



UNIVERSITY OF JAÉN

**School of Engineering and Computing
Computer Science Department**

**FUZZY MULTIPLE CRITERIA DECISION-MAKING METHODS FOR ELECTRIC
VEHICLE CHARGING STATION EVALUATION**

THESIS MEMORY PRESENTED BY

Xiaohong Pan

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TO OBTAIN THE PHD DEGREE IN COMPUTER SCIENCE

SUPERVISORS

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The Thesis entitled *Fuzzy multiple criteria decision-making methods for electric vehicle charging station evaluation*, presented by D. Xiaohong Pan to obtain the PhD degree in Computer Science, has been carried out in the Computer Science Department of the University of Jaén with the supervisors Dr. Luis Martínez López. To be evaluated, this research memory is presented as a set of published articles, according to Article 23, point 3, Regulation of Doctoral Studies of the University of Jaén, approved in February 2012.

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Chapter 1

Introduction

In this chapter, we aim to provide an overview of the motivations and objectives that drive our research, while also presenting the structure of this research memory.

1.1. Motivation

The rapid pace of urbanization, economic development, and population growth often leads to a surge in energy consumption [26, 115]. Despite ongoing efforts to diversify energy sources, fossil fuels still remain the dominant contributors to global energy consumption, accounting for 81% of the total in 2019, as reported by the International Energy Agency (IEA) [1]. However, the heavy reliance on fossil fuels poses two critical challenges: (1) the finite and nonrenewable nature of fossil fuels raises concerns about an impending energy crisis, as their depletion is projected to occur in the foreseeable future [8, 84] and (2) the combustion of fossil fuels releases substantial amounts of carbon dioxide, exacerbating the greenhouse effect and contributing to environmental pollution [77, 79]. In light of these challenges, it is crucial to explore clean and sustainable alternatives. The transport industry, being a significant determinant of energy demand [76], has taken measures to reduce its reliance on fossil fuels. For example, efforts have been made to explore cleaner means of transportation that can replace vehicles powered by fossil fuels.

The electric vehicle, powered by an electric motor and a rechargeable battery, offers several advantages such as low emissions, cost-effectiveness, and high efficiency [6, 56]. Additionally, by adopting an appropriate charging mode, electric vehicles can help manage peak power loads, provide spin reserves, and enhance the integration of renewable energy sources [34, 114]. Consequently, the development and widespread adoption of electric vehicles can address concerns related to fossil fuels and promote the safe, stable, and cost-effective operation of the power grid [38]. As a result, many countries have implemented various strategies to support the production and sales of electric vehicles, leading to a significant increase in their deployment worldwide. At the end of 2020, there were approximately 10 million electric

vehicles on the world, and despite the impact of the COVID-19 pandemic, electric vehicle registrations increased by 41% in 2020 [2]. This rapid growth in electric vehicles has created a substantial demand for Electric Vehicle Charging Station (EVCS).

The EVCS, as the energy provider for electric vehicles, plays a crucial role for the development of the electric vehicle industry. Establishing efficient, convenient, and cost-effective EVCS not only enhances consumers' willingness to purchase electric vehicles but also drives the overall development of the industry. The current EVCSs can be categorized into three main types: conductive charging stations, inductive charging stations, and battery replacement stations [36]. Among them, conductive charging stations are the most widely installed, which utilize a physical connection, typically through cables, to transfer electrical energy from the charging infrastructure to the vehicle's battery system [4, 27, 92, 97, 109]. Conductive charging stations ensure efficient power transfer, allowing for convenient and relatively rapid charging times [124]. Consequently, this research focuses specifically on the evaluation of conductive charging stations. By focusing the research on the evaluation of conductive charging stations, this research aims to delve into the specific considerations, challenges, and solutions related to EVCS evaluation.

In practice, the evaluation of EVCS is often influenced by multiple conflicting criteria from various dimensions, such as social, economic, and environmental factors [38, 117]. Consequently, the EVCS evaluation can be regarded as a Multiple-Criteria Decision-Making (MCDM) problem. So far, numerous studies have employed MCDM methods to address EVCS evaluation problems from different perspectives [7, 9, 38, 39, 59, 83, 99, 114, 130, 132], aiming to provide decision support tools and frameworks for stakeholders to make informed decisions. Despite the significant contributions made by existing researches, there are still several limitations that need to be addressed:

1. The existing researches in EVCS evaluation mainly focus on homogeneous information and single-granular linguistic term sets. However, the criteria influencing EVCS can be broadly classified into two categories: quantitative criteria and qualitative criteria. These two categories of criteria normally require different modeling approaches [18, 128], as they involve different information formats. Specifically, quantitative criteria are typically expressed using numerical data, while qualitative criteria are represented by linguistic terms [20, 94]. Additionally, due to variations in individual background and knowledge, the linguistic terms elicited by different decision makers are often defined on multi-granular linguistic term sets [19, 134]. How to effectively handle the heterogeneous information and multi-granular linguistic terms remains as open challenges in EVCS evaluation researches.
 2. The existing researches in EVCS evaluation often ignore the considerations of the incomparability relation between alternatives. In the literature, there are primarily two types of MCDM methods: utility values-based methods and outranking methods [65]. Utility
-

values-based methods rank alternatives based on aggregated values, while outranking methods use pairwise comparisons to rank alternatives. However, both methods have limitations. Utility values-based methods do not adequately reflect the incomparability relation between alternatives, and the results robustness of the outranking methods may sometimes lack precision [64]. Therefore, there is a need for a new approach that combines the strengths of utility values-based methods and outranking methods, considering the incomparability relation between alternatives to produce more reliable results.

3. Previous researches in EVCS evaluation mainly focus on ranking the alternatives. It is worth noting that the alternative ranked first also has the possibility to be an unsatisfying alternative. Selecting such an alternative could potentially increase decision risk significantly. To address this issue, one promising solution is to introduce the Multi-Criteria Classification (MCC) methods, e.g., Multi-Criteria Decision-Making (MCDM) sorting method and Multi-Criteria Three-Way Decision (MCTWD) method, into EVCS evaluation. MCC methods aim to categorize a set of alternatives into several predefined ordered categories based on multiple criteria [46, 49]. By setting predefined categories, decision risk can be reduced, as alternatives falling into unacceptable categories will not be chosen.

By addressing the limitations of existing studies, this research memory is devoted to developing new fuzzy MCDM methods to address the challenges of heterogeneous information transformation, uncertain criteria weights calculation, incomparability relations description and alternatives classification on EVCS evaluation problems.

1.2. Objectives

Motivated by the challenges outlined previously, this research memory aims to achieve the following objectives:

1. *To evaluate EVCS with the heterogeneous information and multi-granular linguistic term sets:* This objective aims to establish new information transformation mechanisms that can unify the heterogeneous information and multi-granular linguistic term sets involved in EVCS evaluation. Additionally, a new information fusion approach will be proposed to generate the overall expected utilities of potential EVCS alternatives. Afterwards, an improved Minimax Regret Approach (MRA) will be developed for comparing and ranking the potential alternatives. The applicability and feasibility of the proposed method will be demonstrated through a case study on EVCS site selection.
 2. *To consider the incomparability relation between alternatives and individual semantics in EVCS evaluation:* This objective involves developing a new information processing mechanism that reflects individual semantics and enhances Bessons mean ranks. This
-

mechanism will better consider the difference degree between evaluation information, aiming to improve the reliability of the results. Moreover, a fuzzy ORESTE (organisation, rangement et Synthèse de données relationnelles, in French) method will also be developed to analyze conflicts between potential alternatives and select the most desirable option. The application of the proposed method will be studied through case studies.

3. *To study the classification of alternatives in EVCS evaluation:* This objective aims to provide not only ranking order of alternatives, but also their classifications, which consists of two key contents: MCTWD methods, which offer the capability to classify alternatives into positive, negative, and boundary regions corresponding to acceptance, rejection, and deferment; and MCDM sorting methods, which enable us to provide a broader range of classifications based on specific requirements and criteria.

By achieving these objectives, this research aims to provide valuable decision support tools for stakeholders involved in the evaluation of EVCS, ultimately driving the sustainable development of the electric vehicles industry.

1.3. Structure

In accordance with Article 25, point 2, of the current regulations of Doctoral Studies at the University of Jaén (RD. 99/2011), this doctoral thesis will consist of a compilation of articles published or submitted by the PhD student, each contributing to the fulfillment of the objectives outlined in the previous section. The research encompasses four articles, three of which have already been published in internationally recognized journals indexed in the Journal Citation Reports (JCR) database, while the remaining one has been submitted to international journals also indexed in the JCR database.

The structure of this research memory is organized as follows:

- Chapter 2: It presents several fundamental concepts related to the doctoral thesis research, such as EVCS evaluation, interval values, Interval Type-2 Fuzzy Sets (IT2FSs), and shadowed sets. Moreover, some related MCDM methods including TWD method, MCDM sorting method, TODIM (an acronym in Portuguese “TOmada de Decisão Iterativa Multicritério) method, and ORESTE method are also presented in this chapter.
 - Chapter 3: The published proposals that form the research memory will be introduced briefly. In addition, a concise discussion of each result obtained will be presented to illustrate the achievements of our research.
 - Chapter 4: This chapter serves as the core of the doctoral thesis, encompassing four publications that have resulted from the research. Each publication is presented along with information regarding the quality indexes where the proposals have been published.
-

- Chapter 5: The main conclusions of the doctoral thesis are summarized in this chapter, along with the introduction of several promising areas for future research.

Chapter 2

Basics Concepts and Methods

This chapter introduces the EVCS evaluation process to provide an overall understanding of the focus of our research memory; Moreover, some fundamental concepts related to this research memory are reviewed, such as interval values, IT2FSs, and shadowed sets; Finally, several MCDM methods that are closely related to the research topic, including the TWD method, MCDM sorting method, TODIM method, and ORESTE method are presented.

2.1. EVCS evaluation

In the ever-evolving landscape of transportation, EVs have emerged as a promising solution to mitigate environmental concerns and reduce our dependence on fossil fuels [33]. As we are on transition towards a sustainable future, the proliferation of EVs is undeniable. However, the widespread adoption of EVs hinges not only on advances in battery technology and vehicle design but also on the availability and efficiency of the infrastructure supporting them. Central to this infrastructure is EVCS [52, 69]. These stations are the lifeblood of the EV ecosystem, providing the means for EV users to recharge their vehicles conveniently and efficiently. Consequently, evaluating these charging stations becomes essential, not only to ensure the reliability of the EV ecosystem but also to drive further adoption by instilling confidence in potential EV users [70, 72, 80].

The primary objective of EVCS evaluation is to determine the suitability and effectiveness of charging stations in meeting the needs of EV users, investors, and the broader EV industry. By evaluating and comparing different charging stations, stakeholders can make informed decisions regarding the site selection [33, 34, 93], supplier evaluation [111], deployment [14, 104], optimization of charging infrastructure [98, 118], and so forth. In practice, EVCS evaluation encompasses various criteria and factors that influence the overall quality and suitability of charging stations. These criteria often span multiple dimensions, including technical aspects, economic considerations, environmental impact, user experience, and accessibility [10, 21, 28, 50]. Evaluating EVCS requires a comprehensive assessment of such criteria

to support informed decision-making by stakeholders involved in the planning, installation, and operation of charging infrastructure [10, 34, 68, 112].

MCDM methods play a crucial role in the evaluation of EVCS. MCDM is a branch of decision theory that considers multiple criteria or factors when making decisions. In the context of EVCS evaluation, MCDM methods help stakeholders, including government agencies, businesses, and investors, assess and prioritize different charging stations based on various criteria.

Here are some key aspects of the EVCS evaluation and its relationship with MCDM:

- **Multiple Criteria:** When evaluating EVCS, there are various criteria to consider. MCDM methods allow decision makers to weigh these criteria according to their importance and make informed decisions.

- **Objective Decision-Making:** MCDM provides an objective and systematic approach to decision-making. It helps avoid biases and ensures that decisions are based on a rational assessment of the charging stations' performance.

- **Trade-off Analysis:** MCDM enables the exploration of trade-offs among different criteria. For example, a charging station may excel in terms of speed but be less environmentally friendly. MCDM helps in finding a balance between these conflicting criteria.

- **Sensitivity Analysis:** With MCDM, decision makers can perform sensitivity analyses to understand how changes in criteria weights or data inputs affect the ranking of EVCS. This helps in making robust decisions.

- **Scalability:** As the number of EVCS increases, the evaluation process can become complex. MCDM methods are scalable and can handle the assessment of a large number of charging stations efficiently.

In summary, EVCS evaluation is a multifaceted process that considers various criteria, and MCDM methods provide a structured and analytical approach to support decision makers in selecting the most suitable charging stations for further development or investment.

Mathematically, the EVCS evaluation consists of several elements that can be expressed as follows:

1. Objective: The objective of EVCS evaluation is ranking or classifying the EVCS alternatives;
 2. Alternatives: The alternatives vary depending on the specific decision problems, and can be potential suppliers, sites or battery technologies. In this memory, the alternatives are symbolized as $z = \{z_1, \dots, z_m\}$;
 3. Criteria: The criteria for EVCS evaluation also vary depending on the specific decision problem and can be expressed as $g = \{g_1, \dots, g_n\}$;
 4. Experts: Experts are invited to provide their expertise and insights to assist in the evaluation process. They can be symbolized as $e = \{e_1, \dots, e_K\}$;
-

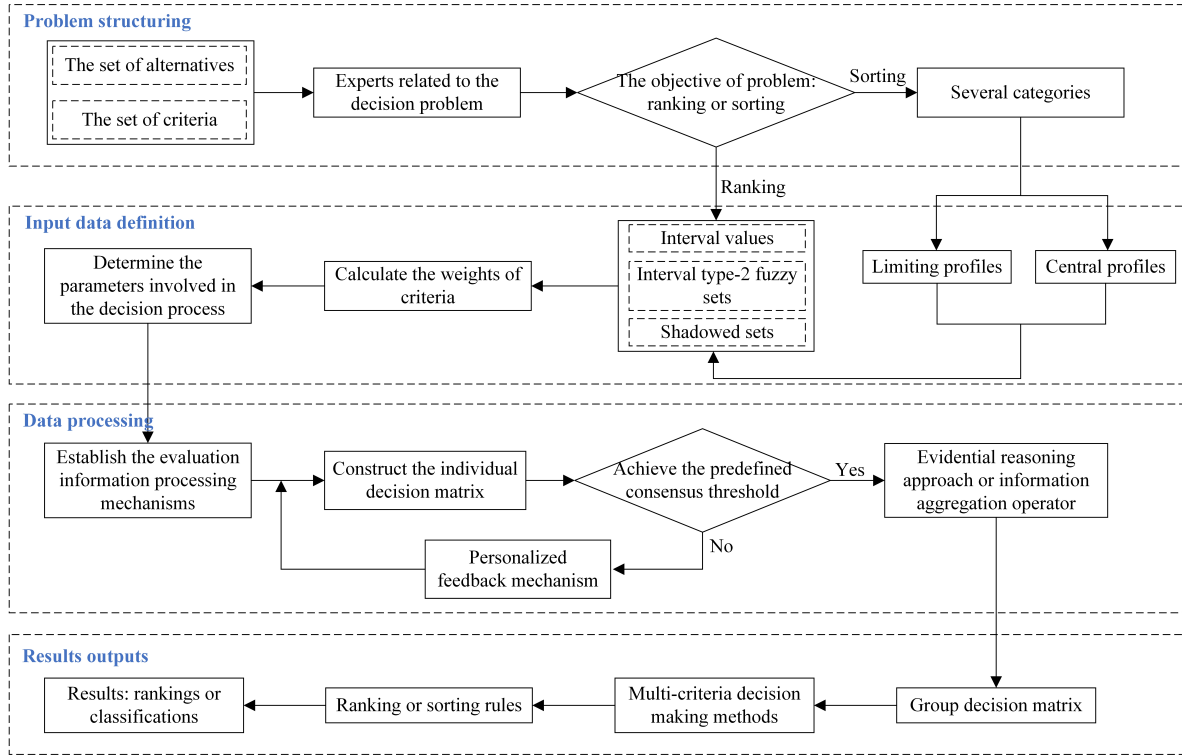


Figure 2.1: The implementation process of EVCS evaluation

5. Criteria weight: Different criteria have varying degrees of influence on the decision outcomes. This difference is usually represented by a weight vector $w = \{w_1, \dots, w_n\}$, where $w_j \geq 0$ and $\sum_{j=1}^n w_j = 1$;
6. Evaluation information: The information provided by expert e_k for alternative z_i with respect to g_j is denoted as $g_j^k(z_i)$.

By symbolizing these elements, the mathematical models can be utilized to assist in evaluating EVCS alternatives. The evaluation process leverages the expertise of domain experts and incorporates multiple criteria to support informed decision-making, ultimately driving the ranking and classification of potential EVCS solutions.

After symbolizing the EVCS evaluation problems, the MCDM methods can be used to rank or classify the alternatives based on the specific objectives. The specific implementation process of EVCS evaluation is visualized in Fig.2.1.

