sustainability

Review

Development of a Generic Decision Tree for the Integration of Multi-Criteria Decision-Making (MCDM) and Multi-Objective Optimization (MOO) Methods under Uncertainty to Facilitate Sustainability Assessment: A Methodical Review

Jannatul Ferdous [1,*], Farid Bensebaa [2], Abbas S. Milani [3], Kasun Hewage [3], Pankaj Bhowmik [4] and Nathan Pelletier [5]

[1] Interdisciplinary Graduate Studies (IGS)-Sustainability, University of British Columbia, Okanagan Campus, 3333 University Way, Kelowna, BC V1V 1V7, Canada
[2] Energy, Mining and Environment, National Research Council Canada, 1200 Montreal Road, Ottawa, ON K1A 0R6, Canada; farid.bensebaa@nrc-cnrc.gc.ca
[3] School of Engineering, University of British Columbia, Okanagan Campus, 3333 University Way, Kelowna, BC V1V 1V7, Canada; abbas.milani@ubc.ca (A.S.M.); kasun.hewage@ubc.ca (K.H.)
[4] Aquatic and Crop Resource Development, National Research Council, 110 Gymnasium Place, Saskatoon, SK S7N 0W9, Canada; pankaj.bhowmik@nrc-cnrc.gc.ca
[5] Faculties of Science (Biology) and Management, University of British Columbia, Okanagan Campus, 3333 University Way, Kelowna, BC V1V 1V7, Canada; nathan.pelletier@ubc.ca
* Correspondence: jannatul.ferdous@ubc.ca

Abstract: The integration of Multi-Objective Optimization (MOO) and Multi-Criteria Decision-Making (MCDM) has gathered significant attention across various scientific research domains to facilitate integrated sustainability assessment. Recently, there has been a growing interest in hybrid approaches that combine MCDM with MOO, aiming to enhance the efficacy of the final decisions. However, a critical gap exists in terms of providing clear methodological guidance, particularly when dealing with data uncertainties. To address this gap, this systematic review is designed to develop a generic decision tree that serves as a practical roadmap for practitioners seeking to perform MOO and MCDM in an integrated fashion, with a specific focus on accounting for uncertainties. The systematic review identified the recent studies that conducted both MOO and MCDM in an integrated way. It is important to note that this review does not aim to identify the superior MOO or MCDM methods, but rather it delves into the strategies for integrating these two common methodologies. The prevalent MOO methods used in the reviewed articles were evolution-based metaheuristic methods. TOPSIS and PROMETHEE II are the prevalent MCDM ranking methods. The integration of MOO and MCDM methods can occur either a priori, a posteriori, or through a combination of both, each offering distinct advantages and drawbacks. The developed decision tree illustrated all three paths and integrated uncertainty considerations in each path. Finally, a real-world case study for the pulse fractionation process in Canada is used as a basis for demonstrating the various pathways presented in the decision tree and their application in identifying the optimized processing pathways for sustainably obtaining pulse protein. This study will help practitioners in different research domains use MOO and MCDM methods in an integrated way to identify the most sustainable and optimized system.

Keywords: multi-objective optimization; multi-criteria decision-making; hybrid methods; decision tree; uncertainty; pulse fractionation

check for updates

Citation: Ferdous, J.; Bensebaa, F.; Milani, A.S.; Hewage, K.; Bhowmik, P.; Pelletier, N. Development of a Generic Decision Tree for the Integration of Multi-Criteria Decision-Making (MCDM) and Multi-Objective Optimization (MOO) Methods under Uncertainty to Facilitate Sustainability Assessment: A Methodical Review. *Sustainability* **2024**, *16*, 2684. https://doi.org/10.3390/su16072684

Academic Editor: Jurgita Antucheviciene

Received: 29 January 2024
Revised: 19 March 2024
Accepted: 21 March 2024
Published: 25 March 2024

1. Introduction

To ensure sustainable development, it is crucial to mitigate the adverse impacts of industrial systems and to seek to improve the efficiency of industrial processes continuously.

One of the ways to carry this out is by identifying the most optimal and sustainable industrial systems considering all three pillars of sustainability. However, this can be complicated as they often conflict with each other. For instance, the most economically feasible systems might have higher environmental impacts and vice versa. Multi-Objective Optimization (MOO) and Multi-Criteria Decision-Making (MCDM) methods are widely used methods to consider multiple conflicting criteria in order to identify optimal solutions on the basis of integrated sustainability assessment. This study primarily aims to identify the methodological approaches to integrating these two methods for sustainability assessment under uncertainty through a systematic review and to develop a generic methodological decision tree to guide practitioners.

1.1. Multi-Objective Optimization (MOO)

Generally defined, "optimization" refers to finding the best solution, or a set of outperforming solutions, given a specific search space shaped by predefined constraints [1]. Outperforming or nondominated solutions refer to outcomes where it is not possible to improve one objective function's value without degrading one or more other objective functions' values. When the problem contains continuous objective functions with two or more conflicting goals, it is often considered to be a Multi-Objective Optimization (MOO) problem [2]. These objectives are designed to either minimize or maximize some functions related to, e.g., economic (i.e., cost, profit), technical (i.e., energy use efficiency, yield), environmental (i.e., GHG emissions, land use footprint), or other factors or decision/design variables. Depending on the nature of the variables (i.e., continuous, categorical, integers, non-integers, binary) and the linearity of objective functions, different MOO methods are used [1]. There is a wide range of optimization methods available but selecting the most suitable method depends on several factors: the linearity vs. non-linearity of the objective functions; deterministic vs. stochastic/approximate methods; computational simplicity; and time constraints [3–6].

Stochastic/approximate optimizations are also known as heuristic methods, which can be classified as either constructive or local search methods depending on how they iteratively search for optimal solutions [7–9]. More recently, metaheuristic methods that are not problem-specific have been developed as general frameworks based on natural and artificial world phenomena to find approximately optimal solutions [8,10]. Metaheuristic methods can be divided into four categories: evolution-based (genetic cross-over, mutation), swarm-based (collective intelligence), physics-based (laws of the physical world), and human-based (sociological behaviour) optimization methods [10–12].

In contrast, deterministic modelling based on mathematical programming methods—linear programming, non-linear programming, integer programming, mixed-integer programming, etc.—are problem-specific [10,13,14]. These methods have limited applicability due to the impossibility of representing all real-world systems as mathematical models. Mathematical programming methods are best suited for specific types of problems but there is no individual method for all types of problems [15]. There are also differences in the performance of metaheuristic and mathematical methods with respect to solution quality, computational time, the scale of the system studied, etc. The problem specificity of mathematical programming makes it relatively inflexible [16,17]. Comparisons among metaheuristic and mathematical programming optimization methods with their strengths and weaknesses are presented in Table S1 (in Supplementary Files). The main differences between the metaheuristic and mathematical programming methods are their flexibility and adaptability. Metaheuristic methods are very efficient in handling complex, non-linear, and multi-modal problems whereas mathematical programming methods are problem-specific and well suited for accurately modelled problems. Mathematical programming models are deterministic and can find the ultimate optimal solution(s) based on rigorous mathematical formulations. On the contrary, metaheuristic methods are non-deterministic and can find the approximate optimal solution(s) but often find merely good ones (Table S1).

1.2. How Multi-Criteria Decision-Making (MCDM) Methods Can Be Linked to MOO

Conventionally, MOO problems are often converted into single-objective optimization problems by aggregating similar objectives or through the weighted sum method [18]. In most cases, objective functions conflict with each other, so multiple objectives are formulated for MOO problems so as to generate a set of Pareto-optimal solutions instead of one unique solution [2,19,20]. Pareto-optimal solution sets represent non-dominated solutions with varying degrees of trade-offs between the objective functions. An additional step for decision-making is required to find the most preferred optimal solution [1,19,21]. Typically, different Multi-Criteria Decision-Making (MCDM) methods (which refer to problems with no explicit objective functions, and rather comprising a decision matrix with a list of alternatives/options along with pre-defined criteria values) are applied to find the best solution from Pareto-optimal sets of MOO according to the preferences of decision-makers (DMs) [20,22–27]. MCDM, in essence, is a management and decision-making support approach which involves multiple alternatives and criteria/objectives [27,28]. In this case, different solutions in the Pareto set become different alternatives in the MCDM problem and the objective functions' values become criteria values.

Choosing an appropriate MCDM method is not an easy task as all of the methods have their advantages and limitations, and decision problems are often complex and delicate, with several conflicting criteria [29]. MCDM methods keep the DMs at the centre of the process and may incorporate their preferences for identifying the best alternative [30]. Numerous MCDM methods have been developed for various fields of research and new and improved methods continue to be developed [31]. The choice among MCDM methods depends on the required input information and its relative richness, the methods' parameters, and the effort required for modelling [30]. The three broad categories of MCDM methods are the full aggregation approach, the outranking approach, and the goal and reference level approach. In the full aggregation approach, alternatives are compared and ranked based on a global score that is generated from the individual scores of the criteria. If the utility function of each criterion is known, multi-attribute utility theory (MAUT) can be used. Otherwise, the analytic hierarchy process (AHP), analytic network process (ANP), and Measuring Attractiveness by a Categorical-Based Evaluation Technique (MACBETH) can be used [30,32]. Outranking or non-compensatory approaches comprise several methods that employ pairwise comparisons and thresholds. When modelling preferences, some options can be incomparable, which does not allow complete ranking. The Preference Ranking Organization Method for Enriched Evaluation (PROMETHEE) [33] and Elimination and Choice Expressing Reality (ELECTRE) [34] are the most commonly used outranking methods. The goal and reference level approach includes a goal or reference value for each criterion and picks the best alternative for each criterion closest to that reference value. The Technique of Order Preference Similarity to the Ideal Solution (TOPSIS) [35], goal programming, and data envelopment analysis (DEA) are commonly used goal and reference level methods [30].

