energies

MDPI

Article

Optimized Grid Partitioning and Scheduling in Multi-Energy Systems Using a Hybrid Decision-Making Approach

Peng Liu [1,*], Tieyan Zhang [1], Furui Tian [2], Yun Teng [1] and Miaodong Yang [3]

[1] School of Electrical Engineering, Shenyang University of Technology, Shenyang 110000, China; zty621103@sina.com (T.Z.); tengyun@sut.edu.cn (Y.T.)
[2] Zhuji Power Supply Company, State Grid Zhejiang Electric Power Co., Ltd., Zhuji 311800, China; sj_tianliqian@sina.com
[3] Liaoning Qinghe Power Generation Co., Ltd., Tieling 112003, China; ymd30666@sina.com
* Correspondence: liupeng@smail.sut.edu.cn

Abstract: This paper presents a thorough review of our state-of-the-art technique for enhancing dynamic grid partitioning and scheduling in multi-energy source systems. We use a hybrid approach to T-spherical fuzzy sets, combining the alternative ranking order method accounting for the two-step normalization (AROMAN) method for alternating ranking order to enable two-step normalisation with the method based on removal effects of criteria (MEREC) for eliminating criteria effects. This enables us to obtain the highest level of accuracy from our findings. To ascertain the relative importance of these criteria, we use MEREC to perform a rigorous examination of the influence that each evaluation criterion has on the outcomes of the decision-making process. In addition, we use AROMAN to provide a strong foundation for assessing potential solutions by accounting for spherical fuzzy sets to account for any ambiguity. We illustrate how our approach successfully considers several factors, such as social acceptability, technical feasibility, environmental sustainability, and economic feasibility, through the analysis of an extensive case study. Our approach provides decision-makers (DMs) with a rigorous and rational framework for assessing and choosing the best grid division and scheduling options. This is done in an effort to support the administration and design of resilient and sustainable multi-energy systems. This research contributes to the growing body of knowledge in this area by offering insights that help to direct policy, planning, and investment decisions in the shift towards more sustainable energy infrastructures. Moreover, it adds to the growing body of information on multi-criteria decision-making (MCDM) in energy system optimization.

Keywords: AROMAN; MEREC; grid partitioning; sustainable energy; T-spherical fuzzy sets; multi-energy systems

check for updates

Citation: Liu, P.; Zhang, T.; Tian, F.; Teng, Y.; Yang, M. Optimized Grid Partitioning and Scheduling in Multi-Energy Systems Using a Hybrid Decision-Making Approach. *Energies* **2024**, *17*, 3253. https://doi.org/10.3390/en17133253

Academic Editor: Ahmed Abu-Siada

Received: 29 May 2024
Revised: 24 June 2024
Accepted: 26 June 2024
Published: 2 July 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Currently, energy systems are undergoing a paradigm shift towards more sustainability and diversification. This shift is happening quickly worldwide [1–3]. The employment of sustainable energy sources such as wind and solar has substantially risen, leading to a decrease in greenhouse gas emissions and lighter loads due to rising energy consumption [4]. In spite of this, a sizable amount of renewable energy generation is decreased annually. This is mostly explained by the erratic and sporadic character of renewable resources in addition to their restricted ability to transport energy [5]. The efficiency of these several energy conversion processes, which involve a significant penetration of renewable energy sources, could be enhanced by the implementation of an integrated energy system (IES). This kind of system may effectively meet the needs of different end users by providing them with different energy sources, leading to the utilisation of energy in a tiered way [6]. Many energy sources have been examined and recommended for usage in IES structures. Gas, power, heat, and cooling are among of these sources. In a power system combining large-scale wind power and power-to-gas technologies, the coupling between electrical energy

and natural gas can be optimised for short-term operations [7]. An innovative combined heat and power (CHP) design was presented in [8], significantly reducing both carbon emissions and operating expenses. This was accomplished by incorporating power-to-grid and carbon capture and storage (CCS) technologies into the system. Because accelerating energy use and climate change are occurring concurrently, the world must immediately begin to transition to more environmentally friendly energy systems.

Multi-energy systems can be integrated with energy storage, demand-side management methods, and renewable power sources to provide more resilient, adaptable, and efficient energy infrastructures. It is now possible to build more robust and efficient energy infrastructure. Similar systems could use current energy carriers such as heat, electricity, hydrogen, and even natural gas, all of which are feasible options. The systems mentioned above have the ability to include a variety of additional energy carriers into their operations. They also promote communication, which benefits a large number of stakeholders and enterprises [9]. Because of their complexity, multi-energy systems are substantially more challenging to run and manage. Given the features of these systems, this may be difficult to accomplish. It is critical to act in order to address the most pressing issue of dynamic grid segmentation. This divide is based on the reality that energy assets, along with energy production and consumption, are subject to time and location uncertainties. This is one of the most pressing issues, and must be handled immediately owing to the magnitude of the situation. Dispersed bidirectional links in multi-energy systems are required in order to mitigate or entirely eliminate supply–demand mismatches while optimising resource efficiency. In contrast, previous energy systems require centralised and unidirectional flow patterns, which is different from how systems are now being set up.

One way to accomplish dynamic grid partitioning is to divide the energy grid into smaller networks with similar temporal and geographical features. These zones or clusters can enable the utilisation of certain resources for demand-side development, management, and storage [10]. Operators may enhance resource allocation, system resilience, and energy losses by adjusting partitioning boundaries based on dynamic factors such as shifting demand patterns or changes in renewable energy generation [11]. Yin et al. [12] proposed a new multi-objective algorithm for use in energy-efficient job shop scheduling with variable spindle speeds. This method finds a balance between energy consumption and productivity. This system enables the values of certain parameters to be maximised, improved, or minimised. Effective scheduling techniques are required to ensure that all of the different energy sources that comprise the multi-energy system work in tandem. Scheduling algorithms may help in finding the ideal unit configuration for energy production, storage, and conversion. To comply with public requirements, efforts are being made to cut expenses and emissions while meeting a variety of other performance criteria. Sophisticated scheduling algorithms are required in dynamic multi-energy systems to accommodate fluctuating renewable energy sources, time-varying demand profiles, and unexpected market conditions. These algorithms must be versatile enough to handle a wide range of time scales and to account for changes as they occur.

The use of MCDM allows for a thorough examination of the different grid partitioning and scheduling approaches utilised in multi-energy systems. Ramana et al. [13] developed an approach for analysing possible solar power plant locations. This strategy takes into account a wide range of elements, including technical, environmental, and economical considerations. The goal of inventing this approach was to increase the effectiveness of the assessment process. Berbiche et al. [14] investigated automated decision-making using fuzzy logic. The ultimate goal of their study was to increase supply chain operations' resilience and flexibility. When stakeholders utilise the MCDM tool, they are able to make more informed choices that reflect their goals and beliefs. To put these concepts into action, many conflicting objectives must be considered. These aims might include achieving social equality, conserving the environment, and increasing economic efficiency. It is possible that MCDM could produce feasible solutions that suit a wide range of expectations while

remaining within the specified budget. To do this, it is important to conduct a detailed evaluation of the associated advantages and drawbacks of competing goals.

1.1. Literature Review

Zadeh's [15] most important contributions was the idea of "fuzzy sets" (FS), which was created to solve the issue of ambiguity in situations involving decision-making. Regardless of how inaccurate or confusing the data were, he made it possible to understand and navigate the labyrinth of decision-making using his mathematical technique. Through the integration of the concept of "intuitionistic fuzzy sets" (IFS) and the investigation of membership and non-membership features, Atanassov [16] enhanced the ability of fuzzy sets to handle intricate decision-making situations. This was achieved by utilising data from earlier studies. According to Cuong [17,18], Picture Fuzzy Sets (PFS) are an effective technique that can be used to obtain more comprehensive models that achieve an acceptable representation of human viewpoints during the decision-making process. Cuong and Hai [19,20] highlighted the essential features and basic operators of the system in their research. Deva and Mohanaselvi [21] introduced picture fuzzy Choquet integral-based geometric aggregation operators to enhance multi-attribute decision-making by integrating the Choquet integral with PFS. Abed and Rashid [22] assessed the maturity of construction risk management in Iraq using a hybrid fuzzy analytical hierarchy process (AHP) and fuzzy synthetic evaluation, highlighting the applicability of fuzzy methods in real-world problems. Projection models [23], specialised similarity measures [24], and universal Dice similarity measurements [25], all specifically designed for PFSs, are among their advancements. Khotimah et al. [26] introduced a hybrid decision support framework combining clustering methods with AHP and TOPSIS to support small and medium enterprises (SMEs) via enhanced strategic decision-making and business performance. Through the investigation of "correlation coefficients for PFS", Singh [27] was able to formulate certain criteria that are employed in the assessment of connections within PFS. Son [28] introduced a novel clustering technique specifically created for the PFS context. Moghrani et al. [29] proposed a hybrid Risk Priority Index (RPI) and MCDM approach for FMEA applied to a belt conveyor system in a mining context, demonstrating improved risk prioritization and maintenance strategies. Kumar et al. [30] evaluated the sustainability disclosures of Indian companies using the Global Reporting Initiative (GRI) G4 framework combined with MCDM techniques, providing a systematic approach for ranking companies based on their sustainability performance. Zhang [31] presented a hybrid approach integrating rough set theory and deep learning to enhance the estimation of thermodynamic parameters, providing more accurate and reliable predictions for various engineering applications. The goal of the study conducted by Phong et al. [32] was to gain a deeper understanding of the fundamental characteristics linked to fuzzy connections in PFS. Initially, Ashraf et al. [33,34] and Li et al. [35] suggested fuzzy sets of cubic PFS and generalised simplified neutrosophic Einstein AOs, respectively. Initially, these two sets of fuzzy sets were proposed by individual users. The invention of "spherical fuzzy sets" (SFS) was specifically prompted by the fact that the sum of the values surpassed one; the creation of SFS was in reaction to the apparent existence of restrictions on PFS [36,37]. An investigation into how intelligent dispatching energy storage systems might utilise trajectory analysis with machine learning inspired by biology was conducted by Mou et al. [38]. The goal of their investigation was to increase the efficiency of energy distribution and storage. These tactics are created by lone individuals. In order to function, these processes employ a range of features. Zeng et al. [39] used T-SF Einstein interactive aggregation operators to investigate photovoltaic cell selection. Liu et al. [40] conducted T-SF research on the application of Muirhead mean operators to enable the grouping of decision-making based on several features. Hu et al. [41] developed a multilayer optimisation approach for daily scheduling of combined heat and power units with integrated thermal and electrical storage in order to highlight the necessity of optimising the electrical and thermal components of energy systems.

