzy linguistic preference relations. *Omega*, *65*, 28–40.

Xu, X., Yin, X., & Chen, X. (2019). A large-group emergency risk decision method based on data mining of public attribute preferences. *Knowledge-Based Systems*, *163*, 495–509.

Xu, X.-H., Du, Z.-J., & Chen, X.-H. (2015). Consensus model for multi-criteria large-group emergency decision making considering non-cooperative behaviors and minority opinions. *Decision Support Systems*, *79*, 150–160.

Zhang, B., Dong, Y., & Xu, Y. (2013). Maximum expert consensus models with linear cost function and aggregation operators. *Computers & Industrial Engineering*, *66* (1), 147–157.

Zhang, B., Liang, H., Gao, Y., & Zhang, G. (2018). The optimization-based aggregation and consensus with minimum-cost in group decision making under incomplete linguistic distribution context. *Knowledge-Based Systems*, *162*, 92–102.

Zhang, G., Dong, Y., Xu, Y., & Li, H. (2011). Minimum-cost consensus models under aggregation operators. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, *41* (6), 1253–1261.

Zhang, H., Kou, G., & Peng, Y. (2019). Soft consensus cost models for group decision making and economic interpretations. *European Journal of Operational Research*, *277* (3), 964–980.

Zhang, N., Gong, Z., & Chiclana, F. (2017). Minimum cost consensus models based on random opinions. *Expert Systems with Applications*, *89*, 149–159.

Zhong, X., Xu, X., & Pan, B. (2022). A non-threshold consensus model based on the minimum cost and maximum consensus-increasing for multi-attribute large group decision-making. *Information Fusion*, *77*, 90–106.