MCDM methods are commonly used in the context of sustainability assessment. Among the MCDM methods reviewed by Huang et al. [36], 48% of the studies used either AHP or ANP and 16% and 13% of them used MAUT and outranking methods, respectively. The main characteristics, advantages, and disadvantages of these common MCDM methods are illustrated in Table S2 (in Supplementary Files), based on information from Aruldoss et al. [37], Figueira et al. [38], Ishizaka and Nemery [30], and Velasquez and Hester [39].

1.3. Uncertainty Consideration

Along with combining MOO and MCDM methods, the consideration of uncertainty in these methods is also of increasing interest among researchers. If MOO methods consider uncertainty, then it is called robust optimization [40,41]. There are similarly robust MCDM methods. For robust decision-making, uncertainty consideration is an integral part [42]. Uncertainty consideration aims to protect DMs from dealing with ambiguity in model parameters/input data and/or subjective preferences [41]. Robust optimization can be applied either by robust regularization, by a probabilistic threshold, or by a possibilistic approach. Robust regularization is a deterministic approach for optimizing based on the worst-case scenario and assumes that any alternative will be better than the worst extreme under uncertainty [41,43,44]. The probabilistic threshold maximizes the probability of obtaining an acceptable solution by including uncertainty ranges in the problem [45–47]. The possibilistic approach applies fuzzy set theory principles and assumes that all the necessary probability distributions are known [48,49]. Robust regularization is less computationally intensive than probabilistic and possibilistic methods [45].

Uncertainty can be included with MOO methods either a posteriori (sensitivity analysis) or a priori (during model development) [2]. On the other hand, uncertainty in MCDM methods is mostly addressed by using stochastic methods to consider the ambiguity in DMs' subjective preferences and the associated weights assigned to each criterion/objective function [27]. It can be quantified via a statistical probability distribution [27,50].

1.4. Current Approaches to MOO/MCDM Meta-Analysis

There are countless research articles on MOO and MCDM methods. As described earlier, integrating these two methods for identifying the best options from among numerous alternatives/Pareto solutions is an emerging research area. The a priori method integrates DMs' preferences for different objective functions before conducting the MOO. The a posteriori method integrates DMs' preferences after obtaining Pareto-optimal solutions from the MOO algorithms [51]. Several recent studies combined MOO and MCDM methods, including optimal planning for electric vehicle charging stations [52], polymer extrusion problems [53], chemical engineering processes [54], reservoir operation [55], developing transport plans [56], etc. Padhye and Deb [57] used two MOO methods, Non-Dominated Sorting Genetic Algorithm (NSGA)-II and Particle Swarm Optimization (PSO) and three MCDM methods (marginal utility method, aspiration point method, and the L_2 metric method) for the selective laser sintering process. A combination of genetic algorithm (GA)/NSGA with TOPSIS was discussed by both Kesireddy et al. [58] and Kabadayi and Dehghanimohammadabadi [59]. Including TOPSIS and the Best-Worst Method (BWM) with MOO methods was reported by Goodarzi et al. [60] for green supplier evaluation and optimal order allocation, and by Ridha et al. [61] for designing battery storage systems. Jafarian-Namin et al. [62] employed an evolutionary algorithm to obtain the Pareto front and then used both DEA and VIKOR (VIekriterijumsko KOmpromisno Rangiranje) as MCDM methods to identify the optimal solution for control chart design.

Numerous review articles summarize the separate uses of MOO and MCDM methods in the different research areas. Only a few review papers to date, however, have focused on integrating MOO and MCDM methods. Ridha et al. [63] considered recent articles investigating the current state of the art of designing standalone photovoltaic systems using MOO and MCDM methods. Pereira et al. [64] reviewed the literature on MOO in mechanical engineering problems and found that employing metaheuristic methods with a posteriori MCDM methods is increasingly popular. Odu and Charles-Owaba [65] reviewed the literature on MOO and MCDM methods and concluded that there is no single superior approach. The selection of a suitable method is mainly dependent on the available information, input type, DMs' preferences, and solution requirements [65]. Durbach and Stewart [66] reviewed the literature to identify different tools for including uncertainty considerations in the MCDM process. Broekhuizen et al. [67] focused on healthcare decisions in their review to classify the approaches used to deal with uncertainties in the MCDM process.

1.5. Motivation and Objectives of the Present Article

To date, and to the best of the authors' knowledge, there has been no systematic report that develops a decision tree with methodological choices for integrating MOO and MCDM methods, including the consideration of data uncertainty under a given application area. To fill this gap, the current manuscript aims first at a systematic review of the limited literature that integrated MOO methods with MCDM methods, either a priori or a posteriori. The review was designed to specifically answer the following questions:

i. What types of MOO methods have been most commonly used in integrated studies? Are there any specific reasons articulated to justify the use of those methods?
ii. How did the reported works integrate MOO methods with MCDM methods?
iii. What types of MCDM methods (weighting and ranking methods) have been most commonly used? Are there any specific reasons articulated to justify the use of those methods?
iv. What is the current practice to include uncertainty considerations within these integrated (hybrid approach) frameworks?

Next, based on the findings from these questions, a novel generalized decision tree is proposed in order to better help practitioners make methodological decisions on how to combine MOO and MCDM under each given application. Finally, the decision tree is demonstrated using a case study on the sustainable optimization of pulse processing pathways based on economic, technical, and environmental criteria.

The remainder of this paper is structured as follows: Section 2 presents the meta-analysis-based review using the PRISMA method. Following this, findings for the above questions are presented in Section 3: Results. Next, a decision tree based on the review findings is developed and demonstrated for the selected case study in Section 4: Discussion. Finally, Section 5: Conclusions highlights the major findings and presents a set of recommendations for potential follow-up studies, along with the limitations of the current study.

2. Methodology Used for The Systematic Review

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method [68,69] was followed to conduct the review of the articles that integrated MOO and MCDM methods. The PRISMA method comprises a 27-item checklist and it has been used in different fields of research [70–74]. There are three stages in the PRISMA method: search strategy, screening criteria, and the extraction and synthesis of data, which are explained in the following sections in detail.

2.1. Search Strategy

For searching published peer-reviewed primary research articles, the Web of Science search engine was used. Different keyword combinations with logical operators 'AND' and 'OR' were used to identify the relevant literature. The combination of search terms was TS ("multi-criteria") AND TS (("multi-objective") OR ("multiple objective*")) AND TS ("optimi*") AND ALL ("uncertain*"). TS stands for 'Topic search', where it only searches in the title, abstract, author keywords, and Keywords Plus. A special operator '*' was also included with the search terms to capture more literature with that group of characters, i.e., "optimi*" will capture optimize, optimization, optimized, etc. both in American and British spellings. For the term "uncertain*", ALL fields were considered, as sometimes authors do not use uncertainty in the title, keywords, and/or abstract despite considering it in their studies.

2.2. Screening Criteria

The Web of Science search identified 224 papers during the initial search, among which 186 papers were primary research articles. The temporal range of these articles was from 2000 to 2022. In the next step, abstracts and highlights (if any) were screened to narrow down the sample size. The literature that did not perform both MOO and MCDM was excluded in this step, resulting in a shortlist of 53 research articles. Among the excluded articles, most used 'multi-criteria optimization' instead of 'multi-objective optimization' but did not use any additional MCDM methods. Also, some of them used only Multiple Objective Optimization on the basis of Ratio Analysis plus Full Multiplicative Form (MULTIMOORA), which is an MCDM method, not an MOO method. After the abstract screening, 10 more papers were excluded based on being published before 2018. Since the main focus is to capture recent research trends, only articles published within the last 5 years (2018–2022) were selected. Moreover, during the full-text review, 2 more articles were excluded as they conducted MOO and MCDM separately. The final sample size was 41 research articles. Figure 1 illustrates the systematic review method for selecting and screening published articles. The screening criteria were (i) studies that are primary research articles, (ii) studies that used both MOO and MCDM methods, (iii) studies in which MOO and MCDM methods were integrated (i.e., outcomes of MOO were input for MCDM problem or vice versa), and (iv) studies that were published between 2018 and 2022.