Özdemirci et al. [42] employed the T-SF DEMATEL approach to evaluate the potential of social banking systems. Altork and Alamayreh [43] optimized hybrid heating systems by identifying ideal stations and conducting economic analyses for home heating in Jordan, offering a comprehensive framework for evaluating and improving residential heating solutions.

Sarkar et al. [44] examined aggregation operators that were developed from the Sugeno–Weber triangular norm. Notably, we performed our analysis in the context of the platform that T-SF Hypersoft created. An important issue for optimising computing resources in a variety of applications is the scheduling of parallel computations utilising work theft techniques. Yang and He [45] conducted an in-depth investigation of this topic. Zhu's [46] adaptive agent decision model has significant repercussions for the fields of service science and logistics due to the fact that it makes use of cognitive algorithms to enhance decision-making procedures. Automatic learning and deep reinforcement learning are the foundations around which this model is constructed.

Numerous methods have been developed for producing criterion weights. The three main categories of weighting systems, namely, hybrid, objective, and subjective, are covered in this article. Decision-makers must determine the weights of the relevant criteria in procedures that are deemed subjective. Subjective procedures include approaches such as SMART, pairwise comparison, direct ranking, and point allocation, among others. One fundamental problem with these approaches is that they need to handle large numbers of criteria. When objective weighing algorithms try to calculate the weights of the criteria, they do not take into account the opinions of decision-makers. Both baseline data and a decision matrix form the basis of the mathematical mechanism used by these strategies to establish the weights of criteria.

Keshavarz-Ghorabaee et al. [47] introduced a novel objective weighing method that they called MEREC in order to determine the objective weights of criteria. Using this method, the relative importance of criteria is ascertained by examining the ways in which each criterion affects the overall potency of the available possibilities. Removing a criterion that significantly affects how well alternatives perform overall is weighted more heavily than keeping other criteria in place during the decision-making process. This viewpoint allows decision-makers to remove certain factors from the decision-making process even though they are equally important to all of the criteria. Nanduri et al. [48] proposed a modified fuzzy approach for the automatic classification of cyber-hate speech on online social networks, improving the accuracy of detecting harmful content.

The fuzzy MEREC technique in Saidin et al. [49] adjusted the normalizing technique and improved the algorithm function during the weighting phase to assess the performance of alternatives. Goswami et al. [50] developed a plan for a workable power plant in India considering five crucial factors. Mani and Munusamy [51] developed a fuzzy rule-based model for predicting heart disease using data lake technologies, leveraging fuzzy logic to handle uncertainties in medical data and providing a reliable tool for early diagnosis and treatment planning. Singh et al. [52] presented parametric evaluation techniques for assessing the reliability of Internet of Things (IoT) systems, highlighting methods for improving the performance and dependability of IoT devices. Popovic et al. [53] developed an appropriate strategy for the growth of e-commerce through the application of a MEREC–COBRA-based model. An enhanced strategy for managing resources in IMS was proposed by Yue et al. [54] for integrated air–ground mobility. This method is a personalised resource allocation methodology aided by channel knowledge maps.

Liu et al. [55] devised a tendon-driven bi-stable origami flexible gripper for high-speed adaptive grasping, opening up the possibility of significantly improving the flexibility and efficiency of robotic manipulation. In their research work, Seidi et al. [56] improved a wire electrical discharge machining process with many objectives by employing regression analysis and multi-attribute decision-making approaches. By implementing an all-encompassing optimisation approach, they provided valuable insights into how to improve machining operations.

Bošković et al. [57] suggested AROMAN, a unique ranking order method based on two-step normalisation, to improve decision-making accuracy and efficiency. This strategy worked well for selecting electric cars. Güclü [58] employed a mix of MPSI, DNMARCOS, AROMAN, and MACONT to assess and compare various MCDM techniques. This contrast and comparison offers fresh perspectives on how well these methods work in different situations involving decision-making. Vasudevan et al. [59] developed and validated a computational fluid dynamics modeling methodology for isolated and urban street canyon configurations using wind tunnel measurements as part of their investigation into the choice of environmentally friendly wastewater treatment systems. In [60], Alrasheedi et al. presented the interval-valued intuitionistic fuzzy AROMAN approach. This method offers a solid foundation for decision-making in the presence uncertainty. Čubranić-Dobrodolac et al. [61] provided a hybridised fuzzy AROMAN–Fuller strategy for professional driver selection, and included a thorough model that tackles the difficulties around decision-making.

Nikolić et al. [62] successfully and methodically increased the operational efficiency of rural postal networks, thereby lessening their impact on the environment, by utilising an interval type-2 fuzzy AROMAN algorithm. This method is meant to increase the resilience of these networks, which is its main objective. By using MCDM for wildfire risk assessment in the state of Arizona, Pishahang et al. [63] demonstrated that AROMAN is effective in managing scenarios that include complicated decision-making in relation to disaster management, as evidenced by the ability to overcome these obstacles shown in their results. Bošković et al. [64] offered an example of the AROMAN technique, showing how concepts for cargo bike distribution might be chosen. They further showed that this approach works well in a range of cases involving decision-making. Dundar [65] examined the efficacy of practical entrepreneurial training offered in several contexts by utilising fuzzy BWM and AROMAN methodologies. Ju et al. [66] investigated the occurrence of distributed three-phase power flows in AC/DC hybrid networked microgrids while taking into consideration the limits imposed by converter limiting. Their study addresses the challenges involved with microgrids that make use of both alternating current (AC) and direct current (DC) systems in an effort to make smart grids more dependable and efficient. A thorough methodology for assessing the efficacy and sustainability of HR practices was offered by Rani et al. [67] in their study on sustainable human resource management in industrial organisations. They called this framework the RANCOM–AROMAN model. Rong et al. [68,69] developed a method to predict bus waiting times in real time using data from a variety of sources. Their method was intended to assist urban transportation systems in operating more effectively.

1.2. Motivation and Contribution

The motivation for the present research derives from the pressing need to resolve issues related to grid partitioning and effective scheduling in multi-energy systems. There is a high demand for decision support tools that can help people to understand the more complicated and unpredictable energy systems that are increasingly present as more towns move towards decentralised power networks and renewable energy sources. The goal of this work is to aid in the creation of more dependable and sustainable energy systems by presenting an innovative mode of operation that blends sound optimisation techniques with intelligent decision-making. Our mission is to arm decision-makers with the knowledge and resources that they need in order to design and oversee energy infrastructure while ensuring that it is technically sound, economically and environmentally viable, socially and environmentally acceptable, and environmentally sustainable.

This paper makes several significant contributions to the field of MCDM in energy system optimization:

- A strategy for modifying the weights of criteria on T-SPFs by combining the MEREC and Adaptive Robust Optimisation approaches.

- A hybrid structure that combines MEREC and AROMAN and is capable of operating in T-SPF environments.
- Support for decision-makers in balancing varied goals such as economic viability, environmental sustainability, social acceptability, and technical feasibility.
- By addressing the challenges of integrating renewable energy sources and ensuring sustainability, this research contributes to the ongoing efforts to transition towards more sustainable energy systems.

1.3. Structure of the Paper

In Section 2, the essential concepts of T-SFS theory are examined in order to lay the groundwork for the proposed strategy. Section 3 describes the technique that forms the basis of the proposed work, which employs T-SFSs and the MEREC–AROMAN approach algorithm. In this section, we discuss the principles of ranking options using the AROMAN technique and establishing weights with MEREC. Section 4 discusses practical applications of the suggested method, providing insights into potential routes for implementing the resulting plans. Case studies and examples are used to demonstrate how to practically analyse the performance of various techniques in the context of multi-energy systems. Finally, Section 5 summarises the important ideas, discusses the theoretical and practical ramifications of the work, and makes recommendations for further research.

2. Preliminaries

Definition 1. *[70] A T-SFS in U is defined as follows:*

$$\psi = \{\langle v, M(v), N(v), L(v) | h \in U \rangle\}, \tag{1}$$

where $M(v), N(v), L(v) \in [0,1]$ such that for every $v \in U$ we have $0 \leq M^t(v) + N^t(v) + L^t(v) \leq 1$. For some $v \in U$, the symbols $M(v), N(v)$, and $L(v)$ stand for membership degree (MD), abstinence degree (AD), and non-membership degree (N-MD), respectively. The representation of this pair is $D = (M_v, N_v, L_v)$. The following requirements apply to it, which is referred to as T-SFN throughout this paper: $M_v^t + N_v^t + L_v^t \leq 1$; $M_v, N_v, L_v \in [0,1]$.

Definition 2. *[70] Before using T-spherical fuzzy numbers (T-SFNs) in practical situations, they must be categorised. In this instance, T-SFN is the corresponding "score function" (SF). We define $SF = (M_v, N_v, L_v)$ as follows:*

$$S(L) = M_v^t - L_v^t. \tag{2}$$

However, as the aforementioned function is not sufficient for categorising T-SFNs in various contexts, it is difficult to determine which is better. One way to accomplish this is to determine an accuracy function Z^λ of L in the manner described below:

$$Q^R(L) = M_v^t + N_v^t + L_v^t. \tag{3}$$

We will provide guidelines for the operational aggregation of T-SFNs.