From Fig.2.1, we can observe that using the MCDM methods to address the EVCS evaluation problems mainly include four phases: problem structuring, input data definition, data processing, and results output. Each phase encompasses several steps, which are outlined in detail below:

Phase 1. Problem structuring. In this phase, the decision problem is structured, which consists of the following components:

1.1 Goal definition: The primary objective of the decision problem is to assign the available alternatives into several specific categories or rank the alternatives from best to worst.

1.2 Role identification: The members involved in the decision process are categorized into three roles: experts, moderator, and decision makers. Experts refer to the users or stakeholders who are invited to express their opinions, providing valuable input for the decision problem. Moderator are invited for managing consensus reaching process. Decision makers are responsible for making the final decision based on the rankings or classifications.

1.3 Criteria and alternatives identification: The criteria can be derived from other publications or expertise. The alternatives are generated through preliminary discussions among decision makers, considering the available options and potential solutions to the decision problem.

1.4 Categories definition: If objective of the problem is to classify the alternatives, we need to define the categories. The categories should be mutually exclusive, meaning that each alternative can only be assigned to one category. The number of categories can be determined based on the specific context and objectives of the decision problem. In the existing literature, two common approaches for defining the categories: using limiting profiles or central profiles.

Phase 2. Input data definition. In this phase, the input data required by the MCDM methods are defined.

2.1 Limiting profiles and central profiles definition: The limiting profiles and central profiles capture the essential features and boundaries of each category, aiding in the subsequent assignment of alternatives into specific categories. If K categories are considered, there will be $K - 1$ limiting profiles or K central profiles required.

2.2 Evaluation information acquisition: The evaluation information for each alternative is obtained by inviting experts to express their opinions. To capture the uncertainty involved in the decision-making process, the evaluation information can be expressed by fuzzy sets, such as interval values, IT2FSs, and shadowed sets, and so on.

2.3 Criteria weights calculation: The criteria weights indicate the relative importance of each criterion. In this research memory, the criteria weights are determined by the decision makers based on their expertise, knowledge, and experience.

2.4 Related parameters definition: This study incorporates various MCDM methods, including the multi-criteria TWD method, MCDM sorting method, TODIM method, and ORESTE method. These methods includes several parameters, such as conditional probability and category thresholds for TWD method, attenuation factor θ for TODIM method, and outranking thresholds for ORESTE method. It is crucial to note that the values assigned to these parameters are context-specific, contingent upon the characteristics of the decision problem, and the preferences articulated by the decision makers.

Phase 3. Data processing. In this phase, evaluation information processing mechanisms are established to facilitate the decision-making process.

3.1 Information preprocessing: The raw evaluation information collected from the experts is usually heterogenous and unstructured. In this step, several information processing mechanisms are established to manage the heterogenous and unstructured information. Through this step, the heterogenous and unstructured information will be conducted into unified form.

3.2 Individual matrix construction: In this step, the unified evaluation information for all alternatives regarding each criterion is collected to construct the individual evaluation matrix.

3.3 Measure the consensus between individuals: The consensus measure involves three levels, i.e., calculate the deviation degree of each individual on each alternative, calculate the deviation degree of each individual on all alternatives and calculate the consensus degree of each individual. Once the consensus degrees of all individuals and group are obtained, the personalized feedback mechanism can be activated.

3.4 The personalized feedback mechanism is to adjust the evaluation values that do not reach consensus. When the consensus degree does not meet the consensus requirement, the moderator should persuade the expert who does not reach consensus to modify his/her opinion according to the personalized feedback mechanism, if the expert refuses to modify his/her opinion, the importance will be reduced according to the weight penalty mechanism. When the consensus degree satisfies the consensus requirement, the final decision results can be obtained.

3.5 Information aggregation: When all individuals reach the predefined consensus threshold, the evidential reasoning approach or information aggregation operator are develop to aggregate the individual decision matrix.

Phase 4. Results outputs. In this phase, the rankings or classifications of alternatives are generated according to the specific objective of the problem.

4.1 Group decision matrix construction: Following the application of the evidential reasoning approach or other information aggregation operators, we proceed to construct the group decision matrix.

4.2 MCDM methods: This stage aims to identify and introduce the appropriate MCDM methods to address the EVCS evaluation problems. The choice of MCDM methods depends on the specific objectives of the evaluation. When the primary objective is to classify the EVCS alternatives into different categories, we recommend utilizing MCDM sorting methods. If the primary aim is to establish a ranking of the EVCS alternatives, then MCDM ranking methods are more appropriate.

4.3 Define the ranking or sorting rules: The ranking or sorting rules act as the foundation for evaluating and comparing the alternatives, ensuring that the final outcome aligns with the desired goals and priorities. Moreover, it is important to recognize that in situations where the evaluation information is uncertain, the ranking or sorting rules must be adaptable to accommodate this uncertain environment.

4.4 Outcomes outputs: The primary goal of this stage is to yield valuable results in the form of decision rankings or classifications for the available alternatives. When our objective is

to establish a ranking of alternatives, these outcomes offer a clear and comprehensive ordering of the alternatives, precisely reflecting their assessed performance, from most preferred to least preferred. Conversely, if our aim is to classify these alternatives, we assign them to specific categories based on their relative relationships with reference profiles. It is worth noting that each alternative can only belong to a single category, and in this categorization, an alternative placed in category C_{k-1} is considered superior to one in category C_k .

2.2. Uncertain information measurement

Expressing evaluation information precisely can be challenging in real-world scenarios due to inherent uncertainties and limitations in human thinking. To address this challenge, researchers have explored various uncertain information measurements that offer potential solutions. This section provides a brief review of some related uncertain information measurements, namely interval values, IT2FSs, and shadowed sets.

2.2.1. Interval values

Interval value is a mathematical concept that has proven to be effective in describing subjective uncertainty derived from human thinking [120, 121]. In the context of EVCS evaluation, interval values allow for the representation of evaluation information. In this subsection, the interval-valued arithmetic algebra and interval-valued ranking approach are reviewed.

(a) Interval-valued arithmetic algebra

To date, several studies have been dedicated to discussing interval-valued arithmetic [35, 37, 74]. Following the principles of Moore interval-valued arithmetic [78], when considering two non-negative interval values $a = [a^L, a^U]$ and $b = [b^L, b^U]$, as well as a non-negative crisp value k , the following relationships hold:

$$a + b = [a^L + b^L, a^U + b^U] \quad (2.1)$$

$$a - b = [a^L - b^U, a^U - b^L] \quad (2.2)$$

$$a \cdot b = [a^L \cdot b^L, a^U \cdot b^U] \quad (2.3)$$

$$a/b = [a^L/b^U, a^U/b^L], \text{ where } b^L \neq 0 \text{ and } b^U \neq 0 \quad (2.4)$$

$$k \cdot b = [k \cdot b^L, k \cdot b^U] \quad (2.5)$$

These interval-valued arithmetic operations allow for the manipulation and computation of intervals, providing a framework to handle uncertainty and imprecision inherent in interval-valued data. In the context of EVCS evaluation, interval-valued arithmetic serves as a fundamental tool to process and analyze uncertain information, contributing to more robust decision-making and comprehensive results.

(b) Interval-valued ranking approach

In order to enable comparison and ranking of interval values, Wang et al.[116] proposed the MRA. Compared to existing interval-valued ranking approaches, the MRA can distinguish the interval values with the same center but different widths. The specific comparison processes are summarized as follows:

Suppose that there are M interval values and $I_j = [I_j^-, I_j^+]$, $j = 1, \dots, M$ is final selected one and $I_{\max} = \max_{l \neq j} \{I_l^+\}$. The decision maker may experience regret if $I_j^- < I_{\max}$ and the maximum possible regret of selecting interval value I_j can be quantified as follows:

$$MR_j = I_{\max} - I_j^- = \max_{l \neq j} \{I_l^+\} - I_j^- \quad (2.6)$$

If $I_j^- \geq I_{\max}$, the regret is 0. Hence, the maximum regret is calculated by:

$$MR_j = \max\{\max_{l \neq j} \{I_l^+\} - I_j^-, 0\} \quad (2.7)$$

Clearly, the best interval value is the one with the minimum regret, which satisfies the following condition.

$$BIV = \min_j \{\max_{l \neq j} \{I_l^+\} - I_j^-, 0\} \quad (2.8)$$

If the objective is to determine the best option, the process can end here. However, if a complete ranking is required, the following elimination steps should be followed:

Step 1. Choose the interval value that has the minimum maximum regret as the optimal one. Suppose that I_{j_1} is selected as the optimal interval value, where $1 \leq j_1 \leq M$.

Step 2. To proceed, the interval value I_{j_1} should be excluded from further consideration, and the maximum regret of the remaining interval values should be recalculated. Assume that I_{j_2} is selected, where $1 \leq j_2 \neq j_1 \leq M$.

Step 3. Remove the interval value I_{j_2} and recalculate the maximum loss of the remaining interval values. Suppose that I_{j_3} is then selected, where $1 \leq j_3 \neq j_1 \neq j_2 \leq M$.

Step 4. Repeat the above elimination process until only one interval value is left. The complete ranking order of all interval values is $I_{j_1} \succ I_{j_2} \succ \dots \succ I_{j_M}$, where ‘ \succ ’ means ‘is preferred to’.

2.2.2. Interval Type-2 Fuzzy Sets

The concept of IT2FS was introduced by Zadeh [129] to extend the notion of ordinary fuzzy sets, known as Type-1 Fuzzy Sets (T1FS). The key distinction between T2FS and T1FS is that the membership function of T2FS is represented by a T1FS instead of an accurate function. This feature makes the T2FS more robust and accurate in revealing vagueness.

Definition 2.1 [51, 119]. A T2FS \tilde{A} defined in the universe of discourse X can be expressed by a type-2 membership function $\mu_{\tilde{A}}(x, u)$, denoted as:

$$\tilde{A} = \int_{x \in X} \int_{\mu \in J_x} \mu_{\tilde{A}}(x, u) / (x, u) \quad (2.9)$$

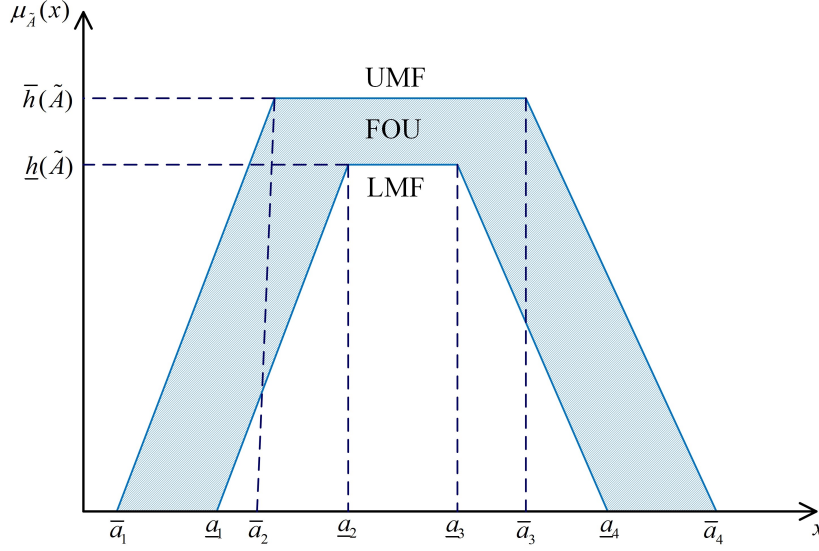


Figure 2.2: A Trapezoidal IT2FS

where J_x is an interval belongs to $[0, 1]$ and $\mu_{\tilde{A}}(x, u)$ represents the secondary membership function at x , which captures the uncertainty and ambiguity in the membership values of elements within the T2FS.

Definition 2.2 [51, 119]. For a T2FS \tilde{A} , if all secondary membership functions are equal to 1, i.e., $\mu_{\tilde{A}}(x, u) = 1$, then \tilde{A} is called an IT2FS, which is denoted as follows:

$$\tilde{A} = \int_{x \in X} \int_{\mu \in J_x} 1/(x, u) J_x \in [0, 1] \quad (2.10)$$

Due to the complexity of operations on IT2FSs, simplified versions such as Trapezoidal IT2FSs (TrIT2FSs) and Gaussian IT2FSs (GIT2FSs) are often studied. In this research memory, we adopt TrIT2FSs (following the results of Chen and Wang [15]) for solving MCDM problems.

Definition 2.3 [91]. A TrIT2FS is a type-2 fuzzy set whose membership function is a non-negative generalized trapezoidal fuzzy set, which can be expressed as follows:

$$\tilde{A} = [(x), \bar{\mu}(x)] = [(\underline{a}_1, \underline{a}_2, \underline{a}_3, \underline{a}_4, \underline{h}(\tilde{A})), (\bar{a}_1, \bar{a}_2, \bar{a}_3, \bar{a}_4, \bar{h}(\tilde{A}))]$$

where \underline{a}_i and \bar{a}_i are expressed by crisp values and satisfy $\underline{a}_i \leq \bar{a}_i$. The Lower Membership Function (LMF), denoted as $\underline{\mu}(x)$, is defined as the minimum of two linear functions defined by $(\underline{a}_1, 0)$, $(\underline{a}_2, \underline{h}(\tilde{A}))$ and $(\underline{a}_3, 0)$, $(\underline{a}_4, \underline{h}(\tilde{A}))$, respectively. The Upper Membership Function (UMF), denoted as $\bar{\mu}(x)$, is defined as the maximum of two linear functions defined by $(\bar{a}_1, 0)$, $(\bar{a}_2, \bar{h}(\tilde{A}))$ and $(\bar{a}_3, 0)$, $(\bar{a}_4, \bar{h}(\tilde{A}))$, respectively (see Fig. 2.2). The LMF and UMF are mathematically expressed as follows:

$$\underline{\mu}(x) = \begin{cases} \frac{\underline{h}(\tilde{A}) \cdot (x - \underline{a}_1)}{\underline{a}_2 - \underline{a}_1}, & \underline{a}_1 \leq x < \underline{a}_2 \\ \underline{h}(\tilde{A}), & \underline{a}_2 \leq x < \underline{a}_3 \\ \frac{\underline{h}(\tilde{A}) \cdot (\underline{a}_4 - x)}{\underline{a}_4 - \underline{a}_3}, & \underline{a}_3 \leq x < \underline{a}_4 \\ 0, & \text{otherwise} \end{cases} \quad (2.11)$$

$$\bar{\mu}(x) = \begin{cases} \frac{\bar{h}(\tilde{A}) \cdot (x - \bar{a}_1)}{\bar{a}_2 - \bar{a}_1}, & \bar{a}_1 \leq x < \bar{a}_2 \\ \bar{h}(\tilde{A}), & \bar{a}_2 \leq x < \bar{a}_3 \\ \frac{\bar{h}(\tilde{A}) \cdot (\bar{a}_4 - x)}{\bar{a}_4 - \bar{a}_3}, & \bar{a}_3 \leq x < \bar{a}_4 \\ 0, & \text{otherwise} \end{cases} \quad (2.12)$$

Definition 2.4 [16]. The arithmetic operations between two TrIT2FSs $\tilde{A} = [(\underline{a}_1, \underline{a}_2, \underline{a}_3, \underline{a}_4, \underline{h}(\tilde{A})), (\bar{a}_1, \bar{a}_2, \bar{a}_3, \bar{a}_4, \bar{h}(\tilde{A}))]$ and $\tilde{B} = [(\underline{b}_1, \underline{b}_2, \underline{b}_3, \underline{b}_4, \underline{h}(\tilde{B})), (\bar{b}_1, \bar{b}_2, \bar{b}_3, \bar{b}_4, \bar{h}(\tilde{B}))]$ are defined as follows:

$$\tilde{A} + \tilde{B} = \left[\begin{array}{l} (\underline{a}_1 + \underline{b}_1, \underline{a}_2 + \underline{b}_2, \underline{a}_3 + \underline{b}_3, \underline{a}_4 + \underline{b}_4, \min\{\underline{h}(\tilde{A}), \underline{h}(\tilde{B})\}), \\ (\bar{a}_1 + \bar{b}_1, \bar{a}_2 + \bar{b}_2, \bar{a}_3 + \bar{b}_3, \bar{a}_4 + \bar{b}_4, \min\{\bar{h}(\tilde{A}), \bar{h}(\tilde{B})\}) \end{array} \right] \quad (2.13)$$

$$\tilde{A} \times \tilde{B} = \left[\begin{array}{l} (\underline{a}_1 \cdot \underline{b}_1, \underline{a}_2 \cdot \underline{b}_2, \underline{a}_3 \cdot \underline{b}_3, \underline{a}_4 \cdot \underline{b}_4, \min\{\underline{h}(\tilde{A}), \underline{h}(\tilde{B})\}), \\ (\bar{a}_1 \cdot \bar{b}_1, \bar{a}_2 \cdot \bar{b}_2, \bar{a}_3 \cdot \bar{b}_3, \bar{a}_4 \cdot \bar{b}_4, \min\{\bar{h}(\tilde{A}), \bar{h}(\tilde{B})\}) \end{array} \right] \quad (2.14)$$

$$k \times \tilde{A} = \left[(k\underline{a}_1, k\underline{a}_2, k\underline{a}_3, k\underline{a}_4, \underline{h}(\tilde{A})), (k\bar{a}_1, k\bar{a}_2, k\bar{a}_3, k\bar{a}_4, \bar{h}(\tilde{A})) \right], k > 0 \quad (2.15)$$

$$\tilde{A}^k = \left[(\underline{a}_1^k, \underline{a}_2^k, \underline{a}_3^k, \underline{a}_4^k, (\tilde{A})), (\bar{a}_1^k, \bar{a}_2^k, \bar{a}_3^k, \bar{a}_4^k, \bar{h}(\tilde{A})) \right], k > 0 \quad (2.16)$$

2.2.3. Shadowed sets

Shadowed sets, initially proposed by Pedrycz [86, 108], can be considered as the three-valued approximation of fuzzy sets. Formally, for a nonempty universal set U , a shadowed set A can be defined by a set-valued mapping in the following form:

$$A : U \rightarrow 0, [0, 1], 1 \quad (2.17)$$

For $x \in U$, if its mapping value is equal to 1, it is fully compatible with the concept conveyed by shadowed sets. All such elements constitute the core area of the shadowed sets and are expressed as:

$$\text{core}(A) = \{x \in U | \mu_A(x) = 1\} \quad (2.18)$$

Here, $\mu_A(x)$ denotes the membership degree of an element x belonging to the shadowed set A .