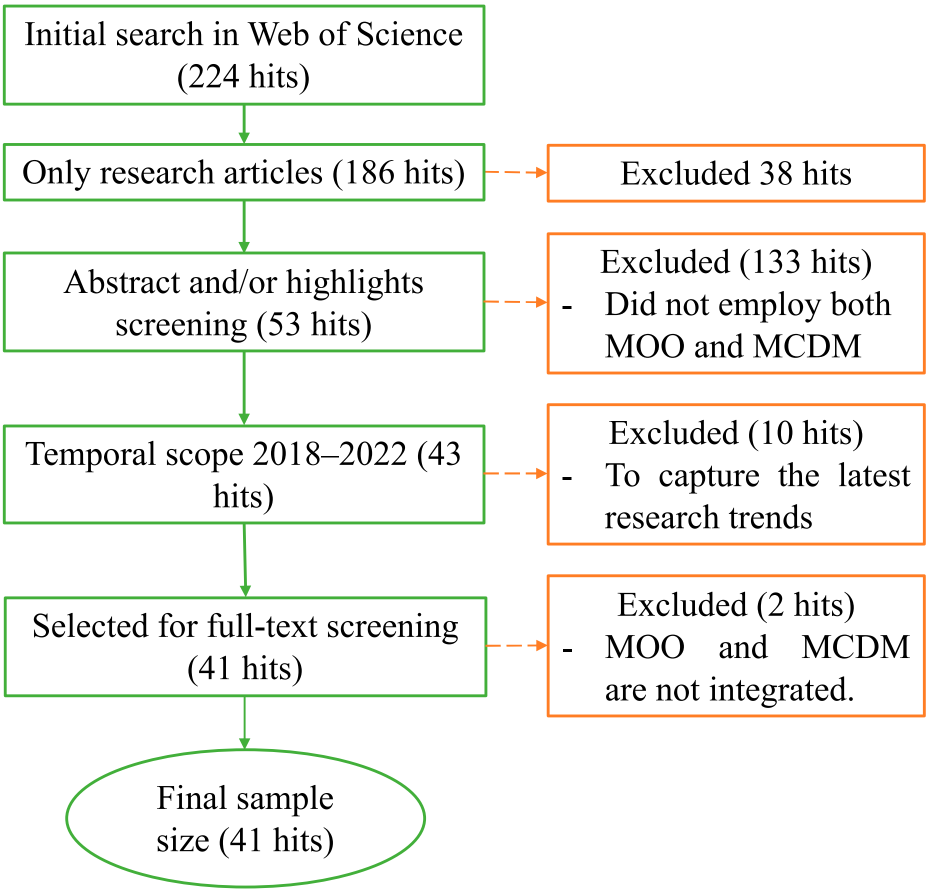

Figure 1. PRISMA systematic review method for finalizing the sample size for review.

2.3. Extraction and Synthesis of Data

To collate information from the reviewed articles, an Excel-based synthesis table was used (Table S3 in Supplementary Files). Review question 1 aimed at identifying the type of MOO method(s) used and the justifications/reasons behind using specific methods. All the MOO methods were classified as either being mathematical-linear, mathematical-non-linear, or metaheuristic. If the authors mentioned why they chose that method, this was also extracted and discussed in the Results Section. For review question 2, the type of integration between MOO and MCDM—either a priori or a posteriori—was identified. For review question 3, the type of MCDM methods utilized was documented, differentiating between weighting and ranking methods. Weighting methods (i.e., entropy, AHP, BWM) can be objective, subjective, or a combination of both. Subjective weighting methods are used to include the subjective preferences of DMs and stakeholders. Ranking methods (i.e., TOPSIS, PROMETHEE, VIKOR) are used to rank the alternatives based on their weighted/non-weighted criteria. Reasons for choosing specific methods were identified for further discussion. Finally, for review question 4, information regarding uncertainty considerations either with MOO and/or MCDM methods was collected to determine current practices. Information regarding sensitivity analyses was also collected as it is mostly related to uncertainty.

2.4. Development of a Decision Tree

As outlined in Section 1.5, one of the main objectives of this review paper was to be able to develop a decision tree with methodological choices for integrating MOO and MCDM methods, thereby identifying the most sustainable and optimized solution in diverse decision contexts. Such a decision tree has not been realized in earlier studies. This was accomplished here based on the findings of review questions 1–4, along with a discussion of the different methodological pathways that can be followed to integrate MOO and MCDM. Additionally, to illustrate the decision tree with an example, a case study on pulse processing pathways in Canada has been elaborated.

3. Results

In this section, the extracted information from the reviewed articles for review questions 1–4 is analyzed and discussed—which MOO methods were used and why; what the commonly used weighting and ranking methods of MCDM are; how MOO and MCDM were integrated; and the current practices of uncertainty considerations in these studies.

3.1. Multi-Objective Optimization (MOO) Methods

Out of the 41 reviewed articles, 29 (70.7%) articles utilized metaheuristic optimization methods and 13 of them developed mathematical models (12 linear and 1 non-linear [75]) to find Pareto-optimal solution sets based on multiple-objective functions and constraints (Table S3). Among the metaheuristic methods, evolutionary optimization methods like genetic algorithms [76–78] and NSGA (17 articles) were the most commonly used methods (Table S3). Seventeen articles (41.5%) used the NSGA-II version (Table S3). Xu et al. [79] and Sharma and Mukherjee [80] proposed improved NSGA-II methods. Wan et al. [81] integrated NSGA-II with differential evolution and named the method Non-dominated Sorting Differential Evolution (NSDE). NSGA-II was selected by the researchers mainly due to its computational speed and better performance in terms of maintaining the diversity/versatility among Pareto-optimal solutions, and better convergence efficiency [2,79,82–84]. Mirghaderi and Modiri [84] applied the Strength Pareto Evolutionary Algorithm (SPEA) to identify an optimized and sustainable supply chain for construction materials and reported that the method outperformed NSGA-II and Pareto Envelope-Based Selection Algorithms for addressing real cases. The application of another evolutionary algorithm—Adaptive Reference Point-Based Optimization—was applied by Liu et al. [50].

The evolutionary method, which is synonymous with GA [11], follows the principles of natural evolution to identify optimal solutions [10]. There are four key features of this evolution-based principle: (i) it starts with a population consisting of individuals with the ability to reproduce; (ii) they have a finite lifespan; (iii) variation across the population is considered; and (iv) reproduction and survival ability are positively correlated [11]. The most commonly used NSGA was originally developed by Srinivas and Deb [85] and currently, there are two updated iterations: NSGA-II and NSGA-III [18,86]. NSGA-II became popular among researchers because of two key features. First, it employs the elitism concept for all generations to ensure the maintenance of the best-performing solutions throughout succeeding generations [11,18]. Otherwise, there can be the possibility of losing the best-performing solutions in any generation as it chooses the solutions probabilistically. The second important feature of NSGA-II is the consideration of the non-dominated sorting concept, which allows it to find solutions that are not dominated by other solutions under any objective functions [18,87]. Evolution-based MOO methods were widely used as they allow for the simultaneous exploration of different regions of the solution space, enhance the diversity of the solutions, and increase the chance of finding global optima. They are suited for non-linear and complex problems with non-differentiable and discontinuous objective functions [88].

The Particle Swarm Optimization (PSO) method was used in five articles (12.2%) [28,77,80,89,90]. The reasons for selecting the PSO method were its key features, like its requirement for fewer parameters, easy operation, fast convergence, better global optimization capability, and high search speed even for a complex model [28,90]. Yang et al. [27] applied the Shuffled Frog-Leaping Algorithm (SFLA), which is a population-based metaheuristic algorithm combining memetics and Particle Swarm Optimization [91]. They chose SFLA as it can combine deterministic and stochastic methods to obtain more precise, high-quality trade-off solutions which are diverse and uniformly distributed and can handle complex and high-dimension problems [27]. The Crow Search Algorithm (CSA) was utilized by Panah et al. [92] as it offers a compromise between elapsed time and calculation burden along with a simple structure. Several researchers described selecting their optimization methods based on the relevant literature [20,78,93,94].

Among mathematical modelling examples, ε-constraint-based optimization methods (i.e., ε-constraint, Augmented ε-constraint) were used in six articles (Table S3). Mirghaderi and Modiri [84] mentioned that the ε-constraint method is well suited for small-scale cases. The ε-constraint method transforms all of the objective functions into constraints, except the objective with the highest priority. An epsilon is defined as the threshold of acceptable limit for each of the objective functions, and considering varying epsilon, the Pareto set is identified [95]. An improved ε-constraint method named Augmented ε-constraint (AUGMECON) was also used by Hasani [96] and Zhong et al. [97]. AUGMECON is more effective than the traditional ε-constraint method. It requires less computational time as it provides a weak Pareto-optimal solution [97]. It also allows the simultaneous minimization of two functions that have conflicting objectives [96]. Other mathematical programming methods used in the reviewed articles were Weighted Goal Programming [93,98], LP metrics [97,99,100], and Mixed Integer Linear Programming [101–103]. Weighted Goal Programming allows the incorporation of DMs' preferences for each objective function more than standard goal programming and converts all of the conflicting variables into a normalized weighted single-objective function [98,104].

3.2. Multi-Criteria Decision-Making (MCDM) Methods

For detailing the methodological choices made in the reviewed articles that reported the use of MCDM methods, information was gathered for weighting and ranking methods separately.