Definition 3. *[40] Let $\mu^C 1 = \langle M_1, N_1, L_1 \rangle$ and $\mu^C 2 = \langle M_2, N_2, L_2 \rangle$ be two T-SFNs; then,*

$$\mu^C 1^G = \left\langle L_1, N_1, M_1 \right\rangle, \tag{4}$$

$$\mu^C 1 \vee \mu^C 2 = \left\langle max\{M_1, M_2\}, min\{N_1, N_2\}, min\{L_1, L_2\} \right\rangle, \tag{5}$$

$$\mu^C 1 \wedge \mu^C 2 = \left\langle min\{M_1, M_2\}, max\{N_1, N_2\}, max\{L_1, L_2\} \right\rangle, \tag{6}$$

$$\mu^C 1 \oplus \mu^C 2 = \left\langle \sqrt[t]{M_1^t + M_2^t - M_1^t M_2^t}, N_1 N_2, L_1 L_2 \right\rangle, \tag{7}$$

$$\mu^C 1 \otimes \mu^C 2 = \left\langle M_1 M_2, \sqrt[t]{N_1^t + N_2^t - N_1^t N_2^t}, \sqrt[t]{L_1^t + L_2^t - L_1^t L_2^t} \right\rangle, \tag{8}$$

$$\sigma\mu^C 1 = \left\langle \sqrt[t]{1 - (1 - M_1^t)^\sigma}, N_1^\sigma, L_1^\sigma \right\rangle, \tag{9}$$

$$\mu^{C\sigma} = \left\langle M_1^\sigma, \sqrt[t]{1 - (1 - N_1^t)^\sigma}, \sqrt[t]{1 - (1 - L_1^t)^\sigma} \right\rangle. \tag{10}$$

Definition 4. *Let $\mu^C 1 = \langle M_1, N_1, L_1 \rangle$ and $\mu^C 2 = \langle M_2, N_2, L_2 \rangle$ be two T-SFNs and let $\mathbb{A}, \mathbb{A}_1, \mathbb{A}_2 > 0$ be the real numbers; then, we have*

1. $\mu^C 1 \oplus \mu^C 2 = \mu^C 2 \oplus \mu^C 1$
2. $\mu^C 1 \otimes \mu^C 2 = \mu^C 2 \otimes \mu^C 1$
3. $\mathbb{A}(\mu^C 1 \oplus \mu^C 2) = (\mathbb{A}\mu^C 1) \oplus (\mathbb{A}\mu^C 2)$
4. $(\mu^C 1 \otimes \mu^C 2)^{\mathbb{A}} = \mu^C 1^{\mathbb{A}} \otimes \mu^C 2^{\mathbb{A}}$
5. $(\mathbb{A}_1 + \mathbb{A}_2)\mu^C 1 = (\mathbb{A}_1 \mu^C 1) \oplus (\mathbb{A}_2 \mu^C 2)$
6. $\mu^C 1^{\mathbb{A}_1 + \mathbb{A}_2} = \mu^C 1^{\mathbb{A}_1} \otimes \mu^C 2^{\mathbb{A}_2}$.

Definition 5. *For T-SFNs $T_j = (j = 1, 2, 3, \ldots, s)$, the T-spherical fuzzy weighted geometric (*T-SFWG*) operator is as follows:*

$$\text{T-SFWG}(S_1, TS_2, \ldots, S_s) = j = 1^s S_j^{O_j}$$

where the weighted vector of $U_j = (j = 1, 2, 3, \ldots, s)$, $O_j > 0$, and $\sum_{j=1}^{s} O_j = 1$ is denoted by $w = (w_1, w_2, \ldots, w_s)^T$. Consequently, the outcome presented in Theorem 1 can be derived by utilising Definition 5.

Theorem 1. *Using the T-SFWG operator, the aggregated value of a set of T-SFNs U_j $(j = 1, 2, 3, \ldots, s)$ is likewise a* T-SFN.

$$\begin{aligned} \text{T-SFWG}(S_1, S_2, \ldots, S_s) = &\left(j = 1^s (Vj^D + \varrho_j^D)^{O_j^D} - j = 1^s \varrho_j^{aO_j^D}, \right. \\ &\left. j = 1^s \varrho_j^{aO_j^D}, \sqrt[n]{1 - j = 1^s (1 - Vj^{O_j^D})} \right). \end{aligned} \tag{11}$$

3. T-Spherical Fuzzy MEREC–AROMAN Method

Let n be larger than or equal to 2 and suppose that there is a set of n alternatives of the form $D = \{V_1, \ldots, V_i, \ldots, V_n\}$. A finite set of criteria is represented by G, which can be written as follows: the expression $G = \{G_1, \ldots, G_j, \ldots, G_m\} (m \geq 2)$ represents G; let $D = \{J_1, \ldots, J_e, \ldots, J_z\} (z \geq 2)$ be the set of DMs that have been invited. Then, the following steps can be used to explain the methodology behind the T-Spherical fuzzy MEREC–AROMAN approach.

Step 1: Each alternative is characterised by eight linguistic terms, which are listed in Table 1. Table 2 provides additional support for these ideas with linguistic idioms related to knowledge. The extensive range of linguistic vocabulary available makes a comprehensive portrayal of the information assessment process possible. Compare the T-SPFNs dataset with the relevant settings after entering it. The influence of several criteria on $V_p; (p = 1, 2, \ldots, n)$ If $U_q; (q = 1, 2, \ldots, m)$.

Table 1. Linguistic terms for evaluation.

Linguistic Term	T-SFN
Very High (VT)	$(\langle 0.90, 0.05, 0.10\rangle)$
High (U)	$(\langle 0.85, 0.10, 0.15\rangle)$
Moderate (AB)	$(\langle 0.80, 0.15, 0.20\rangle)$
Adequate (AA)	$(\langle 0.75, 0.20, 0.25\rangle)$
Acceptable (AD)	$(\langle 0.65, 0.25, 0.30\rangle)$
Limited (L)	$(\langle 0.60, 0.30, 0.35\rangle)$
Poor (P)	$(\langle 0.50, 0.35, 0.40\rangle)$

Table 2. Decision-makers for the case study.

Decision Maker	Profession	Role	Responsibility
Energy Engineer	Engineering	Grid Optimization Specialist	Lead the technical analysis and modeling of grid partitioning and scheduling strategies
Environmental Analyst	Environmental Science	Sustainability Analyst	Assess the environmental impact of alternative strategies and ensure alignment with sustainability goals
Policy Analyst	Public Policy	Regulatory Compliance Officer	Ensure compliance with regulatory requirements and assess the social acceptability of alternative strategies

Step 2: Assuming that Table 1 contains the LTs, rank the DMs according to the importance of T-SFNs. Assume that the T-SFN for the significance of the k-th DM is $\tau_k = \langle M_{vk}, N_{vk}, U_{vk}\rangle$. Therefore, the weight μ_k of the k-th DM can be computed using the formula found in Equation (12):

$$\mu_k = \frac{\tau_k}{\sum_{k=1}^{p} \tau_k}, k = 1, 2, 3, \tag{12}$$

where $\tau_k = M_{vK}^t - L_{vk}^t$ and clearly $\sum_{k=1}^{p} \mu_k = 1$.
Step 3: Utilising Equation (11), compute the aggregated decision matrix (AAM) $M = \left[M_{ij}\right]_{r\times s}$.

3.1. MEREC Weighting Method

Step 4.1: Compute the aggregated matrix score using Equation (2).
Step 4.2: By applying normalisation to the decision matrix using Equation (13), the resulting matrix η_{ij} is created:

$$\eta_{ij} = \begin{cases} \dfrac{v_{ij} - \min\limits_i(v_{ij})}{\max\limits_i(v_{ij}) - \min\limits_i(v_{ij})}, \ for\ benefical\ criteria \\ \dfrac{\max\limits_i(v_{ij}) - v_{ij}}{\max\limits_i(v_{ij}) - \min\limits_i(v_{ij})}, \ for\ cost\ criteria. \end{cases} \tag{13}$$

Step 4.3:
Prior to computing the total performance values of the alternatives, we must address the undefined value of $ln(\eta_{ij})$ for $\eta_{ij} = 0$. Thus, the expression in (14) introduces a standardisation step:

$$Q_{ij} = \frac{\eta_{ij} + \zeta}{\sum_{i=1}^{m}(\eta_{ij} + \zeta)} \tag{14}$$

where, $\eta_{ij} + \zeta > 0$.

Step 4.4:

Equation (15) is used in this step to calculate the overall performance of the alternatives, as it is important to know how well each alternative performs when calculating the weights of the criteria.

$$R_i = ln\left(1 + \left(\delta \sum_j ln(Q_{ij})\right)\right), \quad \delta = \frac{1}{m} \tag{15}$$

Step 4.5:

According to the specificity of the approach, which is based on the impact caused by eliminating the jth criterion, R_{ij}^* in Equation (16) represents the partially achieved performance levels associated with the ith alternatives by deducting each criterion from the total performance amounts.

$$R_{ij}^* = ln\left(1 + \left(\frac{1}{m} \sum_{k,k \neq j} |ln(Q_{ij})|\right)\right). \tag{16}$$

Step 4.6:

Totaling all of the deviations, the value F_j, which is the outcome of removing the jth criterion, is computed using the values obtained from the preceding steps, as shown in Equation (17) below:

$$F_j = \sum_i |R_{ij}^* - R_i|, \ \ \forall j. \tag{17}$$

Step 4.7:

In this step, the consequence of removal F_j is used to compute the weight of each criterion. The weight of the jth criterion is represented by the symbol W_j. The following Equation (18) is used to calculate the weights:

$$W_j = \frac{F_j}{\sum_j F_j}, \ \ \forall j. \tag{18}$$

3.2. AROMAN

Step 5: Normalisation is used to bring the input data in the decision-making matrix into uniformity. The next step involves organising the data into intervals ranging from 0 to 1 when the matrix containing the input data has been created. A pair of discrete techniques (Equations (19) and (20)) are used to standardise the data.

Step 5.1: Normalization 1 (**Linear**):

$$Y_{ij} = \frac{N_{ij} - N_{ij}}{N_{ij} - N_{ij}}, \quad i = 1, 2, \ldots, m; \ j = 1, 2, \ldots, n. \tag{19}$$

Step 5.2: Normalization 2 (**Vector**):

$$Y_{ij}^* = \frac{N_{ij}}{\sqrt{\sum_{i=1}^m N_{ij}^2}}, \quad i = 1, 2, \ldots, r; \ j = 1, 2, \ldots, s. \tag{20}$$

Step 6: To standardise the input data, we apply Averaged Aggregation Normalisation. Throughout the data normalisation process, this methodical approach guarantees consistent and meaningful comparisons across a range of criteria. Equation (21) is used in the aggregated averaged normalisation procedure:

$$Y_{ij}^{\text{norm}} = \frac{\chi Y_{ij} + (1 - \chi) Y_{ij}^*}{2}, \quad i = 1, 2, \ldots, r; \ j = 1, 2, \ldots, s \tag{21}$$

where the aggregated average normalisation result is Y_{ij}^{norm} and χ serves as a weighting factor between 0 and 1. For the particular context we are in, we set the value of χ to 0.5.