If the mapping value of an element x is characterized by the unit interval $[0, 1]$, it is deemed uncertain. Such elements form the shadowed area of the shadowed set A , which can be denoted as:

$$\text{sh}(A) = \{x \in U | \mu_A(x) = [0, 1]\} \quad (2.19)$$

The element whose mapping value is equal to 0 is excluded from the shadowed set A .

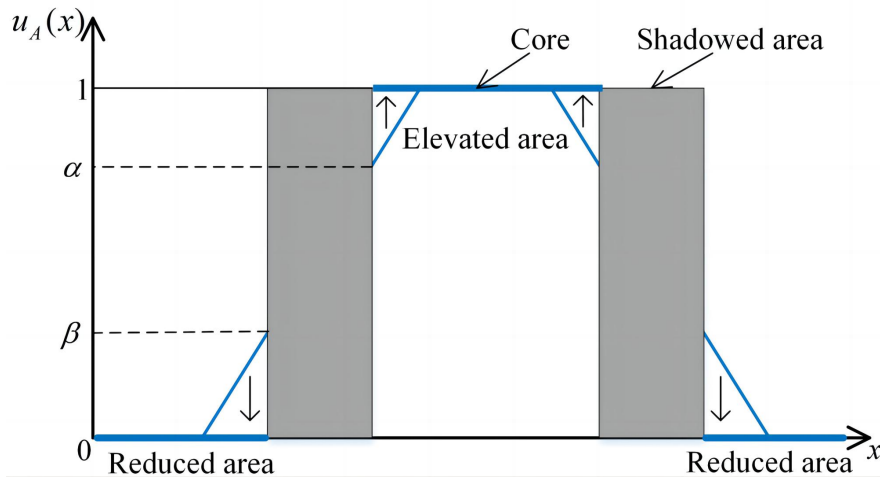


Figure 2.3: The construction of the shadowed set

According to the quantitative three-valued approximation, the shadowed set can also be expressed as [131]:

$$\mu_A(x) = \begin{cases} 0, \mu_A(x) \leq \beta \\ 1, \mu_A(x) \geq \alpha \\ [0, 1], \beta < \mu_A(x) < \alpha \end{cases} \quad (2.20)$$

where β and α are two predefined thresholds used in constructing a shadowed set, which satisfy $0 \leq \beta \leq \alpha \leq 1$.

In the construction process, if the membership degree of an element is larger than the threshold α , we elevate its membership degree to 1; if the element's membership degree is smaller than the threshold β , we reduce the membership degree to 0; if the membership degree of an element is between β and α , its membership degree is mapped into the unit interval $[0, 1]$. Fig. 2.3 provides a visualization of the construction process. The values of the thresholds β and α can be calculated by minimizing the following objective function [58, 86]:

$$\begin{aligned} V_{(\alpha, \beta)}(\mu_A) &= \text{Reduced area}_{(\alpha, \beta)}(\mu_A) + \text{Elevated} \\ &\quad \text{area}_{(\alpha, \beta)}(\mu_A) - \text{Shadowed area}_{(\alpha, \beta)}(\mu_A) \\ &= \sum_{x_i \in U, \mu_A(x_i) \leq \beta} \mu_A(x_i) \\ &\quad + \sum_{x_i \in U, \mu_A(x_i) \geq \alpha} (1 - \mu_A(x_i)) \\ &\quad - \text{Card}(x_i \in U | \alpha < \mu_A(x_i) < \beta) \end{aligned} \quad (2.21)$$

2.3. MCDM methods

MCDM is a powerful and systematic method used to make informed choices when faced

with decisions that involve multiple conflicting criteria or objectives [103]. It is an indispensable tool for individuals, organizations, and decision makers across various domains who need to navigate intricate decisions that go beyond simple, one-dimensional choices.

The MCDM includes several key components:

- **Multiple criteria:** MCDM recognizes that many real-world decisions cannot be adequately addressed by a single criterion. Instead, it considers a range of criteria or factors, each representing a different aspect or dimension of the decision problem. These criteria can include economic, environmental, social, and operational factors, among others.

- **Decision alternatives:** In MCDM, there are typically multiple alternatives or options available for consideration. These alternatives represent different strategies, courses of action, or choices that are subject to evaluation against the specified criteria.

- **Criteria weights:** MCDM enables decision makers to assign weights to each criterion based on their relative importance. This ensures that critical criteria receive appropriate consideration.

- **Trade-off analysis:** MCDM provides a structured framework for evaluating the trade-offs between criteria and alternatives. It helps decision makers understand the potential conflicts and synergies that exist between different criteria and how selecting one alternative over another impacts each criterion.

- **Decision support tools:** Various mathematical, analytical, and computational tools are used in MCDM to aid in the decision-making process. These tools help quantify, assess, and rank the alternatives based on the criteria, allowing for a more objective and systematic evaluation.

MCDM finds application in a wide range of fields, including venture capital decision-making [29, 102], green supplier selection [11], renewable energy evaluation [84, 85], etc. It helps organizations and individuals make well-informed decisions that align with their goals, values, and constraints.

Mathematically, the MCDM problem can be formally represented as follows:

Consider a set of m alternatives denoted as z_i (where $i = 1, \dots, m$). These alternatives need to be evaluated based on a set of n criteria represented as g_j (where $j = 1, \dots, n$). The importance or weight assigned to each criterion is captured by the vector $W = (w_1, \dots, w_n)$, with each w_j satisfying the conditions $w_j \geq 0$ and $\sum_{j=1}^n w_j = 1$. This ensures that the weights collectively account for the entire evaluation process. Moreover, the preference information associated with each alternative z_i concerning attribute g_j is expressed as $g_j(z_i)$. This information provides insight into how well each alternative performs with respect to each attribute. To systematically manage and organize this preference information, it is common practice to

utilize a decision matrix with dimensions $m \times n$.

$$D_{m \times n} = \begin{pmatrix} g_1(z_1) & g_2(z_1) & \cdots & g_n(z_1) \\ g_1(z_2) & g_2(z_2) & \cdots & g_n(z_2) \\ \vdots & \vdots & \vdots & \vdots \\ g_1(z_m) & g_2(z_m) & \cdots & g_n(z_m) \end{pmatrix}$$

The EVCS evaluation involves various factors from multiple dimensions, which can be regarded as a MCDM problem. MCDM methods provide a systematic framework for evaluating and prioritizing various factors that influence the effectiveness and sustainability of charging stations [52]. Whether considering factors from social, economic, and environmental dimensions, or user experience, these methods offer a structured approach to weigh and compare the trade-offs inherent in each decision [33]. By employing MCDM methods, stakeholders in the EV industry can make informed choices that optimize the overall charging infrastructure, ensuring that it meets the evolving needs of a growing community of EV users while aligning with broader sustainability goals [24, 52].

This section introduces several MCDM methods that are relevant to our research, including TWD method, MCDM sorting method, TODIM method, and ORESTE method. Notably, the TWD method serves the purpose of categorizing alternative EVCSs into three predefined categories, facilitating a structured assessment process. The MCDM sorting method is introduced to enhance the flexibility of the TWD method, which allows for the customization of the number of categories based on specific situations and requirements. Additionally, the TODIM method is introduced to our evaluation framework to account for the psychological factors inherent in decision-making processes related to EVCSs. Lastly, the ORESTE method is particularly useful when dealing with situations where there exists an inherent incomparability between alternative solutions.

2.3.1. TWD method

The TWD method was proposed by Yao [126], which involves two states and three actions. The states can be represented by $\Omega = \{C, \neg C\}$, where C denotes that x belongs to the decision class and $\neg C$ denotes that x does not belong to the decision class. The set of actions $A = \{a_P, a_B, a_N\}$ represents the acceptance, deferment and rejection decisions for classifying the object x . The loss functions associated with these actions are denoted by λ_{mn} ($m = P, B, N; n = P, N$). The loss functions can be represented by a 3×2 matrix, as shown in Table 2.1. The loss function for each action depends on whether the object x belongs to the decision class C or not. Specifically, when x belongs to C , the loss functions for a_P , a_B and a_N are denoted by $\lambda_{PP}(x)$, $\lambda_{BP}(x)$ and $\lambda_{NP}(x)$, respectively; when x does not belong to C , the corresponding loss functions are expressed by $\lambda_{PN}(x)$, $\lambda_{BN}(x)$ and $\lambda_{NN}(x)$.

Let $\Pr(C|x)$ denote the conditional probability of object x belonging to state C . The expected loss associated with taking action a_m ($m = P, B, N$) can be calculated using the

Table 2.1: The loss functions of TWD

x_i	C	$\neg C$
a_P	$\lambda_{PP}(x)$	$\lambda_{PN}(x)$
a_B	$\lambda_{BP}(x)$	$\lambda_{BN}(x)$
a_N	$\lambda_{NP}(x)$	$\lambda_{NN}(x)$

following expression.

$$R(a_P|x) = \Pr(C|x) \cdot \lambda_{PP}(x) + \Pr(\neg C|x) \cdot \lambda_{PN}(x) \quad (2.22)$$

$$R(a_B|x) = \Pr(C|x) \cdot \lambda_{BP}(x) + \Pr(\neg C|x) \cdot \lambda_{BN}(x) \quad (2.23)$$

$$R(a_N|x) = \Pr(C|x) \cdot \lambda_{NP}(x) + \Pr(\neg C|x) \cdot \lambda_{NN}(x) \quad (2.24)$$

Because the conditional probability satisfies $\Pr(C|x) + \Pr(\neg C|x) = 1$, we can also use $1 - \Pr(\neg C|x)$ to replace $\Pr(C|x)$ in Eqs.(2.22)-(2.24).

According to the Bayesian theory [127], the optimal decision is the one with the minimum cost, therefore the following rules of TWD can be derived [66]:

(P0) If $R(a_P|x) \leq R(a_B|x)$ and $R(a_P|x) \leq R(a_N|x)$, then $x \in Pos(C)$;

(B0) If $R(a_B|x) \leq R(a_P|x)$ and $R(a_B|x) \leq R(a_N|x)$, then $x \in Bnd(C)$;

(N0) If $R(a_N|x) \leq R(a_P|x)$ and $R(a_N|x) \leq R(a_B|x)$, then $x \in Neg(C)$.

The decision rules (P0)-(N0) can be simplified based on the reasonable semantic interpretation that the loss functions satisfy the conditions $\lambda_{PP}(x) \leq \lambda_{BP}(x) \leq \lambda_{NP}(x)$ and $\lambda_{NN}(x) \leq \lambda_{BN}(x) \leq \lambda_{PN}(x)$ [44]. The simplified rules are provided as follows:

(P1) If $\Pr(C|x) \geq \alpha$ and $\Pr(C|x) \geq \gamma$, then x is classified as $Pos(C)$;

(B1) If $\Pr(C|x) \leq \alpha$ and $\Pr(C|x) \geq \beta$, then x is classified as $Bnd(C)$;

(N1) If $\Pr(C|x) \leq \beta$ and $\Pr(C|x) \leq \gamma$, then x is classified as $Neg(C)$.

The values of thresholds α , β and γ can be obtained as follows:

$$\alpha = \frac{\lambda_{PN}(x) - \lambda_{BN}(x)}{(\lambda_{PN}(x) - \lambda_{BN}(x)) + (\lambda_{BP}(x) - \lambda_{PP}(x))} \quad (2.25)$$

$$\beta = \frac{\lambda_{BN}(x) - \lambda_{NN}(x)}{(\lambda_{BN}(x) - \lambda_{NN}(x)) + (\lambda_{NP}(x) - \lambda_{BP}(x))} \quad (2.26)$$

$$\gamma = \frac{\lambda_{PN}(x) - \lambda_{NN}(x)}{(\lambda_{PN}(x) - \lambda_{NN}(x)) + (\lambda_{NP}(x) - \lambda_{PP}(x))} \quad (2.27)$$

If the thresholds are constrained such that $0 \leq \beta < \gamma < \alpha \leq 1$, then (P1)-(N1) can be equivalently transformed as [67]:

(P2) If $\Pr(C|x) \geq \alpha$, decide $x \in Pos(C)$;

(B2) If $\beta < \Pr(C|x) < \alpha$, decide $x \in Bnd(C)$;

(N2) If $\Pr(C|x) \leq \beta$, decide $x \in Neg(C)$.

Table 2.2: The relative loss functions

	C	$\neg C$
a_P	0	$\lambda_{PN} - \lambda_{NN}$
a_B	$\lambda_{BP} - \lambda_{PP}$	$\lambda_{BN} - \lambda_{NN}$
a_N	$\lambda_{NP} - \lambda_{PP}$	0

The TWD method stands out as a particularly apt choice when confronted with challenges in the domain of MCDM including EVCS evaluation. This method excels in scenarios in which the primary objective is to categorize available alternatives. For instance, consider a scenario where a company is planning the deployment of multiple charging stations within a city. The city's administration has put forth several candidate locations for these stations, and the company seeks to ascertain the suitability of each location.

In such a complex decision-making environment, the TWD method proves to be a valuable tool. Its application streamlines the process by helping to categorize the candidate locations effectively. This categorization effort involves several key steps, ensuring a systematic approach to the problem:

Step 1. Construct the EVCS evaluation matrix. Assume the EVCS evaluation includes m alternatives and n criteria, then the evaluation information can be expressed by a $m \times n$ matrix:

$$D_{m \times n} = \begin{pmatrix} g_1(z_1) & g_2(z_1) & \cdots & g_n(z_1) \\ g_1(z_2) & g_2(z_2) & \cdots & g_n(z_2) \\ \vdots & \vdots & \vdots & \vdots \\ g_1(z_m) & g_2(z_m) & \cdots & g_n(z_m) \end{pmatrix}$$

where $g_j(z_i)$ is the evaluation information for alternative z_i with respect to criterion g_j . Essentially, this matrix compiles the assessments and measurements for all alternatives across all evaluation criteria. This pivotal step sets the stage for the subsequent phases of the EVCS evaluation process, where this data will be systematically analyzed to derive meaningful insights and inform the decision-making process.

Step 2. Transform the EVCS evaluation matrix into relative loss functions. This step is fundamental to the application of the TWD theory within the context of multi-criteria environments. To extend the applicability of the TWD theory to MCDM scenarios, Jia and Liu [44] introduced a distinctive concept known as the relative loss function. The specific form of the relative loss function is detailed in Table 2.2, and its utilization in this phase represents a critical transition point in the EVCS evaluation process.

In this research memory, the relative loss functions of alternatives with respect to criteria can be expressed by the a $m \times n$ matrix, as shown in Table 2.3. Each element in Table 2.3 is expressed by a 3×2 matrix, as shown in Table 2.2.

Table 2.3: The relative loss functions under multiple criteria

	c_1	c_2	\dots	c_n
z_1	$\lambda'(g_1(z_1))$	$\lambda'(g_2(z_1))$	\dots	$\lambda'(g_n(z_1))$
z_2	$\lambda'(g_1(z_2))$	$\lambda'(g_2(z_2))$	\dots	$\lambda'(g_n(z_2))$
\vdots	\vdots	\vdots	\ddots	\vdots
z_m	$\lambda'(g_1(z_m))$	$\lambda'(g_2(z_m))$	\dots	$\lambda'(g_n(z_m))$

Step 3. Calculate the classification thresholds. These thresholds are essential for establishing clear boundaries between different categories or classes. In this research memory, the thresholds can be determined based on Eqs.(2.25)-(2.27) and the relative loss functions derived in the previous step. The accurate determination of classification thresholds is crucial for the success of the EVCS evaluation, as it directly impacts the final categorization of alternatives.