3.2.1. Weighting Methods

Weighting in MCDM methods can be assigned to three main types: objective (derived from input data), subjective (based on DMs' preferences), and a combination of subjective and objective weights (Table S3). Half of the reviewed articles (20 articles, 48.8%) only used subjective weights to include DMs' preferences, mostly through AHP (55%) and BWM (20%) methods. Both BWM and AHP allow for the integration of multiple DMs' and stakeholders' preferences. Although they both use pairwise comparison concepts, BWM performs mostly reference comparisons, which reduces the number of pairwise comparison matrices substantially [84]. Sometimes, the performance of AHP was boosted by fuzzification, which uses a complementary judgement matrix instead of the conventional reciprocal matrix [27]. In Fuzzy AHP, the weight of one factor is not affected by other elements, which preserves the physical significance of weight allocation [27].

Multiple studies (six articles, 14.6%) employed a combination of subjective and objective weights, where entropy was the only objective weighting method. This type of comprehensive weighting method is more effective and stable [97]. Only a few studies were dependent on objective weights solely to avoid uncertainty with subjective weighting [79,89,105]. Eleven articles (26.8%) did not use any type of weighting method (Table S3).

3.2.2. Ranking Methods

Different types of outranking and goal and reference level approaches for MCDM were used in the reviewed articles (Table S3). TOPSIS was employed in the largest share (18 articles, 43.9%). TOPSIS requires a minimal number of inputs and provides very understandable outputs, and subjective and/or objective weights can easily be incorporated [30]. It also ensures less information loss and provides a robust logical structure with strong computational capability [90]. TOPSIS considers both positive and negative ideal solutions, unlike VIKOR, which only considers the distance from the positive ideal [78,90]. The VIKOR method was used in a small number of articles to choose the best option from the Pareto set [80,96,106]. The ELECTRE method was used by Medina-González et al. [103] and Taravatrooy et al. [107].

Only 6 articles out of 41 employed the PROMETHEE ranking method, and 3 used PROMETHEE II (Table S3). PROMETHEE II is preferred as it can conduct a complete ranking based on global net flows as opposed to the partial ranking based on global positive and global negative flows that is supported by PROMETHEE I [20,30]. PROMETHEE II is stable, simple, and clear and can deal with both numerical and scaled values with uncertainty [30,108,109]. It does not require processing original data. Rather, it uses different preference functions [20]. It can address the deviations between alternatives and compare different criteria with various scales [109].

Stochastic Multi-Criteria Acceptability Analysis (SMAA), Grey Correlation Analysis (GCA) and their combination were also reported in some of the reviewed articles (Table S3). In SMAA, DMs do not need to assign any weights in advance. Instead, it explores feasible weight space to give a rank to an alternative [27,50]. With less original data or imprecise or missing information, SMAA and GCA can be performed by using probability distributions and handling uncertainty [27,90]. Other ranking methods used in the reviewed articles were either an improvement of a conventional method, a combination of two methods, or a newly introduced method like Complex Proportional Assessment (COPRAS) [89] or R-method [110] (Table S3).

Despite the fact that the selection of MCDM methods can be tricky, some have argued that the choice of MCDM methods will rarely influence the results as the top few alternatives remain the same or overlap significantly regardless of the MCDM methods used [36]. This is because the top alternatives are superior enough to not be affected by the slight differences between the methods [36,111,112]. Erdogan et al. [52], for example, compared five MCDM methods and found their final results to be largely similar—the first- and second-ranked alternatives were the same for all the methods.

3.3. Integrated MOO/MCDM Methods

MCDM methods can be integrated with MOO methods in two ways: a priori and a posteriori. The most commonly used integration method was a posteriori (32 articles, 78.1%; Table S3). A posteriori integration means performing the MOO problem first to obtain Pareto-optimal solutions, which then become the alternatives for the MCDM problem. The combination of different weighting and ranking methods identifies the best optimal solutions for the studied system. A priori integration refers to identifying the best alternative system through MCDM methods and then optimizing that system [20]. In this case, the weighting methods are used before performing MOO and weights are assigned to objective functions. Sometimes, these weights can be used to convert the MOO problem into a single-objective optimization problem [102]. Only 6 articles out of 41 followed the a priori method. Three other articles integrated MOO and MCDM both a priori and a posteriori. They used the weighting methods before MOO but the ranking methods after performing MOO to rank the Pareto-optimal solutions [97,99,100]. The choice of integration method (a priori or a posteriori, or a combination thereof) is solely dependent on the DM. For integrating MOO and MCDM, there are several modern tools and software including MATLAB [113], Python (i.e., libraries like SciPy, Distributed Evolutionary Algorithms, PyDecision Tree, Scikit-Criteria, etc.) [114], machine learning [54], data mining [115], Multi-Objective Evolutionary Algorithms (MOEA) Frameworks in R and Java [116], General Algebraic Modeling System (GAMS) [117], etc.

3.4. Uncertainty Analysis

Considerations of uncertainty can be performed in two ways: with the MOO model and with the MCDM model. Uncertainties with design variables, model parameters, objective functions, etc. are mainly considered in MOO problems. On the other hand, uncertainties in criteria weights and/or DMs' preferences are of concern in MCDM problems. The following sections describe the current practices found in the reviewed articles for integrating uncertainty concepts in MOO and MCDM problems.

3.4.1. Uncertainty in MOO

In MOO problems, sources of uncertainty are design variables, environmental conditions (for example, flood flow for reservoir-related problems [118]), model parameters, etc. Integrating uncertainty in MOO problems is quite common. In total, 33 articles out of 41 (80.5%) had uncertainty considerations in their MOO models (Table S3). A wide range of different uncertainty propagation methods was reported, including Monte Carlo Simulation, the interval uncertainty method [119,120], triangular fuzzy numbers [121,122], the fuzzy transformation method/fuzzy set theory, generalized likelihood uncertainty estimation [123], etc. Among these, the Monte Carlo Simulation and triangular fuzzy numbers methods were most common (Table S3). Monte Carlo Simulation can handle complex systems with multiple sources of uncertainty. It provides multiple possible outcomes and their associated probabilities based on a large set of random data samples [124]. Triangular fuzzy number-based uncertainty analysis is widely used due to its simplicity and interpretability, and it is very easy to handle mathematically [125]. Based on the reviewed articles, it would appear that there are currently no specific guidelines prioritizing the use of any particular method for uncertainty analysis.

3.4.2. Uncertainty in MCDM

The main sources of uncertainty in MCDM problems are criteria weights. As with MOO problems, however, integrating uncertainty analysis with MCDM methods is not commonplace. Only 12 articles out of 41 (29.3%) have considered uncertainty in MCDM methods—mostly to deal with uncertainty in subjective weights (Table S3). Among them, six articles mentioned using triangular fuzzy numbers/fuzzy set theory and the other four articles mentioned using probabilistic distributions to deal with uncertainty in criteria weights (Table S3).

3.5. Sensitivity Analysis

Sensitivity analysis is directly related to uncertainty analysis. Based on the uncertainty in model parameters, sometimes different studies have generated different scenarios and carried out sensitivity analyses for those scenarios to check the robustness of the model. Uncertainty in criteria weights leads to sensitivity analysis for MCDM methods with different weights. Sensitivity analyses with different model parameters/scenarios and different weights in MCDM methods were equally utilized in the reviewed articles. In total, 16 out of 41 (39%) articles carried out sensitivity analyses and, among them, 8 articles conducted the sensitivity check with different criteria weights and 7 of them conducted it with different model parameters/scenarios in MOO problems. A few used both methods (Table S3).

4. Discussion: Development of Decision Tree and Its Application

Based on the findings from the reviewed articles and information regarding how MOO and MCDM methods can be integrated with uncertainty considerations, a decision tree was developed (Figure 2). This decision tree is intended to support choosing the most suitable methodological pathway for identifying the best-optimized solution/product system with the aid of MOO and MCDM methods. In the decision tree, START indicates the starting point, and the ovals represent the questions that need to be answered for the specific study. The rectangles are the methodological choices based on the answers provided. The hexagons are the interim outcomes/solutions from either MOO or MCDM and the diamond shapes indicate the final outcome from the integrated methodological framework (Figure 2).