Step 7: Per Equation (22), multiply the aggregated averaged normalised decision-making matrix by the criteria weights to obtain a weighted decision-making matrix.

$$\hat{Y}_{ij} = W_{ij} \cdot Y_{ij}^{\text{norm}}, \quad i = 1, 2, \ldots, r; \; j = 1, 2, \ldots, s. \tag{22}$$

Step 8: Using Equation (23), clearly state the normalised weighted values for the criteria types $\min(x_i)$ and (x_i). This formula provides a concise framework for calculating the weighted normalised values, guaranteeing a thorough depiction of the requirements under minimisation and maximisation scenarios.

$$\begin{aligned} x_{T(i)} &= \sum_{j=1}^{n} \widehat{Y_{ij}}^{(\min)}, \quad i = 1, 2, \ldots, r; \; j = 1, 2, \ldots, s. \\ s_{T(i)} &= \sum_{j=1}^{n} \widehat{Y_{ij}}^{(\max)}, \quad i = 1, 2, \ldots, r; \; j = 1, 2, \ldots, s. \end{aligned} \tag{23}$$

Step 9: Establish the final ranking of the options by taking into account all pertinent information and assessments. With a clear order that represents their overall performance and appropriateness in the context of decision-making, this final ranking summarises the thorough evaluation of the options based on the used methodologies and criteria:

$$R_i = {x_{T(i)}}^{Z} \lambda + {s_{T(i)_i}}^{(1-Z^{\lambda})}, \quad i = 1, 2, \ldots, r. \tag{24}$$

Here, the ranked alternatives are labelled (R_i) and the coefficient degree corresponding to the criterion type is denoted by Z^{λ}. After taking into account both types of criteria, Z^{λ} is assigned a value of 0.5. Figure 1 presents the method's sequential reasoning and provides a visual depiction of the decision-making process.

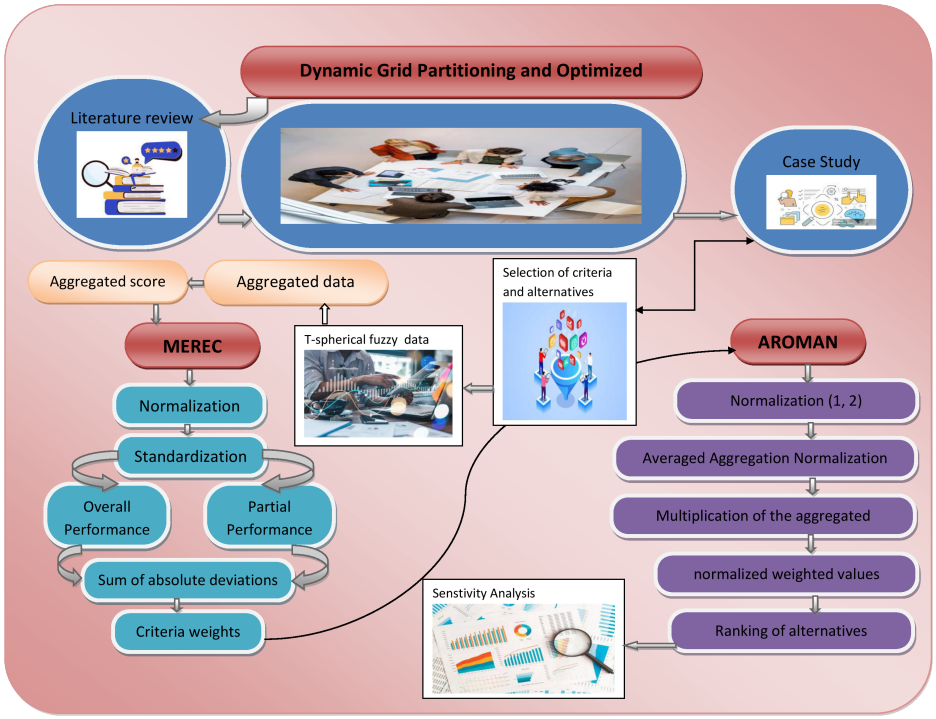


Figure 1. Procedure of the algorithm.

4. Statement of the Problem

Optimising scheduling and dynamic grid partitioning for multi-energy systems is a complex and multifaceted challenge that modern energy infrastructure planning and management must overcome. The challenge is balancing objectives such as technical viability,

social acceptability, environmental sustainability, and economic efficiency while navigating the inherent uncertainties and trade-offs that come with decision-making processes. Energy storage technologies, demand-side management tactics, renewable energy sources, complex grid solutions, and other issues further complicate the decision-making process. This highlights the need for a rigorous approach to assist decision-makers in analysing and selecting the appropriate grid partitioning and scheduling options. When making these judgments, a variety of factors must be considered, including operational restrictions, stakeholder preferences, and sustainability goals. This study provides a combined technique that use both the MEREC approach and the AROMAN method to rank the various methods in order to establish the weights of the criteria. The purpose of this method is to overcome this hurdle so that the desired end may be achieved more easily. Using a complete case study, we demonstrate how our dynamic grid partitioning and scheduling technique can aid in decision-making for multi-energy management systems.

4.1. Data Source

Using data for the present investigation that were derived from a combination of expert opinions and domain-specific experience allowed for the implementation of a review process that was both comprehensive and informed. The following methodological approaches were utilized in order to collect and validate the data:

- The formation of an expert panel was accomplished by bringing together a collection of competent persons with prior experience in the fields of energy systems, sustainability, and MCDM.
- The experts were required to establish and evaluate the most significant criteria and alternatives in order to optimize dynamic grid partitioning and scheduling in systems that contained numerous energy sources.
- The final set of criteria was established based on expert inputs, ensuring that all critical aspects of grid partitioning and scheduling were considered.
- Potential alternatives for grid partitioning and scheduling were also identified through expert consultation. These alternatives were designed to address the diverse challenges and opportunities in managing multi-energy systems.
- The collected data were aggregated and analyzed using the T-SFSs, AROMAN, and MEREC methods to evaluate and rank the alternatives based on the established criteria.
- The data were normalized and weighted to account for the relative importance of each criterion as determined by the experts.

4.2. Definition of Alternatives

- **Baseline Strategy** V_1**:**The current version of this option demonstrates grid scheduling and partitioning, but does not significantly optimise or adapt renewable energy sources. This tool may assist in evaluating the efficacy of various techniques and considering the possible advantages of optimisation.
- **Renewable Energy Integration** V_2**:** This alternative prioritises the use of hydroelectric power, wind power, and solar power in order to enhance the share of renewable energy sources integrated into the energy system. This plan must include techniques for decreasing the unpredictability and intermittency associated with employing renewable energy sources. Another critical component of this process is the practice of increasing the geographical and temporal dispersion of renewable energy-related assets.
- **Demand-Side Management** V_3**:** The primary goal of this approach is to deploy energy management strategies across the firm. The operations that use these technologies have several names; some of the most prevalent include efficiency improvements, demand response, and load shifting. The group hopes to accomplish a number of its objectives by providing discounts or other incentives to consumers who actively reduce their energy use. Some of these aims include increasing the flexibility of the energy system, reducing peak demand, and improving consumption patterns.

- **Energy Storage Integration** V_4**:** This alternative prioritises battery energy storage, pumped hydro energy storage, and thermal energy storage as energy storage technologies in order to increase the system's resilience and adaptability. The objective is to decrease peak shaving, which also maintains system stability and incorporates renewable power sources. This approach focuses on optimising energy storage assets with respect to their size, geographical arrangements, and operational efficiency.
- **Smart Grid Solutions** V_5**:** This technology, which combines smart meters, grid automation, and predictive analytics, optimises grid scheduling and partitioning to achieve the highest possible efficiency. The two primary difficulties that this option aims to address are schedule optimisation and grid segmentation. Dynamic demand response, predictive maintenance, and grid balancing are all strategies for improving the grid's efficiency, dependability, and resilience. The facilitation of these three procedures provides the opportunity to achieve this purpose.

4.3. Definition of Criteria

- **Economic Cost** U_1**:** The existing grid partitioning and scheduling systems are evaluated using factors such as expected revenue production, operational expenditures, and initial investment costs.
- **Environmental Impact** U_2**:** Based on these standards, we assess the environmental impact of each proposal. The loss of resources, contaminating the air and water, and releasing greenhouse gases rank highest in importance in accordance with these criteria.
- **Energy Efficiency** U_3**:** When measuring efficiency, it is critical to consider the likelihood of energy losses occurring during the production, transmission, and consumption phases of the system in addition to the efficiency of the technologies used to convert and store energy.
- **System Reliability** U_4**:** This criterion is used to assess the energy system's reliability and resilience in further detail. The resilience and reliability of the energy system can be evaluated with the use of this indicator. Numerous aspects are taken into account, including the system's fault tolerance, resilience, and ability in maintaining a balance between supply and demand.
- **Flexibility and Adaptability** U_5**:** This criterion is used to assess all of these characteristics, including the capacity to scale up or down and adapt to changes in the market, supply, and demand for energy.
- **Social Acceptance** U_6**:** This criterion evaluates potential solutions based on their practicability and fairness, taking into account local communities, public health, and socioeconomic disparities.
- **Operational Complexity** U_7**:** This criterion is used to evaluate the degree of complexity and the practicability of the plan's operations. Many factors are taken into account, such as the incorporation of infrastructure, the need for certain skills and resources, and any potential institutional or legal barriers.
- **Resilience to Uncertainty** U_8**:** This criterion allows for the assessment of how well the system can handle variations in the amount of renewable energy generated, variations in energy prices, and unforeseen occurrences such as cyberattacks or inclement weather.

4.4. Experimental Results

The following steps comprise the T-SF-based MEREC–AROMAN application procedure:
Step 1: The decision-makers used the T-SFN dataset and a number of criteria listed in Table 3 for each alternative, including language phrases from Table 1.

Table 3. Evaluations of each alternative.