Step 4. Calculate the conditional probability. How to estimate and calculate the conditional probability of TWD method is a crucial problem. In this research memory, the conditional probability is determined by the TOPSIS (the technique for order preference by similarity to ideal solution) method, which includes the following steps: normalize the evaluation information, determine the positive and negative ideal solutions, calculate the distance between alternatives and ideal solutions, calculate the relative closeness of each alternative, and generate the conditional probability of each alternative.

Step 5. Obtain the classifications of EVCS alternatives. In this final phase of the process, we obtain the classifications of EVCS alternatives based on the relationships between the conditional probabilities and thresholds. These categories typically include "Suitable," "Uncertain," and "Unsuitable". The classifications provide valuable insights into the suitability of each alternative in the context of EVCS deployment. Decision makers can use this information to make informed choices and prioritize the most suitable locations or options for establishing charging stations.

TWD, as a decision-making framework, has its advantages and disadvantages. Here are some of the key points to consider:

Advantages:

1. Flexibility: TWD provides a flexible approach to decision-making, allowing for the categorization of alternatives into three distinct classes: "Positive," "Negative," and "Boundary" or "Uncertain." This flexibility helps to manage uncertainty in EVCS evaluation.

2. Handling uncertainty: TWD is particularly useful in situations with significant uncertainty. It acknowledges and accounts for the uncertainty in the decision-making process by explicitly including the "Boundary" or "Uncertain" category. This category helps decision makers identify cases where additional evaluation information or analysis may be needed.

3. Transparency: The TWD framework offers transparency in evaluation outcomes. It clearly communicates the categorization of EVCS alternatives, making it easier for decision makers to understand and interpret the results. This transparency can facilitate effective communication within EVCS evaluation teams and with stakeholders.

4. Risk management: By identifying and separating "Boundary" or "Uncertain" cases, TWD aids in managing the risk in EVCS evaluation. Decision makers can focus their efforts on resolving uncertainties and mitigating risks associated with these cases, potentially leading to more informed decisions.

Disadvantages:

1. Complexity: Implementing a TWD framework can be more complex than traditional binary decision-making methods. It involves defining criteria, preferences, and thresholds for categorization, which may require considerable effort and expertise.

2. Data requirements: TWD relies on data and information to assess and categorize alternatives. In cases where data is scarce or of low quality, the effectiveness of the approach may be limited.

3. Limited to three categories: The TWD framework is inherently limited to three categories, which may not be sufficient for highly nuanced or multifaceted decision problems. In such cases, more complex decision frameworks may be necessary.

2.3.2. MCDM sorting methods

While the TWD method provides a valuable approach for categorizing alternative EVCSs into three predefined categories, real-world scenarios often present greater complexity. For instance, in the context of urban planning, there may be a need to classify EVCSs into four or more categories. In such cases, the conventional TWD method may prove inadequate and invalid. MCDM sorting method is a prominent branch of MCDM that offers a potential solution for this issue. Many MCDM sorting methods rely on active collaboration with the decision makers. These methods often involve extracting preference information from a reference set of designated alternatives provided by the decision makers [3]. This crucial step precedes the final sorting solution, comprising two different phases. The first phase is Preference Disaggregation Analysis (PDA). This initial step involves breaking down the decision maker's holistic preferences into finer details. It dissects the overall decisions made by the decision makers to better understand their underlying criteria and priorities. The second phase is comparison and sorting. Following the PDA, the MCDM sorting methods are introduced to evaluate the alternatives against reference profiles. These profiles represent idealized criteria patterns. Based on this comparison, the alternatives are categorized into different classes or groups that reflect their relative performance against the predefined criteria.

In literature, different MCDM sorting methods have been proposed, which can be roughly classified as: (1) full aggregation approach, (2) outranking approach, (3) goal, aspiration or

reference-level approach, and (4) approaches based on decision rules [3]. These approaches possess different characteristics, making them suitable for varying decision-making contexts. To aid decision makers in selecting the most appropriate method, we offer a concise overview of each of these approaches.

(1) Full aggregation approach. Ishizaka and Nemery [41] introduced the concept of full aggregation approaches in MCDM. In this approach, individual scores are assessed for each criterion, and these scores are then combined to form a comprehensive global score. What sets this approach apart is that a poor score in one criterion can potentially be offset or compensated by a strong score in another criterion. A well-known method that falls within this full aggregation approach is *UTADIS*, which was among the earliest sorting methods developed under this paradigm. *UTADIS* is a method that requires active involvement from the decision maker [137]. The decision maker's role is to define a set of imprecise assignment examples that associate actions with one or more contiguous classes. These assignments serve as reference actions, effectively representing the decision maker's preference information, which are then used to construct a preference model for the decision maker. This model is built through the creation of a set of general additive value functions. *UTADIS^{GMS}* developed by Greco, Mousseau, and Slowinski [30] is a new ordinal regression method, which considers all compatible additive value functions, while the classical *UTADIS* deals with a subset of the entire set of compatible additive value functions. So far, many other full aggregation approaches are developed, such as AHP-Sort (Analytic Hierarchy Process-Sort) method [42, 55, 63, 122], AHPSort II method [75], ANP-Sort method (Analytic Network Process-Sort) [43], etc.

(2) Outranking approach. The outranking approach was initially employed in sorting problems through methods like PROMETHEE-TRI [25] and its extension PROMSORT [5]. The process of assigning alternatives to specific categories involves a multi-step approach, utilizing both profiles and reference alternatives. PROMSORT employs PROMETHEE I to construct an outranking relation, which is utilized for assigning alternatives to categories, with the exception of situations where alternatives are deemed incomparable or indifferent. In cases where the outranking relation indicates that an alternative is either indifferent or incomparable to a particular limit profile, it is not immediately allocated to a category. Instead, the assigned alternatives are determined based on reference actions of the categories, and these assignments are then used to allocate alternatives that have not yet been categorized [3]. Following the PROMETHEE-TRI and PROMSORT, Nemery and Lamboray [81] introduced the FlowSort method based on the PROMETHEE methodology. Subsequently, numerous outranking sorting methods have been proposed, including ELECTRE-Sort [41, 61], ORESTE-Sort [90], Fuzzy-FlowSort [12], SMAA-FlowSort [89], SMAA-FFS-FlowSort [87], and SMAA-Choquet-FlowSort [88].

(3) Goal, aspiration or reference-level approach. In addition to outranking sorting methods, an alternative approach known as the goal, aspiration, or reference-level approach

has been introduced. This approach involves establishing a reference level (or goal) for each criterion and then identifying the option that comes closest to these ideal reference levels. One prominent method that follows this approach is the TOPSIS method, as described by Tzeng et al. [106]. TOPSIS offers solutions based on the relative distance between alternatives and ideal solutions. Over time, the TOPSIS method has seen extensive development to address various MCDM sorting problems. These extensions include TOPSIS-Sort [23, 123], TOPSIS-Sort-B [133], and TOPSIS-Sort-C [54, 96] and so on. VIKOR (VlseKriterijuska Optimizacija I Komoromisno Resenje) method [82] can be regarded as an extension of TOPSIS method, which is able to balance conflicts between criteria and provide compromise solutions for decision makers. The corresponding sorting method for VIKOR is VIKOR-Sort [22], along with its further extensions, fuzzy VIKOR-Sort [53]. Another representative method is Data Envelopment Analysis (DEA) method, which was developed by Charnes, Cooper, and Rhodes [13] to evaluate public programmes. The sorting method associated with DEA has been developed by Karasakal and Aker [49].

(4) Methods based on decision rules. Within this approach, methods based on decision rules are a notable category. One of the representative methods in this category is the rough set method [31]. Additionally, TRINOMFC [57] and Dempster-Shafer [17] are other significant methods that fall under the decision rules-based approach. Methods that are based on decision rules employ logical statements of the form "if , then ". A collection of decision rules serves as a preference model, reflecting the classification decisions made by a decision maker based on a given dataset. One of the most cited papers in the field of decision rules-based sorting approaches is associated with the non-classical approach, specifically the study published by Greco et al. [32]. This paper introduces an extended rough set method for sorting, which is a significant contribution. The extension of the rough set method for sorting problems, as proposed by Greco et al. [32], involves the construction of rough approximations for decision classes using a "granule of knowledge." This extension encompasses three interrelated relations: indiscernibility (defined on qualitative attributes), similarity (defined on quantitative attributes), and dominance (defined on criteria) [3]. What sets this extension apart is its novel approach of jointly considering criteria and regular attributes within sorting problems. Unlike the original rough set method, this extended version can identify inconsistencies related to the consideration of criteria, especially when attributes have preference-ordered domains and scales.

To utilize the MCDM sorting method to solve the EVCS evaluation problems, it is crucial to determine an optimal number of categories tailored to the specific context. This entails categorizing the alternatives based on their relationships with these predefined categories concerning multiple criteria. Mathematically, the alternatives, criteria, and categories can be represented as $Z = (z_1, \dots, z_m)$, $g = (g_1, \dots, g_n)$, and $C = (C_1, \dots, C_K)$, respectively. These categories possess a complete ordering, denoted as $C_1 \cdots \succ C_2 \cdots \succ C_K$, where $C_i \succ C_{i+1}$ signifies the preference of category C_i over category C_{i+1} . To define the K categories, a set of

reference profiles is required. Two commonly used methods for defining categories are limiting profiles and central profiles [81]. For limiting profiles, if K categories need to be established for criterion g_j , $K - 1$ profiles, denoted as $P^j = (p_1^j, \dots, p_{K-1}^j)$, are needed. On the other hand, central profiles require K profiles, represented as $P^j = (p_1^j, \dots, p_K^j)$. The two methods for characterizing categories, namely limiting profiles and central profiles, are visualized in Fig.2.4. Although limiting profiles and central profiles differ in their characterization of categories, the subsequent classification processes for both methods are similar. Therefore, this research memory only employs limiting profiles as an illustrative example to explain the classification process of alternatives.

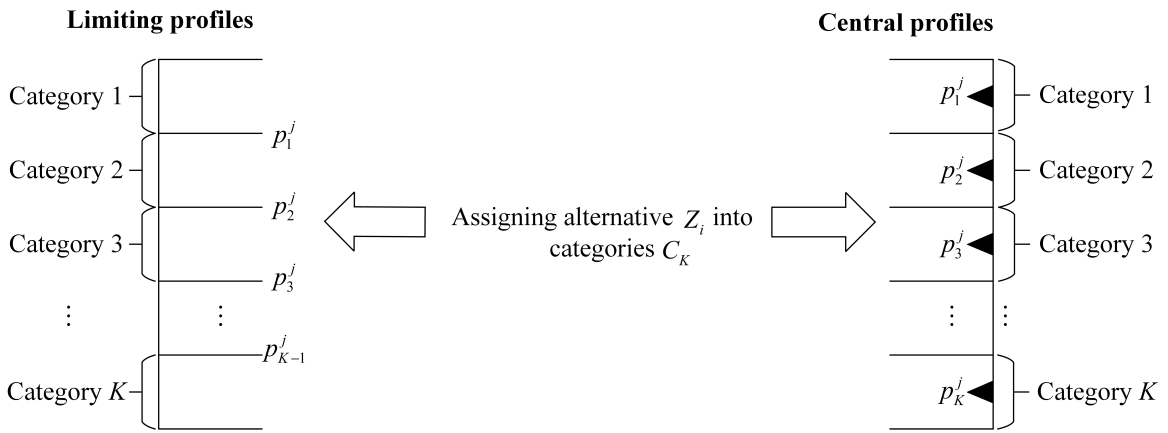


Figure 2.4: Schematic representation of limiting profiles and central profiles

The set of reference profiles, denoted as $P^j = (p_1^j, \dots, p_{K-1}^j)$, plays a crucial role in establishing a complete ordering of categories regarding criterion g_j . Within this set, p_1^j represents the lower limit profile of the best reference profile regarding criterion g_j , while p_{K-1}^j represents the upper limit profile of the worst reference profile regarding criterion g_j [110]. To ensure a consistent and meaningful categorization, it is essential for the reference profiles to adhere to the following condition :

$$\text{Condition: } p_1^j \succ p_2^j \succ \dots \succ p_{K-1}^j$$

Here, the notation $p_k^j \succ p_{k+1}^j$ indicates that the reference profile p_k^j is deemed superior to the reference profile p_{k+1}^j in terms of the criterion g_j .

Utilizing the MCDM sorting method to address the EVCS evaluation problems mainly includes the following steps:

Step 1. Collect the evaluation information for alternatives and profiles with respect to criteria. Assume there are m alternatives, $K - 1$ limiting profiles, and n criteria. The evaluation information for alternatives can be expressed in a $m \times n$ matrix, and the evaluation

information for profiles can be expressed in a $K - 1 \times n$ matrix, as shown below:

$$\Lambda_p = \begin{pmatrix} g_1(z_1) & g_2(z_1) & \cdots & g_n(z_1) \\ g_1(z_2) & g_2(z_2) & \cdots & g_n(z_2) \\ \vdots & \vdots & \ddots & \vdots \\ g_1(z_m) & g_2(z_m) & \cdots & g_n(z_m) \end{pmatrix}$$

$$\psi_p = \begin{pmatrix} g_1(r_1) & g_2(r_1) & \cdots & g_n(r_1) \\ g_1(r_2) & g_2(r_2) & \cdots & g_n(r_2) \\ \vdots & \vdots & \ddots & \vdots \\ g_1(r_{K-1}) & g_2(r_{K-1}) & \cdots & g_n(r_{K-1}) \end{pmatrix}$$

The condition $r_1^p \succ r_2^p \succ \dots \succ r_{K+1}^p$ ensures the complete ordering of categories and requires that the upper limit profile of category C_{k+1} on criterion g_j must be strictly lower than that of category C_k on the same criterion, i.e., $g_j(r_{k+1}) < g_j(r_k)$.

Step 2. Normalize the evaluation matrix. The EVCS evaluation usually involves multiple criteria from different dimensions, to eliminate the influence of dimension, the evaluation values of alternatives and reference profiles need to be normalized by the following rules:

- If the criterion belongs to benefit criteria, then:

$$x_{ij} = \frac{g_j(z_i)}{\sqrt{\sum_{i=1}^m g_j(z_i)}} \quad (2.28)$$

- If the criterion belongs to cost criteria, then:

$$x_{ij} = 1 - \frac{g_j(z_i)}{\sqrt{\sum_{i=1}^m g_j(z_i)^2}} \quad (2.29)$$

By applying these rules, the evaluation information for alternatives and reference profiles can be uniformly normalized into the range of $[0, 1]$, effectively addressing the issue of dimensionality.

Step 3. Introduce the MCDM methods to calculate the comparison index. Different MCDM methods employ various indices to compare the alternatives and reference profiles, each suited for specific evaluation situation. For instance, the TOPSIS method utilizes relative closeness to compare the alternatives and reference profiles, while the ELECTRE method employs the net-flow value for comparison. On the other hand, the TODIM method and prospect theory use the prospect value to assess and compare the alternatives and reference profiles. The selection of an appropriate MCDM method depends on the specific characteristics of the evaluation problem at hand.

Step 4. Assign the alternatives into specific categories. Once the comparison indices are determined, the next step involves defining assignment rules to categorize the alternatives into predefined categories. The specific rules and the number of categories to be established depend on the unique characteristics of the evaluation situation.

MCDM sorting methods offer several advantages and disadvantages:

Advantages:

1. Structured decision-making: MCDM sorting methods provide a structured approach to making complex decisions by categorizing EVCS alternatives into predefined groups. This structured approach enhances decision clarity and transparency.

2. Quantitative comparison: The MCDM sorting method allows for quantitative comparisons between alternatives and reference profiles based on multiple criteria, providing a more comprehensive assessment than qualitative approaches.

3. Flexibility: The MCDM sorting method can set the number of categories based on the specific EVCS evaluation situation. This adaptability ensures that decision makers can tailor their evaluation process to align with the complexity and diversity of EVCS evaluation scenarios, ultimately leading to more accurate and context-specific results.

Disadvantages:

1. Data requirements: MCDM sorting methods demand substantial data on criteria and alternatives, which can be challenging to obtain, especially in real-world EVCS evaluation scenarios.

2. Complexity: Some MCDM methods, such as the TOPSIS method and TODIM method, can be complex and require expertise to implement effectively.

3. Assumption of independence: Many MCDM methods assume that criteria are independent of each other, which may not hold true in some practical EVCS evaluation situations.

2.3.3. TODIM method

In the evaluation of EVCS, it becomes essential not only consider multiple factors but also account for the psychological aspects of human. The TODIM method, known for its capability to incorporate decision makers' psychological behavior into the evaluation process, proves invaluable [71] for this situation. By integrating TODIM method, we gain a more comprehensive understanding of the evaluation process, considering the subjective elements that influence choices. This approach not only enhances the accuracy of the evaluation but also ensures that the selected charging stations align with the preferences and psychological inclinations of EV users [136], ultimately contributing to greater user satisfaction and the wider adoption of electric vehicles.