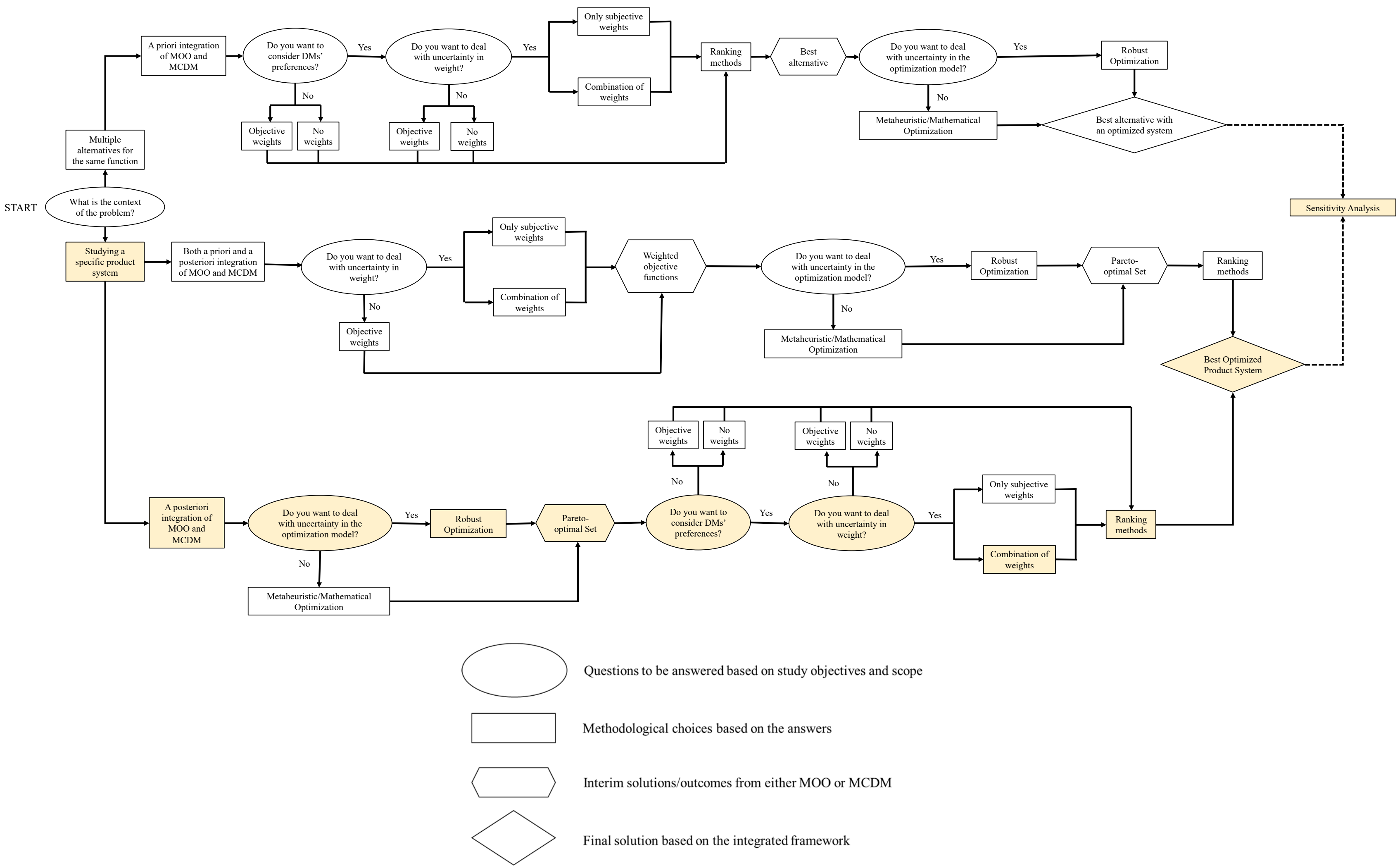

Figure 2. Decision tree for making methodological choices to integrate MOO and MCDM methods with uncertainty considerations. The highlighted path is the recommended path for the present Case Study.

From the starting point, researchers need to determine the context of the study/problem. If they have multiple alternatives for the same function (i.e., identifying the best protein source from multiple protein alternatives), they need to follow the a priori integration pathway, which involves integrating MCDM before conducting MOO. On the other hand, if the study is focused on any specific product system and wants to optimize that system (i.e., finding an optimized pathway for plant-protein extraction), it will have two options to integrate MOO and MCDM. The first option is to integrate MCDM both before and after conducting MOO. The second option allows a posteriori integration, which involves performing MCDM after MOO. The following sections detail these options and other methodological choices from the decision tree.

4.1. A Priori Integration of MOO and MCDM

When the study has multiple discrete alternatives and there are multiple conflicting criteria associated with those alternatives, MCDM methods should be employed first to identify the best alternative and then MOO methods can be applied to optimize the supply chain of that best alternative to obtain the best alternative with an optimized system. For applying MCDM under the compensatory type of methods, researchers often need to answer two more questions about their preferences on criteria weights and uncertainty. If they decide to incorporate DMs' and stakeholders' preferences for the criteria and sometimes for alternatives (i.e., in AHP), they need to decide about uncertainty as well. Without including DMs' preferences, they can either use the objective weighting method (i.e., entropy) or skip weighting (equal weight). But for including DMs' preferences, ideally, they need to deal with uncertainty. Subjective weights based on expert opinion and/or DMs' preferences and/or group decisions, and a combination of objective and subjective weights are the options for the weighting method in MCDM with uncertainty. After deciding on the weighting method and uncertainty consideration, the next step in MCDM is to apply a suitable ranking method to rank the alternatives based on weighted criteria to find the best alternative (interim outcome). From the reviewed articles, it is clear that there is a wide range of MCDM methods and numerous examples of applying them in different fields of research. Moreover, minor differences among these methods do not have any significant effect on the results [36,52,111,112]. TOPSIS or PROMETHEE II may be the most suitable to use as a ranking method based on the review findings (Table S3).

After identifying the best alternative, researchers need to answer another question regarding uncertainty considerations for MOO problems. For MCDM problems, only the alternatives and their respective values for each criterion are required, whereas MOO problems require more information. MCDM problems can be integrated with MOO if all the required input–output functions are available for the identified best process. If the practitioners want to deal with uncertainty in model parameters, they need to conduct robust optimization, which can be via either metaheuristic or mathematical programming. Without considering uncertainty, they can simply conduct any metaheuristic or mathematical programming model. Choosing between metaheuristic and mathematical programming methods can be guided by the decision tree developed by Turner et al. [126]. Deciding between mathematical and metaheuristic methods really depends on the preferences of the researchers with respect to computational intensity, complete vs. approximate searches, and flexibility in model development [126]. From the review findings, it can be said that metaheuristic MOO methods are the most used, especially NSGA-II and PSO methods (Table S3).

4.2. A Posteriori Integration of MOO and MCDM

When the study aims to optimize a specific product system or supply chain, MOO and MCDM can be integrated in two ways: a posteriori and both a priori and a posteriori. In a posteriori integration, researchers first need to use MOO methods based on multiple conflicting objective functions to find the Pareto-optimal solution set, given that they have all the required input–output functions. Here again, they need to choose between robust and normal optimization methods. After obtaining the Pareto-optimal solutions, they can use any MCDM method to find the best of these solutions. In the MCDM problem, different solutions from the Pareto set will become different alternatives, and the values of objective functions will be criteria values. They can decide the path for conducting MCDM based on their choice for weighting and uncertainty considerations, just like performing MCDM in the a priori system (Section 4.1). After choosing suitable weighting methods with/without uncertainty considerations, a suitable ranking method will give them the best solution from the Pareto-optimal solution set.

4.3. Both a Priori and a Posteriori Integration of MOO and MCDM

Another way to integrate MOO with MCDM is both a priori and a posteriori. Here, researchers can include weights for the objective functions of the MOO model using a suitable weighting method for MCDM. Like before, they need to decide about the preference for uncertainty considerations in the weights, and depending on that, they can either use subjective weights based on DMs' preferences, objective weights based on the entropy method, or a combination of subjective and objective weights. Incorporating these weights will produce weighted objective functions, which will be fed into the MOO model. For MOO model development, researchers need to decide on uncertainty considerations, and based on their choice, either robust, simple metaheuristic, or mathematical MOO methods will be employed. MOO methods based on weighted objective functions will give the Pareto-optimal solution set. As the weights based on DMs' preferences are already included in this stage, they just need to use a suitable ranking method to find the best solution from the Pareto set.

4.4. Uncertainty and Sensitivity Analyses

If the pathways with uncertainty considerations either for MOO or MCDM or both have been selected, uncertainty analysis of model parameters of MOO and weights of MCDM should be included in the study. Monte Carlo Simulation and triangular fuzzy numbers can be suitable ways to deal with uncertainty (Table S3). Along with uncertainty analysis, sensitivity analysis is a recommended step in this integrated framework. Sensitivity analyses with different model parameters based on their uncertainty, different criteria weights calculated through different methods, and different ranking methods should be performed to check the robustness of the methodological choices. Sensitivity analysis will identify the most important factor(s) which has/have significant impacts on the final outcome. This optional but recommended step is shown in the decision tree with dashed lines (Figure 2).

4.5. Case Study: Pulse Protein Extraction Pathways

In this section, a case study is illustrated to demonstrate how the proposed decision tree can guide the methodological choices in a given application context, by combining MOO and MCDM methods. Plant-based proteins are attracting increased attention for being environmentally more sustainable [127,128] and healthier than animal-based proteins [129,130]. In recent years, there has been significant growth in innovative food processing technologies to obtain plant-based proteins with improved quality and functionality, which may make the market for meat substitutes grow to USD 140 billion by 2029 [131,132]. Pulses are one of the main sources of plant-based proteins, in part due to their nutritional and sustainability attributes [133–135].