DMs	Alternative	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8
DM_1	V_1	U	AB	L	AA	P	AD	VT	L
	V_2	AB	L	P	VT	AA	AD	U	AA
	V_3	L	VT	U	AD	P	AA	VT	AB
	V_4	P	VT	AD	AB	L	U	VT	P
	V_5	AD	AB	VT	P	U	AA	L	AD
DM_2	V_1	VT	L	AD	U	VT	AB	AA	VT
	V_2	AD	U	AB	VT	P	L	AA	VT
	V_3	P	VT	AA	AB	AD	U	L	U
	V_4	L	VT	P	AA	U	AD	AB	P
	V_5	AA	AB	VT	AD	P	L	U	AD
DM_3	V_1	U	AA	VT	AD	P	AB	VT	AD
	V_2	VT	P	AD	AB	L	AA	U	AD
	V_3	AB	VT	U	P	AA	L	AD	AA
	V_4	L	AD	VT	U	AB	P	AA	P
	V_5	AA	VT	L	AD	U	AB	P	AD

Step 2: The weights provided the decision-makers are calculated using the scoring function in Equation (2); the obtained values are displayed in Table 4.

Table 4. Decision-makers' weights for evaluation.

	DM	Role	Key Responsibilities	Weight
DM_1	VT	AA	AD	0.5032
DM_2	U	P	AA	0.3030
DM_3	VT	P	AD	0.1938

Step 3: Equation (11) is used to construct the ADM $M = \left[M_{ij}\right]_{r\times s}$, with the results shown in Table 5.

Table 5. Aggregated decision matrix.

U_i	$V1$	$V2$	$V3$	$V4$	$V5$
U_1	⟨0.823, 0.117, 0.122⟩	⟨0.834, 0.133, 0.208⟩	⟨0.843, 0.143, 0.254⟩	⟨0.825, 0.132, 0.221⟩	⟨0.825, 0.118, 0.223⟩
U_2	⟨0.745, 0.213, 0.332⟩	⟨0.743, 0.226, 0.332⟩	⟨0.683, 0.251, 0.331⟩	⟨0.865, 0.243, 0.321⟩	⟨0.741, 0.226, 0.254⟩
U_3	⟨0.825, 0.125, 0.187⟩	⟨0.821, 0.143, 0.224⟩	⟨0.776, 0.215, 0.252⟩	⟨0.776, 0.231, 0.236⟩	⟨0.752, 0.231, 0.247⟩
U_4	⟨0.591, 0.420, 0.472⟩	⟨0.651, 0.429, 0.425⟩	⟨0.611, 0.487, 0.542⟩	⟨0.523, 0.0.405, 0.497⟩	⟨0.521, 0.443, 0.512⟩
U_5	⟨0.632, 0.211, 0.417⟩	⟨0.703, 0.341, 0.391⟩	⟨0.670, 0.310, 0.409⟩	⟨0.734, 0.337, 0.443⟩	⟨0.632, 0.371, 0.437⟩
U_6	⟨0.541, 0.515, 0.601⟩	⟨0.590, 0.510, 0.607⟩	⟨0.543, 0.531, 0.613⟩	⟨0.510, 0.532, 0.521⟩	⟨0.665, 0.520, 0.512⟩
U_5	⟨0.591, 0.420, 0.472⟩	⟨0.651, 0.429, 0.425⟩	⟨0.611, 0.487, 0.542⟩	⟨0.523, 0.0.405, 0.497⟩	⟨0.521, 0.443, 0.512⟩
U_7	⟨0.465, 0.574, 0.620⟩	⟨0.520, 0.620, 0.697⟩	⟨0.501, 0.620, 0.690⟩	⟨0.460, 0.544, 0.677⟩	⟨0.591, 0.549, 0.670⟩
U_8	⟨0.420, 0.673, 0.329⟩	⟨0.670, 0.630, 0.699⟩	⟨0.532, 0.621, 0.637⟩	⟨0.545, 0.560, 0.702⟩	⟨0.541, 0.650, 0.778⟩

Step 4: MEREC Method

Step 4.1: Following the formulation of the aggregated T-SFS score values, the formula from Equation (2) is applied to state the results in the aggregated decision score matrix Sc_{ij}^{Agr}.

$$\begin{bmatrix} 0.5321 & 0.4326 & 0.6328 & 0.6537 & 0.3419 & 0.4589 & 0.6329 & 0.4561 \\ 0.4329 & 0.3489 & 0.3582 & 0.3674 & 0.8372 & 0.5431 & 0.6214 & 0.6217 \\ 0.2348 & 0.3729 & 0.7328 & 0.2648 & 0.3472 & 0.7328 & 0.3743 & 0.6321 \\ 0.2824 & 0.3266 & 0.6215 & 0.5123 & 0.4217 & 0.1253 & 0.3417 & 0.5317 \\ 0.3183 & 0.3267 & 0.2361 & 0.2320 & 0.2749 & 0.2729 & 0.4174 & 0.3216 \end{bmatrix}$$

Step 4.2: Using Equation (13), the normalised matrix η_{ij} is obtained.

$$\eta_{ij} = \begin{bmatrix} 0 & 0 & 0.7987 & 1 & 0.1192 & 0.5491 & 1 & 0.4332 \\ 0.3337 & 0.7896 & 0.2458 & 0.3211 & 1 & 0.6877 & 0.9605 & 0.9665 \\ 1 & 0.5632 & 1 & 0.0778 & 0.1286 & 1 & 0.112 & 1 \\ 0.8399 & 1 & 0.7759 & 0.6647 & 0.2611 & 0 & 0 & 0.6767 \\ 0.7191 & 0.9991 & 0 & 0 & 0 & 0.243 & 0.26 & 0 \end{bmatrix}$$

Step 4.3: Equation (14) is used to perform a standardised step in order to prevent the complications in the calculation represented by Q_{ij}.

$$Q_{ij} = \begin{bmatrix} 0.6329 & 0.5320 & 0.5154 & 0.6711 & 0.3132 & 0.4312 & 0.5735 & 0.3882 \\ 0.5149 & 0.4290 & 0.2917 & 0.3772 & 0.7669 & 0.5103 & 0.5631 & 0.5292 \\ 0.2793 & 0.4585 & 0.5968 & 0.2719 & 0.3180 & 0.6885 & 0.3392 & 0.5380 \\ 0.3359 & 0.4016 & 0.5061 & 0.5260 & 0.3863 & 0.1177 & 0.3096 & 0.4526 \\ 0.3786 & 0.4017 & 0.1923 & 0.2382 & 0.2518 & 0.2564 & 0.3782 & 0.2737 \end{bmatrix}$$

Step 4.4: The overall performance values of the alternatives displayed below in Table 6 are assessed using Equation (15).

Table 6. $\mathbb{VRS}$ overall performance results.

Alternatives	$\mathcal{V}_1$	$\mathcal{V}_2$	$\mathcal{V}_3$	$\mathcal{V}_4$	$\mathcal{V}_5$
R_i	0.5055	0.5779	0.5211	0.4984	0.3931

Step 4.5: Matrix R^*_{ij} presents the performance of alternatives by deducting the jth criteria from the R_i value using Equation (16).

$$R^*_{ij} = \begin{bmatrix} 0.8226 & 0.8096 & 0.9052 & 0.9415 & 0.8958 & 0.8983 & 0.9319 & 0.8709 \\ 0.7088 & 0.7369 & 0.7003 & 0.7401 & 0.8238 & 0.7576 & 0.7824 & 0.7572 \\ 0.8318 & 0.7881 & 0.8340 & 0.7767 & 0.8126 & 0.8451 & 0.7707 & 0.8264 \\ 0.8718 & 0.8689 & 0.8698 & 0.8882 & 0.8789 & 0.7997 & 0.8052 & 0.8557 \\ 1.0438 & 1.0480 & 0.9809 & 1.0041 & 1.0268 & 1.0195 & 1.0255 & 0.9744 \end{bmatrix}$$

Step 4.6: The absolute deviation, defined as the difference between the R^*_{ij} and R_i matrices, and its sum as provided in Equation (17), are computed as shown in Table 7.

Table 7. Sum of absolute deviation.

Criteria	$\mathcal{U}_1$	$\mathcal{U}_2$	$\mathcal{U}_3$	$\mathcal{U}_4$	$\mathcal{U}_5$	$\mathcal{U}_6$	$\mathcal{U}_7$	$\mathcal{U}_8$
F_j	1.7829	1.7555	1.7943	1.8545	1.9420	1.8243	1.8198	1.7886

Step 4.7: Lastly, using the absolute deviation values as formulated in Equation (18), the weights W_j of the criteria are computed, with the results shown in Table 8.

Table 8. Weights of criteria.

Criteria	$\mathcal{U}_1$	$\mathcal{U}_2$	$\mathcal{U}_3$	$\mathcal{U}_4$	$\mathcal{U}_5$	$\mathcal{U}_6$	$\mathcal{U}_7$	$\mathcal{U}_8$
W_j	0.1224	0.1206	0.1232	0.1274	0.1334	0.1253	0.1250	0.1228

Step 5: Step 5.1: Apply Equation (19) to perform linear normalisation, also known as Normalisation 1, following the instructions in Table 9.

Table 9. Linear normalization.

u_1	u_2	u_3	u_4	u_5	u_6	u_7	u_8
0.6100	0.2909	0.9330	1	0	0.3752	0.9333	0.3663
0.1720	0	0.0190	0.0379	1	0.3977	0.5581	0.5587
0	0.2773	1	0.0602	0.2257	0.3254	0.2801	0.7978
0.3166	0.4057	1	0.7799	0.5973	0	0.4361	0.8190
0.4655	0.5108	0.0221	0	0.2314	0.2206	1	0.4833

Step 5.2: Use Equation (20) to apply Vector Normalisation, also known as Normalisation 2, following Table 10.

Table 10. Vector normalization.

u_1	u_2	u_3	u_4	u_5	u_6	u_7	u_8
0.6329	0.5320	0.5154	0.6711	0.3132	0.4312	0.5735	0.3882
0.5149	0.4290	0.2917	0.3772	0.7669	0.5103	0.5631	0.5292
0.2793	0.4585	0.5968	0.2719	0.3180	0.6885	0.3392	0.5380
0.3359	0.4016	0.5061	0.5260	0.3863	0.1177	0.3096	0.4526
0.3786	0.4017	0.1923	0.2382	0.2518	0.2564	0.3782	0.2737

Step 6: Formula (21) shown in Table 11 is used in the aggregated averaged normalisation process.