Consider a scenario involving an EVCS evaluation problem, in which we have a finite set of alternatives denoted as $Z = \{Z_1, \dots, Z_m\}$ and a finite set of criteria as $g = \{g_1, \dots, g_n\}$. It is assumed that we possess knowledge about the performance of all alternatives concerning each criterion, and the preference for alternative Z_i regarding criterion g_j is represented as r_{ij} . Given that criteria are often expressed in different units, a normalization step becomes imperative to ensure that all values are dimensionless. In this normalization process, a critical

distinction must be made between benefit criteria and cost criteria. We presume that such a normalization process has been executed, ensuring that all preferences conform to the range $r_{ij} \in [0, 1]$. Moreover, each criterion g_j is assigned an associated weight denoted as $w_j \geq 0$, indicating its relative importance within the evaluation framework. It is essential to emphasize that the weights vector, denoted as $w = \{w_1, \dots, w_n\}$, has undergone normalization to ensure that the sum of all weights equals one.

The TODIM method is based on the calculation of the dominance degree of each alternative over the others with respect to different criteria using a value function [71]. The value function is derived from the prospect theory [48] and can model the asymmetrical attitudes of individuals towards gain and loss. To facilitate analysis and extensions thereafter, the specific implementation steps of the TODIM method can be summarized as follows:

Step 1. Calculate the relative weight of criterion g_j to the reference criterion g_r by:

$$w_{jr} = \frac{w_j}{w_r}, j = 1, \dots, n \quad (2.30)$$

In the literature, the reference criterion is chosen as the criterion with the highest weight, i.e., $w_r = \max_j \{w_j\}$.

Step 2. Calculate the dominance degree of EVCS alternative z_i over alternative z_l under criterion g_j , denoted as $\phi_j(z_i, z_l)$. This is done using the following expression:

$$\phi_j(z_i, z_l) = \begin{cases} \sqrt{\frac{w_{jr}(r_{ij} - r_{lj})}{\sum_{j=1}^n w_{jr}}}, & \text{if } r_{ij} > r_{lj} \\ 0, & \text{if } r_{ij} = r_{lj} \\ -\frac{1}{\theta} \sqrt{\frac{\sum_{j=1}^n w_{jr}(r_{lj} - r_{ij})}{w_{jr}}}, & \text{if } r_{ij} < r_{lj} \end{cases} \quad (2.31)$$

where the parameter θ indicates the attenuation factor of the losses. If $\theta > 1$ the influence of losses is attenuated; if $\theta < 1$ the influence of losses is amplified. So, the decision maker can rank the alternatives according to gains and losses by means of the parameter θ .

Step 3. Calculate the overall dominance degree of alternative z_i over alternative z_l by aggregating the dominance degrees across all criteria. The overall dominance degree, denoted as $\delta(z_i, z_l)$, is calculated as follows:

$$\delta(z_i, z_l) = \sum_{j=1}^n \phi_j(z_i, z_l), i, l = 1, \dots, m \quad (2.32)$$

Step 4. Calculate the global prospect value of the EVCS alternative z_i by:

$$\pi(z_i) = \frac{\sum_{l=1}^m \delta(z_i, z_l) - \min_i \{\sum_{l=1}^m \delta(z_i, z_l)\}}{\max_i \{\sum_{l=1}^m \delta(z_i, z_l)\} - \min_i \{\sum_{l=1}^m \delta(z_i, z_l)\}} \quad (2.33)$$

Step 5. Rank all alternatives according to their global prospect values. The larger the global prospect value $\pi(z_i)$ is, the better the alternative z_i will be.

The TODIM method is a valuable approach for MCDM, but like any methodology, it has its advantages and disadvantages.

Advantages:

1. Robustness to uncertainty: TODIM is well-suited for EVCS evaluation situations characterized by uncertainty, vagueness, or incomplete information. It can handle imprecise data and provide meaningful rankings of EVCS alternatives.

2. Incorporation of decision makers' psychological behavior: TODIM allows decision makers to express their risk attitudes and preferences through parameters like optimism and pessimism levels. This flexibility enables the method to align with decision makers' individual preferences.

3. Ease of application: TODIM's concept is relatively straightforward, making it accessible to both experts and non-experts in EVCS evaluation. Moreover, TODIM distinguishes itself by not necessitating the establishment of predefined reference points, significantly alleviating the workload borne by decision makers.

Disadvantages:

1. Parameter dependency: The TODIM method relies on parameters like membership functions and decision-makers' risk attitudes, which need to be carefully chosen. The selection of these parameters can be subjective and may require expertise.

2. Difficulty in handling non-monotonic relationships: TODIM may struggle to handle situations where criteria relationships are non-monotonic (i.e., they don't follow a simple upward or downward trend). This can limit its applicability in certain decision contexts.

2.3.4. ORESTE method

In EVCS evaluation, the inherent complexity of real-world scenarios, coupled with limited human knowledge, often hinders decision makers from directly providing evaluation values for alternatives across various criteria. Instead, they might offer insights into the pairwise relationships among these alternatives. To tackle this challenge, outranking methods emerge as a promising solution. Among them, the ORESTE (organisation, rangement et Synthèse de données relationnelles, in French) method stands out as an integrated MCDM approach. This method effectively assesses and ranks alternatives based on preference (P), indifference (I), and incomparability (R) relations [40]. Furthermore, ORESTE excels in handling situations where alternatives cannot be directly compared, addressing incomparability relations and, consequently, furnishing more dependable solutions for EVCS evaluation [64].

The classical ORESTE method, originally proposed by Roubens [95], consists of two main stages. The first stage involves calculating the global weak ranking based on preference scores, while the second stage focuses on constructing the PIR structure through indifference and incomparability analysis [40, 64]. The specific steps of the classical ORESTE method can be summarized as follows:

Step 1: Calculation of global preference scores

The global preference score $GP(r_{ij})$ of alternative z_i under criterion c_j is calculated using the following equation:

$$GP(r_{ij}) = \sqrt{\delta \cdot r_j^2 + (1 - \delta) \cdot r_j(z_i)^2} \quad (2.34)$$

Here, δ is a coefficient that measures the importance of criteria and alternatives rankings. The Besson's mean rank r_j^2 represents the preference structure for the criterion weight w_j , while $r_j(z_i)$ indicates the merit of alternative z_i with respect to criterion c_j .

Step 2: Construction of global weak ranking

The global weak ranking $GR(r_{ij})$ is constructed based on the comparison of preference scores. If $GP(r_{ij}) > GP(r_{kj})$, we can conclude that $GR(r_{ij}) > GR(r_{kj})$. Similarly, if $GP(r_{ij}) = GP(r_{kj})$, then $GR(r_{ij}) = GR(r_{kj})$. Here, $i, k = 1, \dots, m$ and $j = 1, \dots, n$.

Step 3: Calculation of global weak ranking of alternatives

The global weak ranking $GR(z_i)$ of alternative z_i is calculated as the sum of the global weak rankings across all criteria:

$$GR(z_i) = \sum_{j=1}^n GR(r_{ij}) \quad (2.35)$$

Step 4: Calculation of preference intensities

The preference intensities between pairs of alternatives are calculated using the average preference intensity and the net preference intensity. The average preference intensity between alternatives z_i and z_k is given by:

$$T(z_i, z_k) = \frac{\sum_{j=1}^n \max[GR(r_{ij}) - GR(r_{kj}), 0]}{(m-1) \cdot n^2} \quad (2.36)$$

The net preference intensity between z_i and z_k is defined as:

$$\Delta T(z_i, z_k) = T(z_i, z_k) - T(z_k, z_i) \quad (2.37)$$

Step 5: Establishment of PIR structure

The PIR structure categorizes alternatives into three relationships: preference (P), indifference (I), and incomparability (R). This subdivision is based on the following principles:

- (1) If $|\Delta T(z_i, z_k)| \geq \sigma$ and $\frac{\min(T(z_i, z_k), T(z_k, z_i))}{|\Delta(z_i, z_k)|} \geq \rho$, then $z_i R z_k$.
- (2) If $|\Delta T(z_i, z_k)| \geq \sigma$, $\Delta T(z_i, z_k) > 0$, and $\frac{\min(T(z_i, z_k), T(z_k, z_i))}{|\Delta(z_i, z_k)|} < \rho$, then $z_i P z_k$.
- (3) If $|\Delta T(z_i, z_k)| \geq \sigma$, $\Delta T(z_k, z_i) > 0$, and $\frac{\min(T(z_i, z_k), T(z_k, z_i))}{|\Delta(z_i, z_k)|} < \rho$, then $z_k P z_i$.
- (4) If $|\Delta T(z_i, z_k)| < \sigma$, two cases arise: if $T(z_i, z_k) < \gamma$ and $T(z_k, z_i) < \gamma$, then $z_i I z_k$; if $T(z_i, z_k) \geq \gamma$ or $T(z_k, z_i) \geq \gamma$, then $z_i R z_k$.

The thresholds σ , ρ , and γ are used to distinguish the PIR relations and are determined by the following principles:

$$\frac{1}{(m-1) \cdot n} > \sigma, \quad \frac{n-2}{4} < \rho, \quad \frac{\lambda}{2} \cdot (m-1) > \gamma \quad (2.38)$$

Here, λ represents the minimal threshold between two indifferent or incomparable alternatives.

The ORESTE method is a MCDM method with its own set of advantages and disadvantages.

Advantages

1. Consideration of outranking relationships: ORESTE is rooted in the outranking theory, which allows it to effectively capture the outranking relationships among alternatives. It provides a comprehensive view of how alternatives compare to each other in terms of criteria.

2. Handling incomparability: ORESTE excels in addressing situations where it is challenging to directly compare alternatives due to incomparability. This is a valuable feature when dealing with complex EVCS evaluation scenarios.

3. Structured decision process: ORESTE offers a structured approach to decision-making, which can be beneficial for decision makers in organizing and analyzing complex information. Moreover, the ORESTE method considers not only preference relations but also indifference and incomparability, providing a more comprehensive evaluation of alternatives.

Disadvantages

1. Complexity: While ORESTE's comprehensiveness is an advantage, it can also be a drawback in certain cases. The method's complexity may make it challenging to apply, especially for decision makers without extensive experience in EVCS evaluation and MCDM.

2. Data requirements: ORESTE relies on specific data, including preference, indifference, and incomparability relations, which may not always be readily available or easy to elicit from decision makers.

3. Computational burden: Implementing ORESTE can sometimes involve computationally intensive processes, particularly when dealing with a large number of alternatives and criteria.

Remark 2.1. The ORESTE method offers valuable insights for addressing conflicts (incomparability relationships) between alternatives. Compared to other MCDM methods, the ORESTE method provides a robust result by objectively calculating the thresholds required to distinguish the PIR relationships [107]. To date, the ORESTE method has been successfully applied in various fields, such as product quality evaluation [45], risk evaluation [62, 113, 135], intelligent transportation [64], and medical evaluation [60].

2.3.5. MCDM method selection

Indeed, considering the diverse advantages and disadvantages of various MCDM methods, it is crucial to choose the most appropriate method based on the specific circumstances. Here are some considerations for selecting the right MCDM method:

1. Nature of the decision problem: The nature of the decision problem plays a

vital role in method selection. Some methods are better suited for classification tasks, while others excel in ranking or prioritization. Understanding the fundamental characteristics of your decision problem is the first step.

2. Data availability: Consider the availability and quality of data. Some methods require precise numerical data, while others can work with qualitative or ordinal data. If you have limited or uncertain data, choose a method that can handle such situations effectively.

3. Decision maker expertise: The expertise of the decision makers involved matters. Some methods, like TODIM and ORESTE, are known for their accessibility and ease of use, making them suitable for decision makers with varying levels of expertise. However, more complex methods might be preferred if decision makers are highly experienced.

4. Handling incomparability: If your decision problem involves incomparability among alternatives (i.e., situations where direct comparison is challenging), methods like ORESTE that handle such cases well might be the better choice.

5. Transparency and interpretability: Consider the need for transparency and interpretability in EVCS evaluation process. Some methods, like TWD and MCDM sorting, provide clear rankings and explanations, which can be beneficial when stakeholders need to understand the rationale behind decisions.

6. Computational resources: Assess the computational resources available for implementing the method. Some methods might require significant computational power or software tools, while others can be applied more straightforwardly.

In conclusion, the selection of the most suitable MCDM method should align with the unique characteristics of decision problems and the specific context in which it is applied. A thoughtful selection process will lead to more effective and informed decision-making.

Chapter 3

Research Results

This chapter provides a concise summary of the main proposals developed in this research memory. The findings and results for each proposal will be briefly discussed. The four proposals are aligned with the different objectives presented in the Introduction chapter:

1. **Defining a new EVCS evaluation method.** The first objective is addressed by introducing a novel EVCS evaluation method that takes into account heterogeneous information and multi-granular linguistic terms.
2. **Modeling the incomparability relation between alternatives.** Our second objective is achieved through the development of models for handling the incomparability relation between alternatives, a critical aspect of EVCS evaluation.
3. **Studying the classification of alternatives.** Within the scope of the third objective, we delve into alternative classification, presenting two significant sub-proposals:
 - A novel fuzzy MCTWD theory.
 - A TODIM-based MCDM sorting method under uncertainty.

3.1. A new EVCS evaluation method considering heterogeneous information and multi-granular linguistic terms

EVCS evaluation is a challenging task due to the presence of conflicting quantitative and qualitative criteria from multiple dimensions. The quantitative criteria are typically represented by numerical data, while qualitative criteria are expressed using linguistic terms. Moreover, the linguistic terms provided by different decision makers often belong to multi-granular linguistic term sets.

To address these challenges, we propose a novel decision-making framework (as shown in Fig.3.1) to facilitate EVCS evaluation under the context of heterogeneous information and multi-granular linguistic terms. First, three information transformation mechanisms are

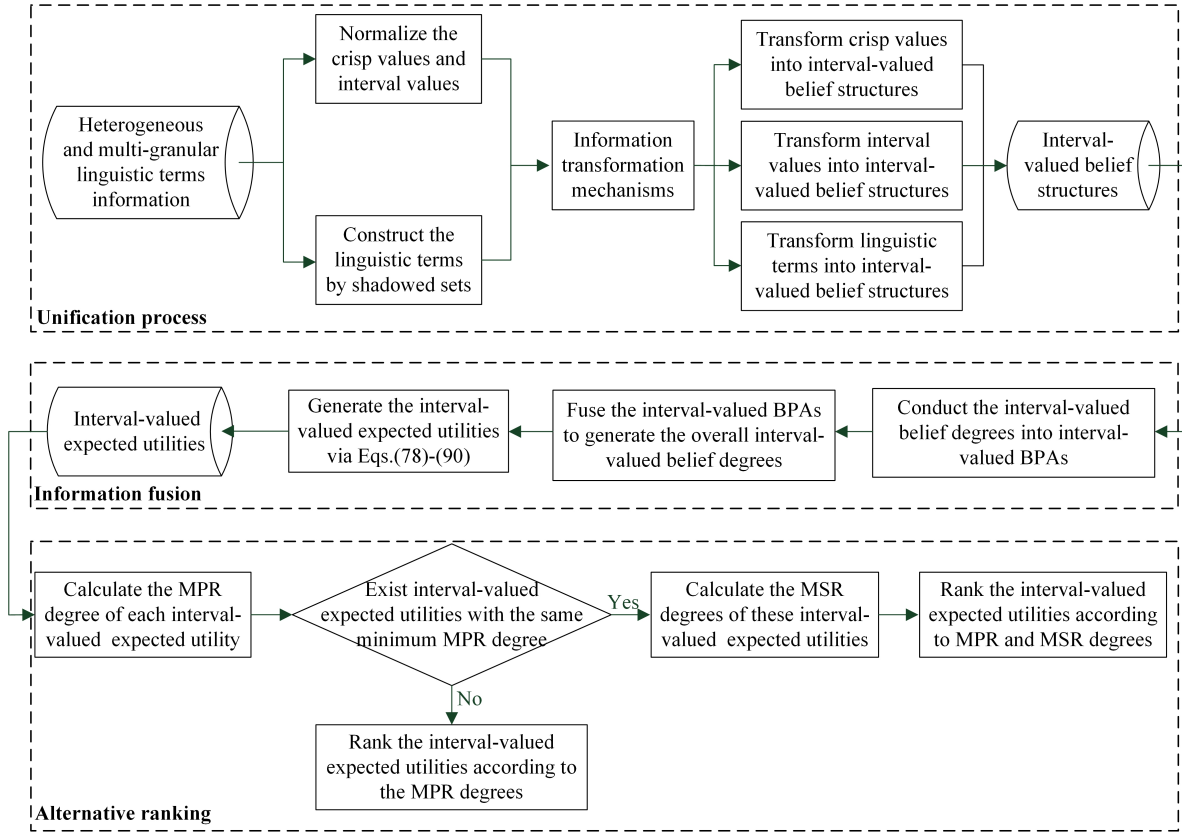


Figure 3.1: The flowchart of the proposed decision-making framework

defined to standardize and unify the heterogeneous information and multi-granular linguistic terms into interval-valued belief structures. Then, a new evaluation information aggregation approach is developed to generate the overall expected utility value for each alternative. Finally, an improved minimax regret approach is developed to compare and rank EVCS alternatives. In this way, we achieve the first objective in Section 1.2.