Canada is one of the largest pulse producers and exporters in the world and produces dry peas, chickpeas, lentils, and beans. Pulse production in Canada is increasing annually, and there is a similarly significant growth in pulse processing. Pulses are processed to obtain pulse flour, pulse protein, pulse fibre, pulse starch, and various other products and ingredients. Though there may be differences in the granular levels from facility to facility, dry fractionation and wet fractionation are the commonly used pathways for pulse protein extraction, and both are energy-intensive pathways [136]. Dry fractionation involves producing pulse protein concentrates from raw pulses through the dehulling, milling, and air classification stages [137]. On the other hand, wet fractionation is more energy-intensive as it requires isoelectric precipitation, centrifugation, and spray drying to procure protein-rich pulse protein isolates [138]. Methods for making these processing pathways more efficient in terms of energy use, economics, and environmental performance continue to evolve. For example, several studies tried to identify more technically feasible and efficient fractionation pathways to produce plant-based proteins [139]. However, simultaneously considering all important factors from a sustainability perspective (i.e., technical, economic, and environmental) is uncommon, which hinders identifying sustainable and optimized extraction pathways. As these objectives may conflict, an MOO model/problem can be formulated to identify the optimized pathways (i.e., dry fractionation and wet fractionation). For example, if we want to optimize the dry fractionation pathway based on environmental (i.e., minimizing environmental impacts in different impact categories in the life cycle assessment model); economic (i.e., minimizing production costs/maximizing profit/revenue); and technical (i.e., maximizing yield and energy use efficiency) criteria, MOO will produce a Pareto-optimal set of solutions showing different trade-offs among the objective functions. The main advantage of performing MOO is to consider multiple conflicting objectives, but before applying MOO methods, we need to make sure that all of the input–output functions are available. After obtaining the solution set, an MCDM method is required to identify the best-optimized pathway from that solution set. In this case, all of the solutions from the Pareto-optimal set will become the alternatives and the objectives (i.e., economic, technical, and environmental) will be the criteria.

Following the developed decision tree (Figure 2), as the case study is about studying a specific product system (pulse protein extraction pathways), there are two options for integrating MOO with MCDM methods. The DMs' and stakeholders' (pulse farmers, pulse processing facilities, Pulse Canada, etc.) preferences can be integrated before or after solving the MOO problem. Conventionally, a posteriori integration is more common, assuming the system input–output functions are available. A more comprehensive analysis would test both a posteriori and the integrated a priori and a posteriori results via sensitivity analysis and compare potential changes in the final optimization outcome. In the a posteriori pathway, the existing fractionation processes will be optimized based on given objective functions regarding environmental, technical, and economic variables. Environmental objective functions could include minimizing GHG emissions, land use footprints, water use footprints, mineral/fossil fuel usage, etc. Technical functions can be formulated with the aim of maximizing total yield from the process, minimizing energy use, maximizing protein content, etc. Economic objective functions could include minimizing production costs/operation costs, maximizing net present value/profit, etc. After formulating these objective functions and considering the constraints (if any), a suitable MOO method should be utilized. Based on the findings of the literature review, an evolutionary-based metaheuristic method like NSGA-II may be useful for finding the non-dominated Pareto-optimal solution set. The uncertainty associated with input data/model parameters also needs to be taken into account. Monte Carlo Simulation and/or triangular fuzzy numbers can be used to deal with the uncertainty in the MOO model.

There will be several optimized pathway options which can indicate the trade-offs among different objective functions. As these solutions are non-dominated, it is not easy to select the best option without the help of MCDM methods. First, a suitable weighting method must be used, ideally including a combination of objective and subjective weights. After assembling all of the stakeholders' preferences, either AHP or BWM can be used to find the subjective weights for all criteria. Then, entropy-derived objective weights can be combined with the subjective weights. As it includes subjective weights, fuzzy AHP or fuzzy BWM should be used for dealing with uncertainty. In the next step, a suitable ranking method—either TOPSIS or PROMETHEE II—can be applied to rank the alternatives from the Pareto set. Finally, sensitivity analyses should be included to check the robustness of the methodological choices. Sensitivity analysis with different model parameters, different weighting methods, and different ranking methods should be outlined to see the changes in the final outcome. The methodological path suggested for the case study is highlighted in the decision tree (Figure 2). Based on the review findings, a posteriori integration between MOO and MCDM methods is prevalent. So, in the highlighted pathway, a posteriori is selected and, for the MOO and MCDM methods, the path leading to uncertainty consideration was selected as well. Especially, for the weighting method, the combination of subjective and objective weights was preferred as it ensures a comprehensive analysis.

5. Conclusions

Multi-Objective Optimization (including both MOO problems with explicit objective functions, and MCDM with discrete decision matrices) has become an important concept in scientific research in numerous fields. Integrating MCDM with MOO methods merits more attention, as a hybrid approach, to elevate the effectiveness of final solutions. In addition, although some past studies included in this review reported both MOO and MCDM, clear guidance with respect to the choice of specific methodologies under each was missing. Accordingly, this review paper aimed at developing a generic decision tree based on the findings from the reviewed articles, in order to better guide practitioners in the future towards performing MOO and MCDM in an integrated way. A key emphasis here was uncertainty considerations, which could enable the integration of robust MOO with robust MCDM methods.

This systematic review answered four specific questions. The first was about the prevalent MOO methods and metaheuristic methods that have been employed in the majority of the reviewed articles, concerning their easy and quick application. The second question addressed the ways of integrating MOO with MCDM. MOO can be integrated with MCDM either a priori, a posteriori, or via a combination of both, where the weights are combined with the objective functions of MOO problems; MCDM ranking methods are then performed to find the best solution from the Pareto-optimal solution set. In the third question, prevalent MCDM methods were discussed and TOPSIS and PROMETHEE II were employed in most of the reviewed articles. Regarding the fourth question, how these articles dealt with uncertainty was explored. Monte Carlo Simulation and triangular fuzzy number/fuzzy set theory were found to be among the most common tools used in uncertainty propagation considerations.

The developed decision tree and associated discussions pointed towards the required methodological choices rather than prescribing which specific MCDM method may be integrated with which MOO method, and whether it is a posteriori or a priori. From the review findings, it is inferred that there is no single method that is ideal for all decision types and application contexts. Each tree path has advantages and drawbacks. Overall, however, the review showed a preference in the literature for evolutionary-based metaheuristic MOO methods, and TOPSIS or PROMETHEE ranking methods. Sensitivity analysis with different methods was recommended in order to support comprehensive analyses. Finally, the decision tree was elaborated for a case study on pulse protein extraction pathways to show how it can guide the practitioner in choosing the suitable path. This will support researchers in choosing the most appropriate way to combine MOO and MCDM methods in the context of their specific sustainability assessments. As this study did not identify the best MOO and MCDM methods for the case study, a follow-up case study may focus on this. Moreover, as this study did not report on the results of using the decision tree for the case study, future studies may focus on implementing the decision tree for diverse case studies. Finally, human behavioural aspects within the sustainability practice can be embedded in the MCDM, particularly in strategic decision-making in organizations [140].

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/su16072684/s1; Table S1: Comparison between Metaheuristic and Mathematical Programming MOO methods; Table S2: Different MCDM methods and their advantages and disadvantages. Table S3: Summary of reviewed articles to identify the methodological choices for integrating MOO and MCDM with uncertainty.

Funding: This work was funded by the National Research Council of Canada (CSTIP Grant Agreement #SPP121) under the Sustainable Protein Production (SPP) program.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
BWM	Best-Worst Method
DEA	Data Envelopment Analysis
DM	Decision-Maker
ELECTRE	Elimination and Choice Expressing Reality
GA	Genetic Algorithm
MACBETH	Measuring Attractiveness by a Categorical-Based Evaluation Technique
MAUT	Multi-Attribute Utility Theory
MCDM	Multi-Criteria Decision-Making
MOO	Multi-Objective Optimization
NSGA	Non-Dominated Sorting Genetic Algorithm
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PROMETHEE	Preference Ranking Organization Method for Enriched Evaluation
PSO	Particle Swarm Optimization
TOPSIS	Technique of Order Preference Similarity to the Ideal Solution
VIKOR	'VIekriterijumsko KOmpromisno Rangiranje', a Serbian term for 'Multi-Criteria Optimization and Compromise Solution'