Table 11. Aggregated averaged matrix.

u_1	u_2	u_3	u_4	u_5	u_6	u_7	u_8
0.3107	0.2057	0.3621	0.4178	0.0783	0.2016	0.3767	0.1886
0.1717	0.1073	0.0777	0.1038	0.4417	0.2270	0.2803	0.2720
0.0698	0.1840	0.3992	0.0830	0.1359	0.4221	0.1548	0.3340
0.1631	0.2018	0.3765	0.3265	0.2459	0.0294	0.1864	0.3179
0.2110	0.2281	0.0536	0.0595	0.1208	0.1193	0.3446	0.1893

Step 7: As stated in Equation (22) in Table 12, the weighted decision-making matrix is calculated by multiplying the aggregated averaged normalised decision-making matrix with the criteria weights. To obtain the weighted decision-making matrix, apply the given formula.

Table 12. Multiplying the aggregated averaged normalised matrix.

u_1	u_2	u_3	u_4	u_5	u_6	u_7	u_8
0.0380	0.0248	0.0446	0.0532	0.0104	0.0253	0.0471	0.0232
0.0210	0.0129	0.0096	0.0132	0.0589	0.0284	0.0350	0.0334
0.0085	0.0222	0.0492	0.0106	0.0181	0.0529	0.0193	0.0410
0.0200	0.0243	0.0464	0.0416	0.0328	0.0037	0.0233	0.0390
0.0258	0.0275	0.0066	0.0076	0.0161	0.0149	0.0431	0.0232

Step 8: Finally, Equation (23) is used to distinguish between the normalised weighted values for the criteria types $\min(x_i)$ and $\max(x_i)$. As indicated in Table 13, the final ranking of alternatives is determined using the Equation (24).

Table 13. Final ranking of alternatives.

Alternatives	Sum of All Min. Criteria	Sum of All Max. Criteria	Final Ranking of Alternatives
V_1	0.0380	0.0232	0.3473
V_2	0.0210	0.0334	0.3278
V_3	0.0085	0.0410	0.2950
V_4	0.0200	0.0390	0.3389
V_5	0.0258	0.0232	0.3132

4.5. Sensitivity Analysis

A sensitivity analysis of the impact of the Z^{λ} parameter on a number of alternatives ($V1$ to $V5$) and their decision outcomes is presented in Table 14. The robustness and stability of the decision-making model are demonstrated across a range of Z^{λ} values. The decision-making process of the framework is affected by varying Z^{λ} values, as shown by the variations in Figure 2.

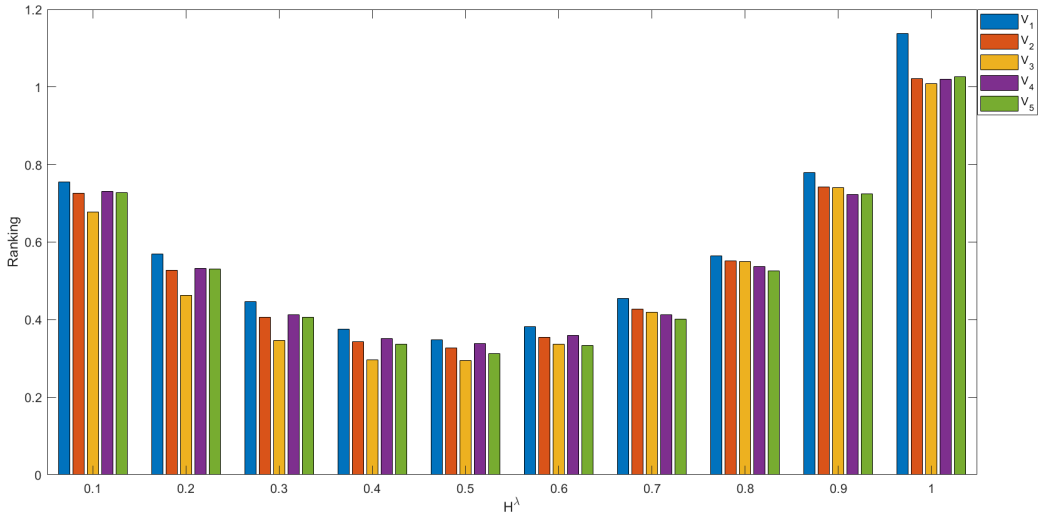


Figure 2. Visualization showing the effect of changing the Z^{λ} parameter.

Table 14. Influence of the Z^{λ} parameter.

Z^{λ}	V_1	V_2	V_3	V_4	V_5	Ranking
$Z^{\lambda} = 0.1$	0.7549	0.7266	0.6776	0.7302	0.7276	$V_1 \succ V_4 \succ V_2 \succ V_5 \succ V_3$
$Z^{\lambda} = 0.2$	0.5693	0.5278	0.4635	0.5319	0.5307	$V_1 \succ V_4 \succ V_5 \succ V_2 \succ V_3$
$Z^{\lambda} = 0.3$	0.4467	0.4065	0.3466	0.4124	0.4058	$V_1 \succ V_4 \succ V_2 \succ V_5 \succ V_3$
$Z^{\lambda} = 0.4$	0.3749	0.3435	0.2960	0.3519	0.3364	$V_1 \succ V_4 \succ V_2 \succ V_5 \succ V_3$
$Z^{\lambda} = 0.5$	0.3473	0.3278	0.2950	0.3389	0.3132	$V_1 \succ V_4 \succ V_2 \succ V_5 \succ V_3$
$Z^{\lambda} = 0.6$	0.3825	0.3553	0.3362	0.3589	0.3336	$V_1 \succ V_4 \succ V_2 \succ V_3 \succ V_5$
$Z^{\lambda} = 0.7$	0.4546	0.4277	0.4193	0.4126	0.4009	$V_1 \succ V_2 \succ V_3 \succ V_4 \succ V_5$
$Z^{\lambda} = 0.8$	0.5641	0.5522	0.5501	0.5365	0.5249	$V_1 \succ V_2 \succ V_3 \succ V_4 \succ V_5$
$Z^{\lambda} = 0.9$	0.7790	0.7428	0.7404	0.7226	0.7237	$V_1 \succ V_2 \succ V_3 \succ V_5 \succ V_4$
$Z^{\lambda} = 1$	1.1380	1.0210	1.0085	1.0200	1.0258	$V_1 \succ V_5 \succ V_2 \succ V_4 \succ V_3$

4.6. Comparative Analysis

We examined the usefulness and efficiency of various decision-making strategies within the recently released T-SFS framework in detail in our extensive comparison study. Our rigorous investigations, validation, and extensive use of robustness checks during the study led to more consistent and reliable results. The main conclusions of the analyses are succinctly summarised in Table 15. By closely examining each component, which produces nuanced revelations when considered as a whole, it is possible to gain a thorough understanding of the advantages and disadvantages of alternative decision-making approaches. This study contributes to the understanding of T-SFS decision-making by providing reliable guidance for the thoughtful integration of T-SFSs.

Table 15. Comparison results.

Authors	Methodologies	Rankings	Best Alternative
Chen [71]	VIKOR	$V_1 \succ V_5 \succ V_4 \succ V_2 \succ V_3$	V_1
Ju et al. [72]	TODIM	$V_1 \succ V_5 \succ V_3 \succ V_2 \succ V_4$	V_1
Fan et al. [73]	COPRAS	$V_1 \succ V_5 \succ V_2 \succ V_4 \succ V_3$	V_1
Zhang and Wei [74]	D-CRITIC and CPT–CoCoSo	$V_1 \succ V_5 \succ V_3 \succ V_2 \succ V_4$	V_1
Ali [75]	CRITIC-MARCOS	$V_1 \succ V_5 \succ V_2 \succ V_4 \succ V_3$	V_1
Proposed	$MEREC - AROMAN$	$V_1 \succ V_5 \succ V_3 \succ V_4 \succ V_2$	V_1

4.7. Discussion

In light of the ever-changing energy landscape, our journey began by determining the best way to optimize scheduling and dynamic grid partitioning in multi-energy systems. In the Background and Conceptual Framework Section, we first clarified important concepts such as spherical fuzzy sets before beginning our investigation based on the problem statement laid out previously. We presented our novel methodology, which provides a systematic way to rank options and weigh criteria, in the Methodology section. This was carried out following the completion of the foundation. As a logical progression into the case study, we offered an extensive examination of a real-world scenario that included a multi-energy system with a range of energy sources, operational constraints, and sustainability goals. The purpose of this specific case study was to assess many methods for enhancing scheduling and decomposing the grid and its elements. The practicality of each concept was assessed by taking into account its influence in real-world circumstances, public response, environmental impact, and financial feasibility. Throughout our in-depth investigation, we took into account a wide range of criteria, including environmental effects, social equality, energy efficiency, and investment expenditures. The first alternative was very well thought out, as it was able to achieve sustainability goals while also taking into account social, environmental, and economic issues. We now have a deeper comprehension of the underlying trade-offs and synergies as a result of improving multi-energy systems. This was achieved by using eight criteria and five different possibilities in our thorough review of the case study. Our research can have a big influence on the industry, as it not only offers stakeholders useful information but also thoroughly analyses the management and design of energy systems.

5. Conclusions

This paper takes a complete strategy towards optimising the efficiency of scheduling algorithms and dynamically dividing grids in multi-energy systems, both of which are very difficult tasks. Through the integration of the AROMAN strategy ranking approach and the MEREC criterion weighting methodology, we have provided decision-makers with an organised framework that enables them to assess and select the most optimal solutions. To demonstrate the value and effectiveness of our approach in achieving a balance between the technical, social, environmental, and economic aspects of the issue, we have presented

a thorough case study. By helping decision-makers manage the inherent uncertainties that come with the planning and management of energy infrastructure, our approach eventually leads to a more sustainable and resilient system. The first option was particularly noteworthy, as it prioritises demand-side management strategies that align with sustainability objectives and achieve equilibrium between social, environmental, and economic factors. Decision-makers can use the insights we have found to build and manage energy infrastructures that meet a range of desired outcomes. Our research directly contributes to the development of resilient and sustainable energy systems. In the future, researchers should focus on improving and expanding our method while taking into account the different situations and changing dynamics of the energy transition and incorporating stakeholder engagement methods with real-time data analytics to better deal with the difficulties of dynamic grid partitioning and scheduling. All of these actions are necessary in order to effectively handle the relevant difficulties. Finally, our integrated methodology provides planners, legislators, and decision-makers with a useful set of tools that can aid in the creation of energy infrastructure in a way that is less damaging to the environment.