3.1.1. Information transformation mechanisms

(1) Conducting crisp values into interval-valued belief structures

To facilitate the transformation between crisp values and belief structures, the relative positional relations between the crisp values and assessment grades are revealed, as shown in Fig.3.2. Based on the relative positional relations, the following rules are provided for

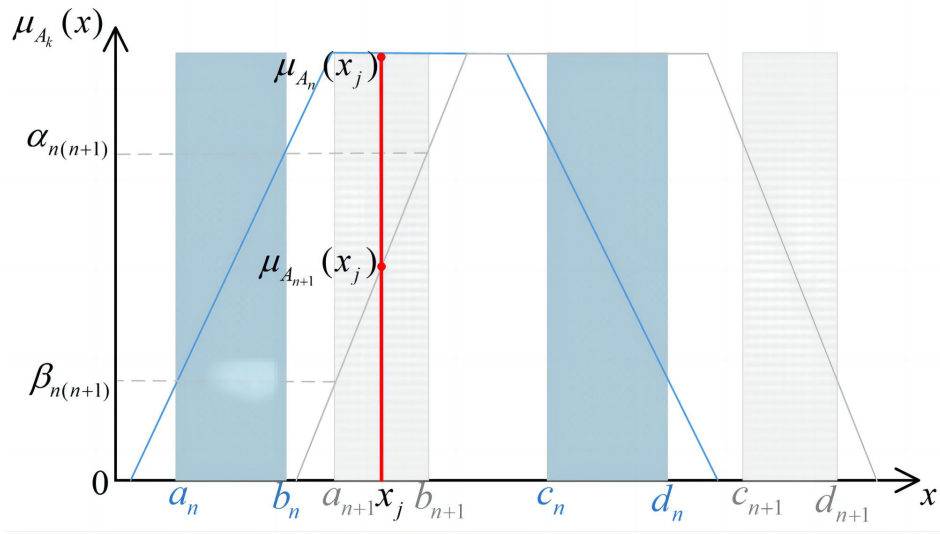


Figure 3.2: The relations between crisp numbers and assessment grades

generating interval-valued belief degrees:

$$\xi^-(x_j \in H_n) = \frac{\mu_{A_n}(x_j)}{\mu_{A_n}(x_j) + \mu_{A_{n+1}}(x_j)} = \frac{1}{1 + \alpha_{n+1}} \quad (3.1)$$

$$\xi^+(x_j \in H_n) = \frac{\mu_{A_n}(x_j)}{\mu_{A_n}(x_j) + \mu_{A_{n+1}}(x_j)} = \frac{1}{1 + \beta_{n+1}} \quad (3.2)$$

$$\xi^-(x_j \in H_{n+1}) = \frac{\mu_{A_{n+1}}(x_j)}{\mu_{A_n}(x_j) + \mu_{A_{n+1}}(x_j)} = \frac{\beta_{n+1}}{1 + \alpha_{n+1}} \quad (3.3)$$

$$\xi^+(x_j \in H_{n+1}) = \frac{\mu_{A_{n+1}}(x_j)}{\mu_{A_n}(x_j) + \mu_{A_{n+1}}(x_j)} = \frac{\alpha_{n+1}}{1 + \beta_{n+1}} \quad (3.4)$$

Using the equations (3.1)-(3.4), the crisp value x_j can be equivalently represented by the following interval-valued belief structure: $S(H_k(x_j)) = \{(H_n, [\xi^-(x_j \in H_n), \xi^+(x_j \in H_n)]), (H_{n+1}, [\xi^-(x_j \in H_{n+1}), \xi^+(x_j \in H_{n+1})])\}$.

(2) Conducting interval values into interval-valued belief structures

This proposal also introduces the interval values to express the quantitative criteria, and develop a new transformation mechanism to conduct the interval values into interval-valued belief structures based on their relative positional relations, as depicted in Fig.3.3. Based on the relative positional relations, the following pair of nonlinear programming models are

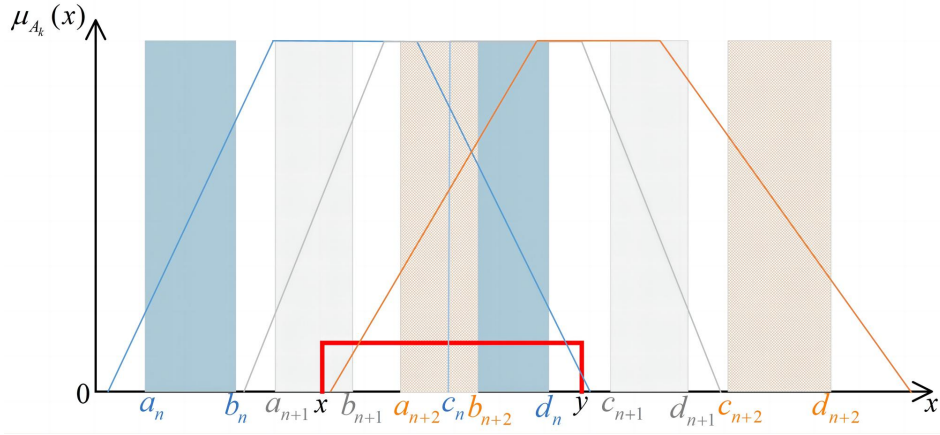


Figure 3.3: The relative positional relations between interval value and fuzzy assessment grades

introduced:

$$\max / \min \quad \xi([x, y] \in H_k) = \frac{l_k(\text{core}) + \mu_{A_k}(x) \cdot l_k(\text{shadow})}{\sum_{k=1}^N (l_k(\text{core}) + \mu_{A_k}(x) \cdot l_k(\text{shadow}))} \quad (3.5)$$

$$s.t. \quad \alpha_k \leq \mu_{A_k}(x) \leq \beta_k, k = 1, \dots, N \quad (3.6)$$

$$l_n(\text{core}) = c_n - x \quad (3.7)$$

$$l_n(\text{shadow}) = d_n - c_n \quad (3.8)$$

$$l_{n+1}(\text{core}) = y - b_{n+1} \quad (3.9)$$

$$l_{n+1}(\text{shadow}) = b_{n+1} - x \quad (3.10)$$

$$l_{n+2}(\text{core}) = y - b_{n+2} \quad (3.11)$$

$$l_{n+2}(\text{shadow}) = b_{n+2} - a_{n+2} \quad (3.12)$$

By solving the above nonlinear programming models, the interval value $[x, y]$ can be equivalently represented by the following interval-valued belief structure: $S(H_k([x, y])) = \{(H_k, [\xi^-([x, y] \in H_k), \xi^+([x, y] \in H_k)]), k = 1, \dots, N\}$.

(3) Conducting linguistic terms into interval-valued belief structures

To handle qualitative criteria expressed using multi-granular linguistic terms, this proposal introduces a new information transformation mechanism to transform these linguistic terms into interval-valued belief structures. Fig.3.4 is provided to show the relative positional relations between linguistic terms and fuzzy assessment grades. Based on the relative

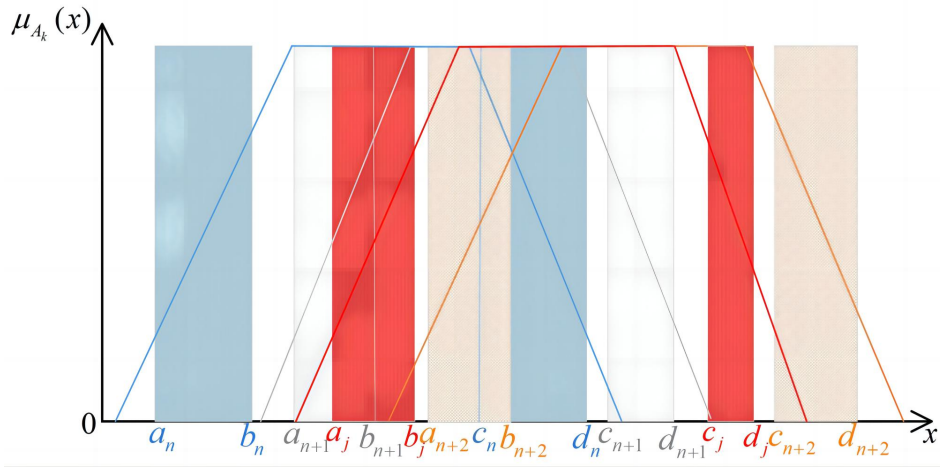


Figure 3.4: The relative position relations between shadowed sets and fuzzy assessment grades

positional relations, the following pair of nonlinear programming models are developed:

$$\max / \min \quad \xi(A_j \in H_k) = S_k / \sum_{k=1}^N S_k \quad (3.13)$$

$$s.t. \quad \alpha_k \leq \mu_{A_k}(x) \leq \beta_k, k = 1, \dots, N \quad (3.14)$$

$$\alpha_j \leq \mu_{A_j}(x) \leq \beta_j \quad (3.15)$$

$$S_k = S_k(\text{core}) + \mu_{A_k}(x)S_k(\text{shadow}) + \mu_{A_j}(x) \quad (3.16)$$

$$S_j(\text{shadow}) + \min\{\mu_{A_k}(x), \mu_{A_j}(x)\}S_{k,j}(\text{shadow})$$

$$S_n(\text{core}) = c_n - b_j \quad (3.17)$$

$$S_n(\text{shadow}) = d_n - c_n \quad (3.18)$$

$$S_{n+1}(\text{core}) = c_{n+1} - b_j \quad (3.19)$$

$$S_{n+1}(\text{shadow}) = d_{n+1} - c_{n+1} \quad (3.20)$$

$$S_{n+2}(\text{core}) = c_j - b_{n+2} \quad (3.21)$$

$$S_{n+2}(\text{shadow}) = b_{n+2} - a_{n+2} \quad (3.22)$$

$$S_j(\text{shadow}) = 2b_j - a_j - b_{n+1} + d_j - c_j \quad (3.23)$$

$$S_{n+1,j}(\text{shadow}) = b_{n+1} - a_j \quad (3.24)$$

Through addressing the above nonlinear programming models, the shadowed set A_j can be equivalently represented by the following interval-valued belief structure: $S(H_k(A_j)) = \{(H_k, [\xi^-(A_j \in H_k), \xi^+(A_j \in H_k)]) | k = 1, \dots, N\}$.

3.1.2. Evaluation information aggregation approach

A new aggregation approach is developed to fuse the interval-valued belief information under multiple criteria. In this approach, both the belief structures and the criteria weights are expressed by interval values, enhancing the flexibility to account for subjective uncertainty.

After aggregating the interval-valued belief information, a pair of nonlinear optimization models are utilized to determine the interval-valued expected utility for each alternative.

This approach is built upon the foundation of the ER algorithm proposed in [125]. The novelty of our proposal is that it offers a comprehensive and rigorous framework for EVCS evaluation under uncertainty, providing a systematic way to combine and analyze different forms of evaluation information. Its ability to handle uncertainty and conflicting information makes it a valuable tool in real-world decision-making problems.

3.1.3. An improved minimax regret approach

In order to compare and rank interval values, we have developed an improved MRA. Before introducing this improved MRA, let us briefly review the concept of MRA as follows:

Definition 3.1 [116]. Consider N interval values, denoted as $I_j = [I_j^-, I_j^+]$ for $j = 1, \dots, N$. The Maximum Primary Regret (MPR) degree of the interval value I_k (also known as the maximum primary loss of expected utility I_k) can be calculated as follows:

$$MPR(I_k) = \max[\max_{j \neq k}(I_j^+) - I_k^-, 0], j = 1, \dots, N \quad (3.25)$$

To establish a complete ranking order for all interval values, Wang et al. [116] introduced the following eliminating steps:

Step 1. Calculate the MPR degree for each interval value and select the one with the minimum MPR degree as the best interval. Suppose I_{k_1} is chosen as the best one, where $1 \leq k_1 \leq N$.

Step 2. Eliminate I_{k_1} from further consideration and recalculate the MPR degree of the remaining interval values. Suppose I_{k_2} has the minimum MPR degree, where $1 \leq k_2 \leq N$.

Step 3. Repeat the above processes until only one interval value is left. The final ranking order of the N interval values is $I_{k_1} \succ I_{k_2} \succ \dots \succ I_{k_N}$, where \succ means be superior to.

While the MRA effectively differentiates between interval values with equal centers but different widths, it still has one notable limitation: it may discard some valuable information. To address this shortcoming, we propose an improved MRA. This improved method incorporates the following rules:

(1) If $\min\{MPR(I_k)\} < \min\{MPR(I_j)\}$ ($j = 1, \dots, N, j \neq k, k = 1, \dots, N$), then interval value I_k is considered to be superior to interval value I_j .

(2) If $\min\{MPR(I_k)\} = \min\{MPR(I_t)\} < \min\{MPR(I_j)\}$ ($j \neq k \neq t, k = 1, \dots, N, t = 1, \dots, N$), the Minimax Secondary Regret (MSR) degrees of $I_k = [I_k^-, I_k^+]$ and $I_t = [I_t^-, I_t^+]$ are calculated to distinguish them.

(2.1) If $\min\{MSR(I_k)\} < \min\{MSR(I_t)\}$ ($k \neq t, k = 1, \dots, N, t = 1, \dots, N$), then I_k is better than I_t and the ranking of the three interval values is $I_k \succ I_t \succ I_j$.

(2.2) If $\min\{MSR(I_k)\} > \min\{MSR(I_t)\}$ ($k \neq t, k = 1, \dots, N, t = 1, \dots, N$), then I_k is better than I_t and the ranking of the three interval values is $I_t \succ I_k \succ I_j$.

(2.3) If $\min\{MSR(I_k)\} = \min\{MSR(I_t)\}$ ($k \neq t, k = 1, \dots, N, t = 1, \dots, N$), then I_k is equal to I_t and the ranking of the three interval values is $I_k \approx I_t \succ I_j$.

By utilizing the improved MRA, we not only effectively distinguish interval values with equal centers but different widths, but also minimize information loss, thereby enhancing the reliability of the EVCS evaluation results.

The paper related to this proposal is the following one:

Wang, Y. M., Pan, X. H., He, S. F., Dutta, B., García-Zamora, D., & Martínez, L. (2022). A New Decision-Making Framework for Site Selection of Electric Vehicle Charging Station With Heterogeneous Information and Multigranular Linguistic Terms. *IEEE Transactions on Fuzzy Systems*, 31(2), 485-499.

3.2. Modeling the incomparability relation between alternatives

To achieve the second objective mentioned in Section 1.2, this section is devoted to the following two main directions:

- (1) Utilizing IT2FSs to model individual semantics and enhance Bessons mean ranks.
- (2) Proposing an IT2F-ORESTE method to manage the incomparability relation.

3.2.1. Modeling individual semantics and enhancing Bessons mean ranks

As human thinking is subjective, decision makers often express their evaluation information using linguistic terms. However, the interpretation of the same word may differ among individuals [73]. The IT2FSs can effectively model this difference by setting Footprint of Uncertainty (FOU), so this proposal introduces the interval type-2 fuzzy computing with model to conduct the linguistic evaluation information into IT2FSs. By employing this model, we can effectively capture the diverse interpretations of linguistic terms, ensuring that the individual semantics are accurately represented in the MCDM process.

Additionally, Besson's mean ranks have been found to cause information loss and may lead to inaccurate conclusions [40]. To address this, a novel interval type-2 fuzzy distance model is proposed to enhance Besson's mean ranks. This model is based on α -cut theory, which subdivides membership functions into different situations to measure the information of each point effectively. By doing so, the proposed model maximizes information elicited from decision makers while avoiding information loss.

To demonstrate the advantages of the proposed interval type-2 fuzzy distance model over Besson's mean ranks, an illustrative example is provided. The results indicate that the proposed model more accurately captures differences in evaluation information, thereby enhancing the reliability of the outcomes. This improvement in the evaluation process is crucial for making informed decisions, especially in situations where individual interpretations and

uncertainties play significant roles.

3.2.2. Managing the incomparability relation

Stage 1. Constructing a weak ranking

i) Calculate the interval type-2 global preference score of alternative z_i towards criterion c_j using the equation:

$$GP(\tilde{r}_{ij}) = [\xi d(\tilde{r}_{ij}, \tilde{r}_j^+) + (1 - \xi)d(w_j, w^+)]^{1/2} \quad (3.26)$$

ii) Generate the interval type-2 fuzzy preference score of alternative z_i as $GP(z_i) = (1/n) \cdot \sum_{j=1}^n GP(\tilde{r}_{ij})$.

iii) Establish the weak ranking by comparing $GP(z_i)$. If $GP(z_i) > GP(z_k)$, then $r(z_i) > r(z_k)$ and $z_k P z_i$; if $GP(z_i) = GP(z_k)$, then $r(z_i) = r(z_k)$ and $z_i I z_k$.