References

1. Arora, R.K. *Optimization: Algorithms and Applications*; Chapman and Hall/CRC: Boca Raton, FL, USA, 2015; ISBN 978-0-429-16252-7.
2. Zong, C.; Margesin, M.; Staudt, J.; Deghim, F.; Lang, W. Decision-Making under Uncertainty in the Early Phase of Building Façade Design Based on Multi-Objective Stochastic Optimization. *Build. Environ.* **2022**, *226*, 109729. [CrossRef]
3. Chen, X.; Zhou, Y.; Tang, Z.; Luo, Q. A Hybrid Algorithm Combining Glowworm Swarm Optimization and Complete 2-Opt Algorithm for Spherical Travelling Salesman Problems. *Appl. Soft Comput.* **2017**, *58*, 104–114. [CrossRef]
4. Kvasov, D.E.; Mukhametzhanov, M.S. Metaheuristic vs. Deterministic Global Optimization Algorithms: The Univariate Case. *Appl. Math. Comput.* **2018**, *318*, 245–259. [CrossRef]
5. Neumaier, A. Complete Search in Continuous Global Optimization and Constraint Satisfaction. *Acta Numer.* **2004**, *13*, 271–369. [CrossRef]
6. Silver, E.A. An Overview of Heuristic Solution Methods. *J. Oper. Res. Soc.* **2004**, *55*, 936–956. [CrossRef]
7. Baykasoğlu, A.; Ozsoydan, F.B. Evolutionary and Population-Based Methods versus Constructive Search Strategies in Dynamic Combinatorial Optimization. *Inf. Sci.* **2017**, *420*, 159–183. [CrossRef]
8. Blum, C.; Roli, A. Metaheuristics in Combinatorial Optimization: Overview and Conceptual Comparison. *ACM Comput. Surv.* **2003**, *35*, 268–308. [CrossRef]
9. Stefanoiu, D. *Optimization in Engineering Sciences: Metaheuristics, Stochastic Methods and Decision Support*; Control, Systems and Industrial Engineering Series; ISTE Ltd.: London, UK; John Wiley and Sons Inc.: London, UK; Hoboken, NJ, USA, 2014; ISBN 978-1-84821-498-9.
10. Fausto, F.; Reyna-Orta, A.; Cuevas, E.; Andrade, Á.G.; Perez-Cisneros, M. From Ants to Whales: Metaheuristics for All Tastes. *Artif. Intell. Rev.* **2020**, *53*, 753–810. [CrossRef]
11. Simon, D. *Evolutionary Optimization Algorithms: Biologically-Inspired and Population-Based Approaches to Computer Intelligence*; John Wiley & Sons Inc.: Hoboken, NJ, USA, 2013; ISBN 978-0-470-93741-9.
12. Tang, J.; Liu, G.; Pan, Q. A Review on Representative Swarm Intelligence Algorithms for Solving Optimization Problems: Applications and Trends. *IEEE/CAA J. Autom. Sin.* **2021**, *8*, 1627–1643. [CrossRef]
13. Eiselt, H.A.; Sandblom, C.-L.; Spielberg, K. *Integer Programming and Network Models: With 43 Tables*; Springer: Berlin/Heidelberg, Germany, 2010; ISBN 978-3-642-08651-9.
14. Venkataraman, P. *Applied Optimization with MATLAB Programming*, 2nd ed.; John Wiley & Sons: Hoboken, NJ, USA, 2009; ISBN 978-0-470-08488-5.
15. Wolpert, D.H.; Macready, W.G. No Free Lunch Theorems for Optimization. *IEEE Trans. Evol. Comput.* **1997**, *1*, 67–82. [CrossRef]

16. Silveira, C.L.B.; Tabares, A.; Faria, L.T.; Franco, J.F. Mathematical Optimization versus Metaheuristic Techniques: A Performance Comparison for Reconfiguration of Distribution Systems. *Electr. Power Syst. Res.* **2021**, *196*, 107272. [CrossRef]
17. Biskas, P.N.; Ziogos, N.P.; Tellidou, A.; Zoumas, C.E.; Bakirtzis, A.G.; Petridis, V.; Tsakoumis, A. Comparison of Two Metaheuristics with Mathematical Programming Methods for the Solution of OPF. In Proceedings of the 13th International Conference on, Intelligent Systems Application to Power Systems, Budapest, Hungary, 16–19 September 2005; IEEE: Arlington, VA, USA, 2005; pp. 510–515.
18. Deb, K.; Pratap, A.; Agarwal, S.; Meyarivan, T. A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II. *IEEE Trans. Evol. Computat.* **2002**, *6*, 182–197. [CrossRef]
19. Branke, J. (Ed.) *Multiobjective Optimization: Interactive and Evolutionary Approaches*; Lecture notes in computer science, State-of-the-art survey; Springer: Berlin/Heidelberg, Germany; New York, NY, USA, 2008; ISBN 978-3-540-88907-6.
20. Wu, Y.; Xu, C.; Ke, Y.; Chen, K.; Sun, X. An Intuitionistic Fuzzy Multi-Criteria Framework for Large-Scale Rooftop PV Project Portfolio Selection: Case Study in Zhejiang, China. *Energy* **2018**, *143*, 295–309. [CrossRef]
21. Kiani-Moghaddam, M.; Shivaie, M.; Weinsier, P.D. Introduction to Multi-Objective Optimization and Decision-Making Analysis. In *Modern Music-Inspired Optimization Algorithms for Electric Power Systems*; Power Systems; Springer International Publishing: Cham, Switzerland, 2019; pp. 21–45; ISBN 978-3-030-12043-6.
22. Fang, J.; Gao, Y.; Sun, G.; Xu, C.; Li, Q. Multiobjective Robust Design Optimization of Fatigue Life for a Truck Cab. *Reliab. Eng. Syst. Saf.* **2015**, *135*, 1–8. [CrossRef]
23. Mukkavaara, J.; Shadram, F. An Integrated Optimization and Sensitivity Analysis Approach to Support the Life Cycle Energy Trade-off in Building Design. *Energy Build.* **2021**, *253*, 111529. [CrossRef]
24. Qiu, N.; Gao, Y.; Fang, J.; Feng, Z.; Sun, G.; Li, Q. Crashworthiness Analysis and Design of Multi-Cell Hexagonal Columns under Multiple Loading Cases. *Finite Elem. Anal. Des.* **2015**, *104*, 89–101. [CrossRef]
25. Shao, Y.; Geyer, P.; Lang, W. Integrating Requirement Analysis and Multi-Objective Optimization for Office Building Energy Retrofit Strategies. *Energy Build.* **2014**, *82*, 356–368. [CrossRef]
26. Wang, R.; Li, X.; Xu, C.; Li, F. Study on Location Decision Framework of Electric Vehicle Battery Swapping Station: Using a Hybrid MCDM Method. *Sustain. Cities Soc.* **2020**, *61*, 102149. [CrossRef]
27. Yang, Z.; Wang, Y.; Yang, K. The Stochastic Decision Making Framework for Long-Term Multi-Objective Energy-Water Supply-Ecology Operation in Parallel Reservoirs System under Uncertainties. *Expert Syst. Appl.* **2022**, *187*, 115907. [CrossRef]
28. Xu, X.; Chen, X.; Liu, Z.; Yang, J.; Xu, Y.; Zhang, Y.; Gao, Y. Multi-Objective Reliability-Based Design Optimization for the Reducer Housing of Electric Vehicles. *Eng. Optim.* **2022**, *54*, 1324–1340. [CrossRef]
29. Darko, A.; Chan, A.P.C.; Ameyaw, E.E.; Owusu, E.K.; Pärn, E.; Edwards, D.J. Review of Application of Analytic Hierarchy Process (AHP) in Construction. *Int. J. Constr. Manag.* **2019**, *19*, 436–452. [CrossRef]
30. Ishizaka, A.; Nemery, P. *Multi-Criteria Decision Analysis: Methods and Software*, 1st ed.; Wiley: Hoboken, NJ, USA, 2013; ISBN 978-1-119-97407-9.
31. Wallenius, J.; Dyer, J.S.; Fishburn, P.C.; Steuer, R.E.; Zionts, S.; Deb, K. Multiple Criteria Decision Making, Multiattribute Utility Theory: Recent Accomplishments and What Lies Ahead. *Manag. Sci.* **2008**, *54*, 1336–1349. [CrossRef]
32. Bana E Costa, C.A.; Vansnick, J.-C. The MACBETH Approach: Basic Ideas, Software, and an Application. In *Advances in Decision Analysis*; Meskens, N., Roubens, M., Eds.; Mathematical Modelling: Theory and Applications; Springer: Dordrecht, The Netherlands, 1999; Volume 4, pp. 131–157; ISBN 978-90-481-5167-7.
33. Brans, J.P.; Mareschal, B. The Promethee Methods for MCDM; The Promcalc, Gaia And Bankadviser Software. In *Readings in Multiple Criteria Decision Aid*; Bana E Costa, C.A., Ed.; Springer: Berlin/Heidelberg, Germany, 1990; pp. 216–252; ISBN 978-3-642-75937-6.
34. Taherdoost, H.; Madanchian, M. A Comprehensive Overview of the ELECTRE Method in Multi Criteria Decision-Making. *J. Manag. Sci. Eng. Res.* **2023**, *6*, 5–16. [CrossRef]
35. Łatuszyńska, A. Multiple-Criteria Decision Analysis Using Topsis Method For Interval Data In Research Into The Level Of Information Society Development. *Folia Oeconomica Stetin.* **2014**, *13*, 63–76. [CrossRef]
36. Huang, I.B.; Keisler, J.; Linkov, I. Multi-Criteria Decision Analysis in Environmental Sciences: Ten Years of Applications and Trends. *Sci. Total Environ.* **2011**, *409*, 3578–3594. [CrossRef]
37. Aruldoss, M.; Lakshmi, T.M.; Venkatesan, V.P. A Survey on Multi Criteria Decision Making Methods and Its Applications. *Am. J. Inf. Syst.* **2013**, *1*, 31–43.
38. Figueira, J.; Greco, S.; Ehrogott, M. *Multiple Criteria Decision Analysis: State of the Art Surveys*; International Series in Operations Research & Management Science; Springer: New York, NY, USA, 2005; Volume 78, ISBN 978-0-387-23067-2.
39. Velasquez, M.; Hester, P.T. An Analysis of Multi-Criteria Decision Making Methods. *Int. J. Oper. Res.* **2013**, *10*, 56–66.
40. Averbakh, I.; Zhao, Y.-B. Explicit Reformulations for Robust Optimization Problems with General Uncertainty Sets. *SIAM J. Optim.* **2008**, *18*, 1436–1466. [CrossRef]
41. Gabrel, V.; Murat, C.; Thiele, A. Recent Advances in Robust Optimization: An Overview. *Eur. J. Oper. Res.* **2014**, *235*, 471–483. [CrossRef]
42. Ji, Y.; Ma, Y. The Robust Maximum Expert Consensus Model with Risk Aversion. *Inf. Fusion* **2023**, *99*, 101866. [CrossRef]
43. Gancarova, M.; Todd, M.J. A Robust Robust Optimization Result. *Oper. Res. Lett.* **2012**, *40*, 2–5. [CrossRef]