Author Contributions: Conceptualization, P.L. and T.Z.; methodology, F.T. and Y.T.; software, M.Y. and F.T.; validation, M.Y. and P.L.; writing—original draft preparation, T.Z.; writing—review and editing, F.T.; visualisation. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data used to support the findings of the study are included within the article.

Conflicts of Interest: Author Furui Tian was employed by Zhuji Power Supply Company, State Grid Zhejiang Electric Power Co., Ltd. Author Miaodong Yang was employed by Liaoning Qinghe Power Generation Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Zhang, C.; Xu, Y.; Dong, Z.Y. Robustly coordinated operation of a multi-energy micro-grid in grid-connected and islanded modes under uncertainties. *IEEE Trans. Sustain. Energy* **2020**, *11*, 640–651. [CrossRef]
2. Zheng, S.; Hai, Q.; Zhou, X.; Stanford, R.J. A novel multi-generation system for sustainable power, heating, cooling, freshwater, and methane production: Thermodynamic, economic, and environmental analysis. *Energy* **2024**, *290*, 130084. [CrossRef]
3. Hong, B.; Chen, J.; Zhang, W.; Shi, Z.; Li, J.; Miao, W. Integrated energy system planning at modular regional-user level based on a two-layer bus structure. *CSEE J. Power Energy Syst.* **2018**, *4*, 188–196. [CrossRef]
4. Fan, J.; Zhou, X. Optimization of a hybrid solar/wind/storage system with bio-generator for a household by emerging meta-heuristic optimization algorithm. *J. Energy Storage* **2023**, *73*, 108967. [CrossRef]
5. Cheng, S.; Wang, R.; Xu, J.; Wei, Z. Multi-time scale coordinated optimization of an energy hub in the integrated energy system with multi-type energy storage systems. *Sustain. Energy Technol. Assess.* **2021**, *47*, 101327. [CrossRef]
6. Gong, Q.; Li, J.; Jiang, Z.; Wang, Y. A hierarchical integration scheduling method for flexible job shop with green lot splitting. *Eng. Appl. Artif. Intell.* **2024**, *129*, 107595. [CrossRef]
7. Li, G.; Zhang, R.; Jiang, T.; Chen, H.; Bai, L.; Li, X. Security-constrained bi-level economic dispatch model for integrated natural gas and electricity systems considering wind power and power-to-gas process. *Appl. Energy* **2017**, *194*, 696–704. [CrossRef]
8. Lu, C.; Zheng, J.; Yin, L.; Wang, R. An improved iterated greedy algorithm for the distributed hybrid flowshop scheduling problem. *Eng. Optim.* **2023**, *56*, 792–810... [CrossRef]
9. Yu, B.; Fang, D.; Xiao, K.; Pan, Y. Drivers of renewable energy penetration and its role in power sector's deep decarbonization towards carbon peak. *Renew. Sustain. Energy Rev.* **2023**, *178*, 113247. [CrossRef]
10. Yu, F.; Lu, C.; Yin, L.; Zhou, J. Modeling and optimization algorithm for energy-efficient distributed assembly hybrid flowshop scheduling problem considering worker resources. *J. Ind. Inf. Integr.* **2024**, *40*, 100620. [CrossRef]
11. Shi, M.; Wang, H.; Xie, P.; Lyu, C.; Jian, L.; Jia, Y. Distributed energy scheduling for integrated energy system clusters with peer-to-peer energy transaction. *IEEE Trans. Smart Grid* **2023**, *14*, 142–156. [CrossRef]
12. Yin, L.; Li, X.; Gao, L.; Lu, C.; Zhang, Z. Energy-efficient job shop scheduling problem with variable spindle speed using a novel multi-objective algorithm. *Adv. Mech. Eng.* **2017**, *9*, 755449641. [CrossRef]
13. Ramana, S.V.; Devakumar, M.L.S.; Hemalatha, S. Ranking of Sites of Solar Power Plants in Fuzzy Environment. *Int. J. Sustain. Dev. Plann.* **2023**, *18*, 3845–3854. [CrossRef]
14. Berbiche, N.; Hlyal, M.; El Alami, J. Enhancing Supply Chain Resilience and Efficiency through Fuzzy Logic-based Decision-Making Automation in Volatile Environments. *Ing. Syst. Inf.* **2024**, *29*, 191–203. [CrossRef]

15. Zadeh, L.A. Fuzzy sets. *Inf. Control* **1965**, *8*, 338–353. [CrossRef]
16. Atanassov, K.T. Intuitionistic fuzzy sets. *Fuzzy Sets Syst.* **1986**, *20*, 87–96. [CrossRef]
17. Cuong, B.C. *Picture Fuzzy Sets-First Results. Part 1, Seminar Neuro-Fuzzy Systems with Applications*; Technical Report; Institute of Mathematics: Hanoi, Vietnam, 2013.
18. Cuong, B.C. *Picture Fuzzy Sets-First Results. Part 2, Seminar Neuro-Fuzzy Systems with Applications*; Technical Report; Institute of Mathematics: Hanoi, Vietnam, 2013.
19. Cuong, B.C.; Hai, P.V. Some fuzzy logic operators for picture fuzzy sets. In Proceedings of the Seventh International Conference on Knowledge and Systems Engineering, Ho Chi Minh City, Vietnam, 8–10 October 2015; pp. 132–137.
20. Cuong, B.C. Picture fuzzy sets. *J. Comput. Sci. Technol.* **2014**, *30*, 409–420.
21. Deva, K.; Mohanaselvi, S. Picture Fuzzy Choquet Integral Based Geometric Aggregation Operators and Its Application to Multi Attribute Decision-Making. *Model. Eng. Probl.* **2022**, *9*, 1043–1052. [CrossRef]
22. Abed, H.R.; Rashid, H.A. Assessment of Construction Risk Management Maturity Using Hybrid Fuzzy Analytical Hierarchy Process and Fuzzy Synthetic Approach: Iraq as Case Study. *Math. Model. Eng. Probl.* **2023**, *10*, 2. [CrossRef]
23. Wei, G.W.; Alsaadi, F.E.; Hayat, T.; Alsaedi, A. Projection models for multiple attribute decision-making with picture fuzzy information. *Int. J. Mach. Learn. Cybern.* **2018**, *9*, 713–719. [CrossRef]
24. Wei, G.W. Some similarity measures for picture fuzzy sets and their applications. *Iran. J. Fuzzy Syst.* **2018**, *15*, 77–89.
25. Wei, G.W.; Gao, H. The generalized dice similarity measures for picture fuzzy sets and their applications. *Informatica* **2018**, *29*, 107–124. [CrossRef]
26. Khotimah, K.K.; Anamisa, D.R.; Kustiyahningsih, Y.; Fauziah, A.N.; Setiawan, E. Enhancing Small and Medium Enterprises: A Hybrid Clustering and AHP-TOPSIS Decision Support Framework. *Ingén. Syst. Inf.* **2024**, *29*, 313–321. [CrossRef]
27. Singh, P. Correlation coefficients for picture fuzzy sets. *J. Intell. Fuzzy Syst* **2014**, *27*, 2857–2868. [CrossRef]
28. Son, L.H. DPFCM: A novel distributed picture fuzzy clustering method on picture fuzzy sets. *Expert Syst. Appl.* **2015**, *2*, 51–66. [CrossRef]
29. Moghrani, R.; Aoulmi, Z.; Attia, M. Hybrid RPI-MCDM Approach for FMEA: A Case Study on Belt Conveyor in Bir El Ater Mine, Algeria. *J. Eur. Syst. Autom.* **2023**, *56*, 465–473. [CrossRef]
30. Kumar, M.; Raj, N.; Singh, R.R. Ranking Indian Companies on Sustainability Disclosures Using the GRI-G4 Framework and MCDM Techniques. *Int. J. Sustain. Dev. Plan.* **2023**, *18*, 2791–2799. [CrossRef]
31. Zhang, M. Enhanced Estimation of Thermodynamic Parameters: A Hybrid Approach Integrating Rough Set Theory and Deep Learning. *Int. J. Heat Technol.* **2023**, *41*, 6. [CrossRef]
32. Phong, P.H.; Hieu, D.T.; Ngan, R.T.H.; Them, P.T. Some compositions of picture fuzzy relations. In Proceedings of the 7th National Conference on Fundamental and Applied Information Technology Research, FAIR'7, Thai Nguyen, Vietnam, 19–20 June 2014; pp. 19–20.
33. Ashraf, S.; Abdullah, S.; Mahmood, T.; Aslam, M. Cleaner production evaluation in gold mines using novel distance measure method with cubic picture fuzzy numbers. *Int. J. Fuzzy Syst.* **2019**, *21*, 2448–2461. [CrossRef]
34. Ashraf, S.; Abdullah, S.; Mahmood, T. Aggregation operators of cubic picture fuzzy quantities and their application in decision support systems. *Korean J. Math.* **2020**, *28*, 1976–8605.
35. Li, B.; Wang, J.; Yang, L.; Li, X. Novel generalized simplified neutrosophic number einstein aggregation operator. *Int. J. Appl. Math.* **2016**, *48*, 1–6.
36. Ashraf, S.; Abdullah, S.; Mahmood, T.; Ghani, F.; Mahmood, T. Spherical fuzzy sets and their applications in multi-attribute decision-making problems. *J. Intell. Fuzzy Syst.* **2019**, *36*, 2829–2844. [CrossRef]
37. Gundogdu, F.K.; Kahraman, C. Spherical fuzzy sets and spherical fuzzy TOPSIS method. *J. Intell. Fuzzy Syst.* **2019**, *36*, 337–352. [CrossRef]
38. Mou, J.; Duan, P.; Gao, L.; Pan, Q.; Gao, K.; Singh, A.K. Biologically Inspired Machine Learning-Based Trajectory Analysis in Intelligent Dispatching Energy Storage System. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 45094518. [CrossRef]
39. Zeng, S.; Munir, M.; Mahmood, T.; Naeem, M. Some T-spherical fuzzy Einstein interactive aggregation operators and their application to selection of photovoltaic cells. *Math. Probl. Eng.* **2020**, *2020*, 1904362. [CrossRef]
40. Liu, P.; Khan, Q.; Mahmood, T.; Hassan, N. T-spherical fuzzy power Muirhead mean operator based on novel operational laws and their application in multi-attribute group decision making. *IEEE Access* **2019**, *7*, 22613–22632. [CrossRef]
41. Hu, J.; Zou, Y.; Soltanov, N. A multilevel optimization approach for daily scheduling of combined heat and power units with integrated electrical and thermal storage. *Expert Syst. Appl.* **2024**, *250*, 123729. [CrossRef]
42. Özdemirci, F.; Yüksel, S.; Dinçer, H.; Eti, S. An assessment of alternative social banking systems using T-Spherical fuzzy TOP-DEMATEL approach. *Decis. Anal. J.* **2023**, *6*, 100184. [CrossRef]
43. Altork, Y.; Alamayreh, M.I. Optimizing Hybrid Heating Systems: Identifying Ideal Stations and Conducting Economic Analysis Heating Houses in Jordan. *Int. J. Heat Technol.* **2024**, *42*, 529–540. [CrossRef]
44. Sarkar, A.; Senapati, T.; Jin, L.; Mesiar, R.; Biswas, A.; Yager, R.R. Sugeno–Weber Triangular Norm-Based Aggregation Operators Under T-Spherical Fuzzy Hypersoft Context. *Inf. Sci.* **2023**, *645*, 119305. [CrossRef]
45. Yang, J.; He, Q. Scheduling Parallel Computations by Work Stealing: A Survey. *Int. J. Parallel Program.* **2018**, *46*, 173–197. [CrossRef]