Stage 2. Establishing the PIR structure

i) Calculate the preference intensity between z_i and z_k under criterion c_j using:

$$T_j(z_i, z_k) = \max\{(GP(z_{kj}) - GP(z_{ij})), 0\} \quad (3.27)$$

ii) Define the average preference intensity between z_i and z_k as:

$$T(z_i, z_k) = (1/n) \cdot \sum_{j=1}^n \max\{(GP(z_{kj}) - GP(z_{ij})), 0\} \quad (3.28)$$

iii) Calculate the net preference intensity between z_i and z_k by:

$$\Delta T(z_i, z_k) = T(z_i, z_k) - T(z_k, z_i) \quad (3.29)$$

Using the above rules, the PIR structure of alternatives under IT2FSs environment is established as:

- (1) If $|\Delta T(z_i, z_k)| \geq \sigma$ and $\Delta T(z_i, z_k) > 0$, then $z_i P z_k$.
- (2) If $|\Delta T(z_i, z_k)| \geq \sigma$ and $\Delta T(z_k, z_i) > 0$, then $z_k P z_i$.
- (3) If $|\Delta T(z_i, z_k)| < \sigma$, then there are two cases: if $T(z_i, z_k) < \gamma$ and $T(z_k, z_i) < \gamma$, then $z_i I z_k$; if $T(z_i, z_k) \geq \gamma$ or $T(z_k, z_i) \geq \gamma$, then $z_i R z_k$.

By utilizing the IT2F-ORESTE method, the incomparability relationship between alternatives can be well addressed through the PIR structures. Therefore, the proposed IT2F-ORESTE method provides a promising solution for the EVCS evaluation, ensuring an robust and reliable evaluation outcome.

The paper related to this proposal is the following one:

Pan X.H., Wang Y.M., He S.F., Labella A., & Martínez, L. (2023). An interval type-2 fuzzy ORESTE method for waste-to-energy plant site selection: A case study in China. *Applied Soft Computing*, 136, 110092.

3.3. Studying the classification of alternatives

The methods proposed in subsection 3.1 and 3.2 mainly focus on ranking the alternatives based on their performance. However, it is essential to recognize that even if an alternative is ranked as the top choice, it may still be unsatisfactory. In such cases, the exploration of alternative classification methods becomes a promising approach.

In this research memory, we first investigate the MCTWD method, which can classify alternatives into positive, negative, and boundary decision regions corresponding to acceptable, unacceptable, and alternatives that need further discussion. However, it is important to acknowledge that these three predefined classifications may not always fulfill all the decision-making requirements. To address this limitation, we further explore the TODIM-based sorting method, which offers more flexibility in decision-making by empowering decision makers to determine the number of classifications as needed.

3.3.1. A novel fuzzy MCTWD method

The MCTWD methods have shown promise in enhancing the flexibility of traditional MCDM methods. In this section, we extend the MCTWD method to operate in an interval-valued environment, thereby strengthening its capability to handle uncertainty. The following are the key contributions of this research:

(1) Interval-valued relative loss functions: Due to the complexity of real-world decision situations, this proposal addresses the challenges of reflecting the risks associated with different actions by introducing an interval-valued relative loss function generation approach and discussing the calculation rules of interval-valued thresholds.

(2) Interval-valued relative loss functions for multiple criteria: In most of existing studies, the loss functions of different objects generated by TWD method are the same, which is in contradiction with the real-world decision situations [44]. To eliminate such a contradiction, this proposal explores several rules to generate the interval-valued relative loss functions regarding multiple criteria under uncertain context.

(3) Calculation of interval-valued thresholds: This proposal determines the lower and upper bounds of interval-valued thresholds by extending traditional thresholds calculation method using interval-valued arithmetic algebra. Furthermore, we explore and mathematically prove corresponding axioms related to interval-valued thresholds.

(4) Interval-valued conditional probability: Extending the TOPSIS method to an interval-valued environment, we propose a novel method for calculating interval-valued conditional probabilities. This advancement enhances the applicability of the TOPSIS method in uncertain environments, a feature previously unavailable in existing methods.

It should be highlighted that inputs and outcomes of the proposed models are both interval values. This feature ensures that there is no information transformation during the calculation

process, preserving the completeness of input information and enhancing the information processing capability of the TWD method.

The paper related to this proposal is the following one:

Pan X.H., He S.F., Wang Y.M., & Martínez, L. (2022). A novel interval-valued three-way decision theory under multiple criteria environment. *Knowledge-Based Systems*, 253: 109522.

3.3.2. A TODIM-based sorting method under uncertainty

The MCTWD method, with its three classifications of acceptance, rejection, and further discussion, may lack the desired flexibility for evaluation. To address this limitation, we further introduce the MCDM sorting method into EVCS evaluation. Existing MCDM sorting methods are typically based on the rational expected utility theory [100], which has shown limitations in capturing the true psychological behavior of individuals [47, 105], leading to the concept of bounded rationality [101]. To reflect the bounded rationality of human beings in MCDM sorting problems, we propose an extension of the TODIM method that can better represent the psychological behavior of decision makers and handle MCDM sorting problems in the presence of uncertain information. According to the global prospect values $\pi(\varphi_t) = [\pi(\varphi_t)^-, \pi(\varphi_t)^+]$ generated by the extended TODIM method, the following assignment processes are explored to sort alternatives.

Situation 1. For categories delimited by reference profiles $\pi(r_k)^-, k = 1, \dots, K + 1$.

- (1) If $\pi(r_{k+1})^- < \pi(z_i)^- < \pi(z_i)^+ < \pi(r_k)^-$, the alternative z_i will be completely assigned into category C_k . In this case, the assignment result of alternative z_i can be expressed as $H(z_i)^- = \{C_k, 1\}$.
- (2) If $\pi(r_{k+1})^- < \pi(z_i)^- < \pi(r_k)^- < \pi(z_i)^+ < \pi(r_{k-1})^-$, the alternative z_i will be divided into two parts: $\frac{\pi(r_k)^- - \pi(z_i)^-}{\pi(z_i)^+ - \pi(z_i)^-}$ of alternative z_i belongs to category C_k ; $\frac{\pi(z_i)^+ - \pi(r_k)^-}{\pi(z_i)^+ - \pi(z_i)^-}$ of alternative z_i belongs to category C_{k-1} . Consequently, the assignment result of alternative z_i can be expressed by $H(z_i)^- = \{(C_{k-1}, \frac{\pi(z_i)^+ - \pi(r_k)^-}{\pi(z_i)^+ - \pi(z_i)^-}), (C_k, \frac{\pi(r_k)^- - \pi(z_i)^-}{\pi(z_i)^+ - \pi(z_i)^-})\}$.
- (3) If the alternative z_i only intersects one category C_k and has non-empty intersection subset with any other category, then it completely belongs to category C_k , no matter whether it is entirely included in category C_k or not.

Situation 2. For categories delimited by reference profiles $\pi(r_k)^+, k = 1, \dots, K + 1$. The assignment rules of situation 2 are similar to that of situation 1, as shown below:

- (1) If $\pi(r_{k+1})^+ < \pi(z_i)^- < \pi(z_i)^+ < \pi(r_k)^+$, the alternative z_i will be completely assigned into category C_k , and the assignment result of alternative z_i can be expressed as $H(z_i)^+ = \{C_k, 1\}$.

- (2) If $\pi(r_{k+1})^+ < \pi(z_i)^- < \pi(r_k)^+ < \pi(z_i)^+ < \pi(r_{k-1})^+$, the alternative z_i will be divided into two parts: $\frac{\pi(r_k)^+ - \pi(z_i)^-}{\pi(z_i)^+ - \pi(z_i)^-}$ of alternative z_i belongs to category C_k ; $\frac{\pi(z_i)^+ - \pi(r_k)^+}{\pi(z_i)^+ - \pi(z_i)^-}$ of alternative z_i belongs to category C_{k-1} . Consequently, the assignment result of alternative z_i can be expressed by $H(z_i)^+ = \{(C_{k-1}, \frac{\pi(z_i)^+ - \pi(r_k)^+}{\pi(z_i)^+ - \pi(z_i)^-}), (C_k, \frac{\pi(r_k)^+ - \pi(z_i)^-}{\pi(z_i)^+ - \pi(z_i)^-})\}$.
- (3) If the alternative z_i only intersects one category C_k and has non-empty intersection subset with any other category, then it completely belongs to category C_k , no matter whether it is entirely included in category C_k or not and the result can be expressed as $H(z_i)^- = \{C_k, 1\}$.

By introducing the TODIM method, the proposed method enables the consideration of the influence of decision makers' psychological behavior on the assignment results. This is an important contribution for MCDM sorting problems, because the decision makers are usually bounded rationality and their psychological behavior will significantly affect the final results, especially in the states of risk and uncertainty.

The paper related to this proposal is the following one:

Pan, X. H., He, S. F., Wang, Y. M., & Martínez, L. (2023). A TODIM based Multi-Criteria Group Decision-Making Sorting Method under Uncertainty. *European Journal of Operational Research*, Under Review.

Chapter 4

Conclusions and Future Works

Chapter 4 presents the concluding remarks of our research and identifies potential areas for future exploration. We summarize the main proposals and results obtained in this research memory and outline promising directions for further investigation.

4.1. Conclusions

Fuzzy MCDM is a powerful and flexible approach used to tackle decision problems that involve multiple conflicting criteria and uncertainty. Unlike traditional MCDM methods, which rely on crisp numerical values, fuzzy MCDM incorporates the concept of fuzzy sets to manage imprecise and uncertain information. By capturing imprecision and uncertainty in decision-making processes, fuzzy MCDM offers a more comprehensive and realistic perspective for decision analysis.

The EVCS plays a vital role in supporting the widespread adoption of electric vehicles and promoting sustainable transportation. Evaluating EVCS under uncertain environments with multiple criteria demands sophisticated MCDM methods. Therefore, fuzzy MCDM has found applications in EVCS evaluation. Although existing studies have made significant contributions, they still face challenges in managing heterogeneous information and multi-granular linguistic terms, capturing psychological behavior of human, managing incomparability relation, and more, as outlined in Chapter 1. Therefore, this research memory conducts a more in-depth study on fuzzy MCDM and its application to EVCS evaluation.

Through our research, we have obtained novel, remarkable, and relevant results, addressing the outlined challenges while fulfilling the objectives stated in Section 1.2. Our contributions can be summarized as follows:

1. We have proposed a new fuzzy MCDM framework specifically for addressing EVCS evaluation problems. Within this framework, three information transformation mechanisms are introduced to unify EVCS evaluation information under different criteria elicited by decision makers. Leveraging the evidential reasoning algorithm, we have introduced a

new information fusion approach for generating overall evaluation information of alternatives. Additionally, we have developed an improved MRA approach, enhancing the comparison and ranking of EVCS alternatives.

2. To manage MCDM problems under uncertain environments, we have proposed an interval type-2 fuzzy ORESTE method. The proposal includes establishing a sustainable evaluation index system based on the BOCR model, which provides a potential solution for analyzing the criteria of EVCS evaluation. Furthermore, we have introduced the ORESTE method to establish the PIR structure under IT2FSs environments, effectively managing both the incomparability relationship and individual semantics, successfully achieving the third objective outlined in Section 1.2.
3. We have introduced TWD theory into MCDM methods, establishing a novel decision-making framework. In this framework, both input and output information are expressed as interval values, effectively reducing information loss and enhancing uncertainty processing capability. Moreover, to further improve the flexibility of TWD method, we have proposed a novel MCDM sorting approach, named as IVG-TODIM-S method. By incorporating the personalized CRP model, the IVG-TODIM-S method improves decision makers' consistency and enhances the reliability of assignment results. Additionally, through the introduction of the TODIM method, our proposal considers the influence of decision makers' psychological behavior on the decision results, successfully achieving the fourth objective outlined in Section 1.2.

4.2. Future Works

While our research has made significant contributions, there are still exciting opportunities for future investigations:

1. Hybrid approaches: By integrating different approaches, we can leverage the strengths of each method and overcome their limitations. Thus, exploring hybrid approaches that combine fuzzy MCDM with other methodologies, such as machine learning, artificial intelligence, or optimization techniques, could yield more powerful and efficient tools for addressing MCDM problems.
 2. Minimum cost consensus model: In the process of consensus adjustment, we not only need to persuade individuals with low consensus to adjust their opinions to achieve consensus, but also need to minimize the consensus cost. Therefore, investigating the integration of the minimum cost consensus model with fuzzy MCDM methods is a promising research direction.
 3. Decision support system: The decision support system can streamline the MCDM process, reduce the computational burden, and facilitate the use of the proposed methods.
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Therefore, developing a decision support system based on the proposed fuzzy MCDM approaches can provide stakeholders with user-friendly tools for EVCS evaluation and other applications.

By pursuing these future research directions, we aim to continue advancing the field of fuzzy MCDM and its application to EVCS evaluation, ultimately contributing to sustainable transportation and informed MCDM practices.

Additional Publications

Regarding the diffusion of our scientific results, besides the publications included in this research memory, we highlight the following contributions that have been published:

† International journals:

- Pan X.H., He S.F., Wang Y.M., Chin K.S. Multi-granular hybrid information-based decision-making framework and its application to waste to energy technology selection. *Information Sciences*, 2022, 587: 450-472.
- Pan X.H., Wang Y.M., Chin K.S. A large-scale group decision-making method for site selection of waste to energy project under interval type-2 fuzzy environment. *Sustainable Cities and Society*, 2021, 71: 103003.

† Book chapters:

- Xiao-Hong Pan, Shi-Fan He, Diego García-Zamora, Luis Martínez. “Interval type-2 fuzzy decision analysis framework based on Online Textual Reviews”. In: *Advances in Complex Decision Making: Using Machine Learning and Tools for Service-Oriented Computing*. Taylor & Francis Group, LLC CRC, Routledg; 2023

Appendix A

Resumen escrito en Español

A.1. Motivación

El rápido ritmo de la urbanización, el desarrollo económico y el crecimiento de la población a menudo conduce a un aumento del consumo de energía [26, 115]. A pesar de los esfuerzos en curso para diversificar las fuentes de energía, los combustibles fósiles siguen siendo los principales contribuyentes al consumo mundial de energía, representando el 81% del total en 2019, según informa la Agencia Internacional de la Energía (AIE) [1]. Sin embargo, la fuerte dependencia de los combustibles fósiles plantea dos retos críticos: (1) la naturaleza finita y no renovable de los combustibles fósiles hace temer una crisis energética inminente, ya que se prevé su agotamiento en un futuro próximo [8, 84] y (2) la combustión de combustibles fósiles libera cantidades sustanciales de dióxido de carbono, lo que agrava el efecto invernadero y contribuye a la contaminación medioambiental [77, 79]. Ante estos retos, es crucial explorar alternativas limpias y sostenibles. La industria del transporte, al ser un importante determinante de la demanda de energía [76], ha tomado medidas para reducir su dependencia de los combustibles fósiles. Por ejemplo, se han hecho esfuerzos para explorar medios de transporte más limpios que puedan sustituir a los vehículos propulsados por combustibles fósiles.

El vehículo eléctrico, propulsado por un motor eléctrico y una batería recargable, ofrece varias ventajas, como bajas emisiones, rentabilidad y alta eficiencia [6, 56]. Además, mediante la adopción de un modo de carga adecuado, los vehículos eléctricos pueden ayudar a gestionar los picos de carga de energía, proporcionar reservas de giro y mejorar la integración de las fuentes de energía renovables [34, 114]. En consecuencia, el desarrollo y la adopción generalizada de los vehículos eléctricos pueden hacer frente a las preocupaciones relacionadas con los combustibles fósiles y promover el funcionamiento seguro, estable y rentable de la red eléctrica [38]. Como resultado, muchos países han puesto en marcha diversas estrategias para apoyar la producción y venta de vehículos eléctricos, lo que ha llevado a un aumento significativo de su despliegue en todo el mundo. A finales de 2020, había aproximadamente 10 millones de vehículos eléctricos en el mundo, y a pesar del impacto de la pandemia COVID-

19, las matriculaciones de vehículos eléctricos aumentaron un 41% en 2020 [2]. Este rápido crecimiento de los vehículos eléctricos ha creado una importante demanda de estaciones de carga para vehículos eléctricos (EVCS).

El EVCS, como proveedor de energía para los vehículos eléctricos, desempeña un papel crucial para el desarrollo de la industria del vehículo eléctrico. El establecimiento de EVCS eficientes, convenientes y rentables no sólo aumenta la disposición de los consumidores a comprar vehículos eléctricos, sino que también impulsa el desarrollo general de la industria. Los EVCS actuales se pueden clasificar en tres tipos principales: estaciones de carga conductiva, estaciones de carga inductiva y estaciones de sustitución de baterías [36]. Entre ellas, las estaciones de carga conductiva son las más instaladas, que utilizan una conexión física, normalmente a través de cables, para transferir energía eléctrica desde la infraestructura de carga al sistema de baterías del vehículo [4, 27, 92, 97, 109]. Las estaciones de carga conductoras garantizan una transferencia de energía eficiente, lo que permite tiempos de carga cómodos y relativamente rápidos [124]. En consecuencia, esta investigación se centra específicamente en la evaluación de las estaciones de carga conductoras. Al centrar la investigación en la evaluación de las estaciones de carga conductoras, esta investigación tiene como objetivo profundizar en las consideraciones específicas, desafíos y soluciones relacionadas con la evaluación EVCS.

En la práctica, la evaluación de los EVCS suele estar influida por múltiples criterios contradictorios de varias dimensiones, como los factores sociales, económicos y medioambientales [38, 117]. En consecuencia, la evaluación de EVCS puede considerarse un problema de toma de decisiones con criterios múltiples (MCDM). Hasta ahora, numerosos estudios han empleado métodos MCDM para abordar los problemas de evaluación EVCS desde diferentes perspectivas [7, 9, 38, 39, 59, 83, 99, 114, 130, 132], con el objetivo de proporcionar herramientas de apoyo a la toma de decisiones y marcos para que las partes interesadas tomen decisiones informadas. A pesar de las importantes contribuciones realizadas por las investigaciones existentes, sigue habiendo varias limitaciones que deben abordarse:

1. Las investigaciones existentes en materia de evaluación de EVCS se centran principalmente en la información homogénea y los conjuntos de términos con una única granularidad. Sin embargo, los criterios que influyen en la EVCS pueden clasificarse a grandes rasgos en dos categorías: criterios cuantitativos y criterios cualitativos. Estas dos categorías de criterios requieren normalmente diferentes enfoques de modelización [18, 128], ya que implican diferentes formatos de información. En concreto, los criterios cuantitativos suelen expresarse mediante datos numéricos, mientras que los criterios cualitativos se representan mediante términos lingüísticos [20, 94]. Además, debido a las variaciones en la formación, experiencia y conocimientos individuales, los términos lingüísticos obtenidos por los diferentes responsables de la toma de decisiones a menudo se definen usando conjuntos de términos lingüísticos multigranulares [19, 134]. La forma de gestionar eficazmente la información heterogénea y los términos lingüísticos multi-
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granulares sigue siendo un reto pendiente en la investigación sobre la evaluación de la EVCS.

2. Las investigaciones existentes en evaluación de EVCS a menudo ignoran las consideraciones de la relación de incomparabilidad entre alternativas. En la literatura, existen principalmente dos tipos de métodos MCDM: los métodos basados en valores de utilidad y los métodos de outranking [65]. Los métodos basados en valores de utilidad clasifican alternativas basadas en valores agregados, mientras que los métodos de outranking utilizan comparaciones por pares para clasificar alternativas. Sin embargo, ambos métodos tienen limitaciones. Los métodos basados en valores de utilidad no reflejan adecuadamente la relación de incomparabilidad entre alternativas, y la solidez de los resultados de los métodos de outranking puede carecer a veces de precisión [64]. Por lo tanto, es necesario un nuevo enfoque que combine los puntos fuertes de los métodos basados en valores de utilidad y los métodos de outranking, teniendo en cuenta la relación de incomparabilidad entre alternativas para producir resultados más fiables.
3. Los estudios anteriores sobre evaluación de EVCS se centran principalmente en la clasificación de las alternativas. Cabe señalar que la alternativa clasificada en primer lugar también tiene la posibilidad de ser una alternativa insatisfactoria. La selección de una alternativa de este tipo podría aumentar significativamente el riesgo de decisión. Para resolver este problema, una solución prometedora es introducir en la evaluación EVCS los métodos de clasificación multicriterio (MCC), como el método de clasificación multicriterio (MCS) y el método de decisión tridireccional multicriterio (MCTWD). Los métodos MCC pretenden clasificar un conjunto de alternativas en varias categorías ordenadas predefinidas en función de múltiples criterios [46, 49]. Al establecer categorías predefinidas, se puede reducir el riesgo de decisión, ya que no se elegirán las alternativas que caigan en categorías inaceptables.

Al abordar las limitaciones de los estudios existentes, esta memoria de investigación se dedica a desarrollar nuevos métodos MCDM difusos para abordar los retos de la transformación de información heterogénea, el cálculo de pesos de criterios bajo incertidumbre, la descripción de relaciones de incomparabilidad y la clasificación de alternativas en problemas de evaluación EVCS.

A.2. Objetivos

Motivada por los retos expuestos anteriormente, esta memoria de investigación pretende alcanzar los siguientes objetivos:

1. *Evaluar EVCS con información heterogénea y conjuntos de términos lingüísticos multi-granulares*: Este objetivo pretende establecer nuevos mecanismos de transformación de
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la información que puedan unificar la información heterogénea y los conjuntos de términos lingüísticos multigranulares implicados en la evaluación de EVCS. Además, se propondrá un nuevo enfoque de fusión de la información para generar las utilidades globales esperadas de las alternativas potenciales de EVCS. A continuación, se desarrollará un enfoque mejorado Minimax Regret Approach (MRA) para comparar y clasificar las alternativas potenciales. La aplicabilidad y viabilidad del método propuesto se demostrará mediante un estudio de caso sobre la selección de emplazamientos para EVCS.

2. *Considerar la relación de incomparabilidad entre alternativas y la semántica individual en la evaluación EVCS:* Este objetivo consiste en desarrollar un nuevo mecanismo de procesamiento de la información que refleje la semántica individual y mejore los rangos medios de Bessons. Este mecanismo tendrá más en cuenta el grado de diferencia entre la información de evaluación, con el fin de mejorar la fiabilidad de los resultados. Además, también se desarrollará un método ORESTE (organisation, rangement et Synthèse de données relationnelles, in French) difuso para analizar los conflictos entre alternativas potenciales y seleccionar la opción más deseable. La aplicación del método propuesto se estudiará mediante casos prácticos.
3. *Estudiar la categorización/clasificación de alternativas en problemas de evaluación EVCS:* Este objetivo pretende proporcionar no sólo el orden de clasificación de las alternativas, sino también su clasificación, que consta de dos contenidos clave: Los métodos MCTWD, que ofrecen la capacidad de clasificar las alternativas en positivas, negativas y regiones límite correspondientes a la aceptación, el rechazo y el aplazamiento; y los métodos de categorización/clasificación MCDM, que nos permiten ofrecer una gama más amplia de clasificaciones basadas en requisitos y criterios específicos.

Con la consecución de estos objetivos, esta investigación pretende proporcionar valiosas herramientas de apoyo a la toma de decisiones para las partes interesadas implicadas en la evaluación de los EVCS, impulsando en última instancia el desarrollo sostenible de la industria de los vehículos eléctricos.

A.3. Estructura

De acuerdo con el artículo 25, punto 2, de la vigente normativa de Estudios de Doctorado de la Universidad de Jaén (RD. 99/2011), esta tesis doctoral consistirá en una recopilación de artículos publicados o presentados por el doctorando, contribuyendo cada uno de ellos al cumplimiento de los objetivos expuestos en el apartado anterior. La investigación comprende cuatro artículos, tres de los cuales ya han sido publicados en revistas de reconocido prestigio internacional indexadas en la base de datos Journal Citation Reports (JCR), mientras que el restante ha sido enviado a revistas internacionales también indexadas en la base de datos JCR.

La estructura de esta memoria de investigación se organiza del siguiente modo:

- **Capítulo 2:** Presenta varios conceptos fundamentales relacionados con la investigación de la tesis doctoral, como la metodología de evaluación EVCS, el modelado de información mediante conjuntos difusos tipo-2 intervalares (IT2FS) y los conjuntos sombreados. Además, en este capítulo también se presentan algunos métodos MCDM relacionados, como el método TWD, el método de ordenación MCDM, el método TODIM (an acronym in Portuguese TOMada de Decisão Iterativa Multicritério) y el método ORESTE.
- **Capítulo 3:** Se presentarán brevemente las propuestas publicadas que conforman la memoria de investigación. Además, se presentará una discusión concisa de cada resultado obtenido para ilustrar los logros de nuestra investigación.
- **Capítulo 4:** Este capítulo constituye el núcleo de la tesis doctoral, ya que engloba cuatro publicaciones fruto de la investigación. Cada publicación se presenta junto con la información relativa a los índices de calidad en los que se han publicado las propuestas.
- **Capítulo 5:** En este capítulo se resumen las principales conclusiones de la tesis doctoral, junto con la introducción de varias áreas prometedoras para futuras investigaciones.

A.4. Resumen

En los últimos años, los vehículos eléctricos han cobrado un impulso considerable como alternativa sostenible a los vehículos tradicionales con motor de combustión interna. Las estaciones de recarga de VE sirven de enlace vital entre los usuarios de VE y la electrificación de sus vehículos. Son esenciales para proporcionar opciones de recarga cómodas y accesibles para los VE, garantizando que los conductores puedan elegir con confianza la movilidad eléctrica. En consecuencia, la evaluación de la calidad, el rendimiento y la accesibilidad de estas estaciones de recarga se ha convertido en un elemento crucial para promover la transición al transporte eléctrico. En este proceso de evaluación intervienen múltiples factores, como los sociales, económicos y medioambientales. Para equilibrar la influencia de estos factores, se han introducido muchos métodos MCDM en la evaluación de EVCS y se han obtenido resultados satisfactorios. Sin embargo, sigue siendo innegable que existen retos y limitaciones que justifican nuevos estudios, como la gestión de información heterogénea y conjuntos de términos lingüísticos multigranulares, la incorporación del comportamiento psicológico humano y el tratamiento de las relaciones de incomparabilidad. Para abordar estos retos, esta memoria de investigación pretende:

1. Establecer mecanismos novedosos de transformación de la información capaces de unificar la información heterogénea y los conjuntos de términos lingüísticos multigranulares inherentes a la evaluación EVCS. Además, propondrá un enfoque innovador de fusión de
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la información para calcular las utilidades globales esperadas de las alternativas EVCS potenciales. Posteriormente, se desarrollará un método MRA mejorado para facilitar una comparación y clasificación exhaustivas de estas alternativas potenciales. La viabilidad y eficacia de esta metodología propuesta se demostrará mediante un estudio de caso sobre la selección de emplazamientos para EVCS.

2. Desarrollar un nuevo mecanismo de tratamiento de la información que tenga en cuenta la semántica individual y mejore los rangos medios de Besson. Este mecanismo tendrá debidamente en cuenta los distintos grados de diferencia entre la información de evaluación, aumentando así la fiabilidad de los resultados. Además, se desarrollará un método ORESTE difuso para analizar los conflictos entre alternativas potenciales y seleccionar la opción más deseable. La aplicación de este método propuesto se examinará rigurosamente mediante estudios de casos.
3. Proporcionar no sólo un orden de clasificación de las alternativas, sino también sus clasificaciones, abarcando dos componentes críticos: Los métodos MCTWD, que poseen la capacidad de clasificar las alternativas en positivas, negativas y regiones límite correspondientes a la aceptación, el rechazo y el aplazamiento; y los métodos de clasificación MCDM, que nos permiten ofrecer una gama más amplia de clasificaciones basadas en requisitos y criterios específicos del problema.

A.5. Conclusiones y Trabajos Futuros

El capítulo A.5 presenta las observaciones finales de nuestra investigación e identifica posibles áreas de exploración futura. Resumimos las principales propuestas y resultados obtenidos en esta memoria de investigación y esbozamos direcciones prometedoras para futuras investigaciones.

A.5.1. Conclusiones

El MCDM difuso es un enfoque potente y flexible que se utiliza para abordar problemas de decisión que implican múltiples criterios contradictorios e incertidumbre. A diferencia de los métodos tradicionales de MCDM, que se basan en valores numéricos precisos, el MCDM difuso incorpora el concepto de conjuntos difusos para gestionar la información imprecisa e incierta. Al captar la imprecisión y la incertidumbre en los procesos de toma de decisiones, el MCDM difuso ofrece una perspectiva más completa y realista para el análisis de decisiones.

Los EVCS desempeñan un papel vital en el apoyo a la adopción generalizada de vehículos eléctricos y la promoción del transporte sostenible. La evaluación de los EVCS en entornos inciertos con múltiples criterios exige métodos MCDM sofisticados. Por ello, el MCDM difuso ha encontrado aplicaciones en la evaluación de EVCS. Aunque los estudios existentes

han hecho contribuciones significativas, todavía se enfrentan a retos en la gestión de información heterogénea y términos lingüísticos multigranulares, la captura del comportamiento psicológico del ser humano, la gestión de la relación de incomparabilidad, y más, tal y como se indica en el capítulo 1. Por lo tanto, esta memoria de investigación realiza un estudio más profundo sobre MCDM difuso y su aplicación a la evaluación de EVCS.

A través de nuestra investigación, hemos obtenido resultados novedosos, notables y relevantes, abordando los retos expuestos y cumpliendo los objetivos planteados en la Sección A.2. Nuestras contribuciones pueden resumirse como sigue:

1. Hemos propuesto un nuevo marco difuso MCDM específicamente para abordar los problemas de evaluación EVCS. Dentro de este marco, se introducen tres mecanismos de transformación de la información para unificar la información de evaluación EVCS bajo diferentes criterios obtenidos por los responsables de la toma de decisiones. Aprovechando el algoritmo de razonamiento basado en la evidencia, hemos introducido un nuevo enfoque de fusión de información para generar información de evaluación global de alternativas. Además, hemos desarrollado un enfoque MRA mejorado, que mejora la comparación y la clasificación de las alternativas EVCS.
 2. Para gestionar problemas de MCDM en entornos inciertos, hemos propuesto un método ORESTE difuso de tipo intervalo-2. La propuesta incluye el establecimiento de un sistema de índice de evaluación sostenible basado en el modelo BOCR, que proporciona una solución potencial para analizar los criterios de evaluación EVCS. Además, hemos introducido el método ORESTE para establecer la estructura PIR bajo entornos IT2FSs, gestionando eficazmente tanto la relación de incomparabilidad como la semántica individual, logrando con éxito el tercer objetivo planteado en la Sección A.2.
 3. Hemos introducido la teoría TWD en los métodos MCDM, estableciendo un novedoso marco de toma de decisiones. En este marco, tanto la información de entrada como la de salida se expresan como valores de intervalo, lo que reduce eficazmente la pérdida de información y mejora la capacidad de procesamiento de la incertidumbre. Además, para mejorar aún más la flexibilidad del método TWD, hemos propuesto un novedoso enfoque de clasificación MCDM, denominado método IVG-TODIM-S. Al incorporar el modelo CRP personalizado, el método IVG-TODIM-S mejora la coherencia de los responsables de la toma de decisiones y aumenta la fiabilidad de los resultados de la asignación. Además, mediante la introducción del método TODIM, nuestra propuesta tiene en cuenta la influencia del comportamiento psicológico de los decisores en los resultados de la decisión, logrando con éxito los tres objetivos descritos en la Sección A.2.
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A.5.2. Trabajos Futuros

Aunque nuestra investigación ha hecho aportaciones significativas, aún quedan interesantes oportunidades para futuras investigaciones:

1. Enfoques híbridos: Integrando distintos enfoques, podemos aprovechar los puntos fuertes de cada método y superar sus limitaciones. Así, la exploración de enfoques híbridos que combinen la GCDM difusa con otras metodologías, como el aprendizaje automático, la inteligencia artificial o las técnicas de optimización, podría dar lugar a herramientas más potentes y eficientes para abordar los problemas de GCDM.
2. Modelo de consenso de coste mínimo: En el proceso de ajuste del consenso, no sólo necesitamos persuadir a los individuos con bajo consenso para que ajusten sus opiniones y alcancen el consenso, sino que también necesitamos minimizar el coste del consenso. Por lo tanto, investigar la integración del modelo de consenso de coste mínimo con los métodos difusos de MCDM es una dirección de investigación prometedora.
3. Sistema de apoyo a la toma de decisiones: El sistema de apoyo a la toma de decisiones puede agilizar el proceso de MCDM, reducir la carga computacional y facilitar el uso de los métodos propuestos. Por lo tanto, el desarrollo de un sistema de apoyo a la toma de decisiones basado en los enfoques MCDM difusos propuestos puede proporcionar a las partes interesadas herramientas fáciles de usar para la evaluación de EVCS y otras aplicaciones.

Siguiendo estas futuras líneas de investigación, nuestro objetivo es continuar avanzando en el campo de la MCDM difusa y su aplicación a la evaluación de EVCS, contribuyendo en última instancia al transporte sostenible y a las prácticas de MCDM informadas.

Publicaciones adicionales En cuanto a la difusión de nuestros resultados científicos, además de las publicaciones incluidas en esta memoria de investigación, destacamos las siguientes contribuciones que han sido publicadas:

† Revistas internacionales:

- Pan X.H., He S.F., Wang Y.M., Chin K.S. Multi-granular hybrid information-based decision-making framework and its application to waste to energy technology selection. *Information Sciences*, 2022, 587: 450-472.
- Pan X.H., Wang Y.M., Chin K.S. A large-scale group decision-making method for site selection of waste to energy project under interval type-2 fuzzy environment. *Sustainable Cities and Society*, 2021, 71: 103003.

† Capítulos de libros:

- Xiao-Hong Pan, Shi-Fan He, Diego García-Zamora, Luis Martínez. "Interval type-2 fuzzy decision analysis framework based on Online Textual Reviews". In: *Advances*

in Complex Decision Making: Using Machine Learning and Tools for Service-Oriented Computing. Taylor & Francis Group, LLC CRC, Routledg; 2023

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