46. Zhu, C. An Adaptive Agent Decision Model Based on Deep Reinforcement Learning and Autonomous Learning. *J. Logist. Inform. Serv. Sci.* **2023**, *10*, 107–118.
47. Keshavarz-Ghorabaee, M.; Amiri, M.; Zavadskas, E.K.; Turskis, Z.; Antucheviciene, J. Determination of objective weights using a new method based on the removal effects of criteria (MEREC). *Symmetry* **2021**, *13*, 525. [CrossRef]
48. Nanduri, A.K.; Sravanthi, G.L.; Pavan Kumar, K.V.K.V.L.; Babu, S.R.; Rama Krishna, K.V.S.S.S. Modified Fuzzy Approach to Automatic Classification of Cyber Hate Speech from the Online Social Networks (OSN's). *Rev. Intell. Artif.* **2021**, *35*, 139–144. [CrossRef]
49. Saidin, M.S.; Lee, L.S.; Marjugi, S.M.; Ahmad, M.Z.; Seow, H.V. Fuzzy Method Based on the Removal Effects of Criteria (MEREC) for Determining Objective Weights in Multi-Criteria Decision-Making Problems. *Mathematics* **2023**, *11*, 1544. [CrossRef]
50. Goswami, S.S.; Mohanty, S.K.; Behera, D.K. Selection of a green renewable energy source in India with the help of MEREC integrated PIV MCDM tool. *Mater. Today Proc.* **2022**, *52*, 1153–1160. [CrossRef]
51. Mani, D.B.; Munusamy, S. Fuzzy Rule Based-Model for Proficient Heart Disease Prediction in Data Lake. *Rev. d'Intell. Artif.* **2023**, *37*, 907. [CrossRef]
52. Singh, K.; Singh, Y.; Barak, D.; Yadav, M.; Özen, E. Parametric evaluation techniques for reliability of Internet of Things (IoT). *Int. J. Comput. Methods Exp. Meas.* **2023**, *11*, 123–134. [CrossRef]
53. Popovic, G.; Pucar, Đ.; Smarandache, F. MEREC-COBRA approach in e-commerce development strategy selection. *J. Process. Manag. New Technol.* **2022**, *10*, 66–74.
54. Yue, W.; Li, J.; Li, C.; Cheng, N.; Wu, J. A Channel Knowledge Map-Aided Personalized Resource Allocation Strategy in Air-Ground Integrated Mobility. *IEEE Trans. Intell. Transp. Syst.* **2024**, *9*, 1–14 . [CrossRef]
55. Liu, W.; Bai, X.; Yang, H.; Bao, R.; Liu, J. Tendon Driven Bistable Origami Flexible Gripper for High-Speed Adaptive Grasping. *IEEE Robot. Autom. Lett.* **2024**, *9*, 5417–5424. [CrossRef]
56. Seidi, M.; Yaghoubi, S.; Rabiei, F. Multi-objective optimization of wire electrical discharge machining process using multi-attribute decision making techniques and regression analysis. *Sci. Rep.* **2024**, *14*, 10234. [CrossRef]
57. Bošković, S.; Švadlenka, L.; Jovčić, S.; Dobrodolac, M.; Simić, V.; Bacanin, N. An alternative ranking order method accounting for two-step normalization (AROMAN)—A case study of the electric vehicle selection problem. *IEEE Access* **2023**, *11*, 39496–39507. [CrossRef]
58. Güçlü, P. Comparative Analysis of the MCDM Methods with Multiple Normalization Techniques: Three Hybrid Models Combine MPSI with DNMARCOS, AROMAN, and MACONT Methods. *Bus. Econ. Res. J.* **2024**, *15*, 129–154. [CrossRef]
59. Vasudevan, M.; Basu, B.; Pilla, F.; Mcnabola, A. Development and validation of a computational fluid dynamics modelling methodology for isolated and urban street canyon configurations using wind tunnel measurements. *Int. J. Comput. Methods Exp. Meas.* **2022**, *10*, 104–116. [CrossRef]
60. Alrasheedi, A.F.; Mishra, A.R.; Pamucar, D.; Devi, S.; Cavallaro, F. Interval-valued intuitionistic fuzzy AROMAN method and its application in sustainable wastewater treatment technology selection. *J. Intell. Fuzzy Syst.* **2022**, *preprint*. [CrossRef]
61. Cubranic-Dobrodolac, M.; Jovcic, S.; Boskovic, S.; Babic, D. A decision-making model for professional drivers selection: A hybridized fuzzy–AROMAN–Fuller approach. *Mathematics* **2023**, *13*, 2831. [CrossRef]
62. Nikolić, I.; Milutinović, J.; Božanić, D.; Dobrodolac, M. Using an interval type-2 fuzzy AROMAN decision-making method to improve the sustainability of the postal network in rural areas. *Mathematics* **2023**, *11*, 3105. [CrossRef]
63. Pishahang, M.; Jovcic, S.; Hashemkhani Zolfani, S.; Simic, V.; Görçün, Ö.F. MCDM-based wildfire risk assessment: A case study on the state of Arizona. *Fire* **2023**, *6*, 449. [CrossRef]
64. Bošković, S.; Švadlenka, L.; Dobrodolac, M.; Jovčić, S.; Zanne, M. An extended AROMAN method for cargo bike delivery concept selection. *Decis. Mak. Adv.* **2023**, *1*, 1–9. [CrossRef]
65. Dündar, S. Evaluation of hands-on entrepreneurship trainings on the basis of provinces, NUTS-I and NUTS-II regions by fuzzy BWM and AROMAN methods. *Pamukkale üNiversitesi Sos. Bilim. EnstitüSü Derg.* **2024**, *61*, 371–391. [CrossRef]
66. Ju, Y.; Liu, W.; Zhang, Z.; Zhang, R. Distributed Three-Phase Power Flow for AC/DC Hybrid Networked Microgrids Considering Converter Limiting Constraints. *IEEE Trans. Smart Grid* **2022**, *13*, 1691–1708. [CrossRef]
67. Rani, P.; Mishra, A.R.; Alrasheedi, A.F.; Xie, B.; Dwivedi, R. Evaluating the Sustainable Human Resource Management in Manufacturing Firms Using Single-Valued Neutrosophic Distance Measure-Based RANCOM-AROMAN Model. *Preprints* **2023**, 2023091698. [CrossRef]
68. Rong, Y.; Xu, Z.; Liu, J.; Liu, H.; Ding, J.; Liu, X.; Luo, W.; Zhang, C.; Gao, J. Du-Bus: A Realtime Bus Waiting Time Estimation System Based On Multi-Source Data. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 24524–24539. [CrossRef]
69. Wang, R.; Gu, Q.; Lu, S.; Tian, J.; Yin, Z.; Yin, L.; Zheng, W. FI-NPI: Exploring Optimal Control in Parallel Platform Systems. *Electronics* **2024**, *13*, 1168... [CrossRef]
70. Mahmood, T.; Ullah, K.; Khan, Q.; Jan, N. An approach towards decision-making and medical diagnosis problems using the concept of spherical fuzzy Sets. *Neural. Comput. Appl.* **2018**, *31*, 7041–7053. [CrossRef]
71. Chen, T.Y. An evolved VIKOR method for multiple-criteria compromise ranking modeling under T-spherical fuzzy uncertainty. *Adv. Eng. Inform.* **2022**, *54*, 101802. [CrossRef]
72. Ju, Y.; Liang, Y.; Luo, C.; Dong, P.; Gonzalez, E.D.S.; Wang, A. T-spherical fuzzy TODIM method for multi-criteria group decision-making problem with incomplete weight information. *Soft Comput.* **2021**, *25*, 2981–3001. [CrossRef]

73. Fan, J.; Han, D.; Wu, M. T-spherical fuzzy COPRAS method for multi-criteria decision-making problem. *J. Intell. Fuzzy Syst.* **2022**, *43*, 2789–2801. [CrossRef]
74. Zhang, H.; Wei, G. Location selection of electric vehicle charging stations by using the spherical fuzzy CPT–CoCoSo and D-CRITIC method. *Comput. Appl. Math.* **2023**, *42*, 60. [CrossRef]
75. Ali, J. A novel score function based CRITIC-MARCOS method with spherical fuzzy information. *Comput. Appl. Math.* **2021**, *40*, 280. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.