44. Gaspar-Cunha, A.; Covas, J.A. Robustness in Multi-Objective Optimization Using Evolutionary Algorithms. *Comput. Optim. Appl.* **2008**, *39*, 75–96. [CrossRef]
45. Beyer, H.-G.; Sendhoff, B. Robust Optimization—A Comprehensive Survey. *Comput. Methods Appl. Mech. Eng.* **2007**, *196*, 3190–3218. [CrossRef]
46. Carè, A.; Garatti, S.; Campi, M.C. The Wait-and-Judge Scenario Approach Applied to Antenna Array Design. *Comput. Manag. Sci.* **2019**, *16*, 481–499. [CrossRef]
47. Parsaeefard, S.; Sharafat, A.R.; Rasti, M. Robust Probabilistic Distributed Power Allocation by Chance Constraint Approach. In Proceedings of the 21st Annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, Toronto, ON, Canada, 5–8 September 2010; IEEE: Istanbul, Turkey, 2010; pp. 2162–2167.
48. Babazadeh, R. Application of Fuzzy Optimization to Bioenergy-Supply-Chain Planning under Epistemic Uncertainty: A New Approach. *Ind. Eng. Chem. Res.* **2019**, *58*, 6519–6536. [CrossRef]
49. Pishvaee, M.S.; Khalaf, M.F. Novel Robust Fuzzy Mathematical Programming Methods. *Appl. Math. Model.* **2016**, *40*, 407–418. [CrossRef]
50. Liu, H.-C.; Yang, M.; Zhou, M.; Tian, G. An Integrated Multi-Criteria Decision Making Approach to Location Planning of Electric Vehicle Charging Stations. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 362–373. [CrossRef]
51. Kellner, F.; Lienland, B.; Utz, S. A Multi-criteria Decision-making Approach for Assembling Optimal Powertrain Technology Portfolios in Low GHG Emission Environments. *J. Ind. Ecol.* **2021**, *25*, 1412–1429. [CrossRef]
52. Erdogan, N.; Pamucar, D.; Kucuksari, S.; Deveci, M. An Integrated Multi-Objective Optimization and Multi-Criteria Decision-Making Model for Optimal Planning of Workplace Charging Stations. *Appl. Energy* **2021**, *304*, 117866. [CrossRef]
53. Cunha, A.G.; Ferreira, J.C.; Covas, J.A.; Recio, G. Selection of Solutions in Multi-Objective Optimization: Decision Making and Robustness. In Proceedings of the 2014 IEEE Symposium on Computational Intelligence in Multi-Criteria Decision-Making (MCDM), Orlando, FL, USA, 9–12 December 2014; IEEE: Orlando, FL, USA, 2014; pp. 16–23.
54. Wang, Z.; Li, J.; Rangaiah, G.P.; Wu, Z. Machine Learning Aided Multi-Objective Optimization and Multi-Criteria Decision Making: Framework and Two Applications in Chemical Engineering. *Comput. Chem. Eng.* **2022**, *165*, 107945. [CrossRef]
55. Wei, N.; Yang, F.; Lu, K.; Xie, J.; Zhang, S. A Method of Multi-Objective Optimization and Multi-Attribute Decision-Making for Huangjinxia Reservoir. *Appl. Sci.* **2022**, *12*, 6300. [CrossRef]
56. Stoilova, S. An Integrated Multi-Criteria and Multi-Objective Optimization Approach for Establishing the Transport Plan of Intercity Trains. *Sustainability* **2020**, *12*, 687. [CrossRef]
57. Padhye, N.; Deb, K. Multi-objective Optimisation and Multi-criteria Decision Making in SLS Using Evolutionary Approaches. *Rapid Prototyp. J.* **2011**, *17*, 458–478. [CrossRef]
58. Kesireddy, A.; Garcia Carrillo, L.R.; Baca, J. Multi-Criteria Decision Making—Pareto Front Optimization Strategy for Solving Multi-Objective Problems. In Proceedings of the 2020 IEEE 16th International Conference on Control & Automation (ICCA), Sapporo, Japan, 9–11 October 2020; IEEE: Singapore, 2020; pp. 53–58.
59. Kabadayi, N.; Dehghanimohammadabadi, M. Multi-Objective Supplier Selection Process: A Simulation–Optimization Framework Integrated with MCDM. *Ann. Oper. Res.* **2022**, *319*, 1607–1629. [CrossRef]
60. Goodarzi, F.; Abdollahzadeh, V.; Zeinalnezhad, M. An Integrated Multi-Criteria Decision-Making and Multi-Objective Optimization Framework for Green Supplier Evaluation and Optimal Order Allocation under Uncertainty. *Decis. Anal. J.* **2022**, *4*, 100087. [CrossRef]
61. Ridha, H.M.; Hizam, H.; Mirjalili, S.; Lutfi Othman, M.; Effendy Ya'acob, M.; Ahmadipour, M.; Ismaeel, N.Q. Multi-Objective Optimization and Multi-Criteria Decision Making Aided by Numerical Method: Framework and a Case Study of Malaysia and South Africa. *Energy Convers. Manag.* **2022**, *274*, 116468. [CrossRef]
62. Jafarian-Namin, S.; Kaviani, M.A.; Ghasemi, E. An Integrated MOEA and MCDM for Multi-Objective Optimization (Case Study: Control Chart Design). In Proceedings of the 2016 International Conference on Industrial Engineering and Operations Management, Detroit, MI, USA, 23–25 September 2016.
63. Ridha, H.M.; Gomes, C.; Hizam, H.; Ahmadipour, M.; Heidari, A.A.; Chen, H. Multi-Objective Optimization and Multi-Criteria Decision-Making Methods for Optimal Design of Standalone Photovoltaic System: A Comprehensive Review. *Renew. Sustain. Energy Rev.* **2021**, *135*, 110202. [CrossRef]
64. Pereira, J.L.J.; Oliver, G.A.; Francisco, M.B.; Cunha, S.S.; Gomes, G.F. A Review of Multi-Objective Optimization: Methods and Algorithms in Mechanical Engineering Problems. *Arch. Comput. Methods Eng.* **2022**, *29*, 2285–2308. [CrossRef]
65. Odu, G.O.; Charles-Owaba, O.E. Review of Multi-Criteria Optimization Methods—Theory and Applications. *IOSR J. Eng.* **2013**, *3*, 1–14. [CrossRef]
66. Durbach, I.N.; Stewart, T.J. Modeling Uncertainty in Multi-Criteria Decision Analysis. *Eur. J. Oper. Res.* **2012**, *223*, 1–14. [CrossRef]
67. Broekhuizen, H.; Groothuis-Oudshoorn, C.G.M.; van Til, J.A.; Hummel, J.M.; IJzerman, M.J. A Review and Classification of Approaches for Dealing with Uncertainty in Multi-Criteria Decision Analysis for Healthcare Decisions. *Pharmacoeconomics* **2015**, *33*, 445–455. [CrossRef] [PubMed]
68. Moher, D.; Liberati, A.; Tetzlaff, J.; Altman, D.G.; The PRISMA Group. Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *PLoS Med.* **2009**, *6*, e1000097. [CrossRef]

69. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews. *BMJ* **2021**, *372*, n71. [CrossRef]
70. Bei, T.; Yang, L.; Huang, Q.; Wu, J.; Liu, J. Effectiveness of Bone Substitute Materials in Opening Wedge High Tibial Osteotomy: A Systematic Review and Meta-Analysis. *Ann. Med.* **2022**, *54*, 565–577. [CrossRef] [PubMed]
71. Heidari, M.D.; Turner, I.; Ardestani-Jaafari, A.; Pelletier, N. Operations Research for Environmental Assessment of Crop-Livestock Production Systems. *Agric. Syst.* **2021**, *193*, 103208. [CrossRef]
72. Ferdous, J.; Bensebaa, F.; Pelletier, N. Integration of LCA, TEA, Process Simulation and Optimization: A Systematic Review of Current Practices and Scope to Propose a Framework for Pulse Processing Pathways. *J. Clean. Prod.* **2023**, *402*, 136804. [CrossRef]
73. Panic, N.; Leoncini, E.; de Belvis, G.; Ricciardi, W.; Boccia, S. Evaluation of the Endorsement of the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) Statement on the Quality of Published Systematic Review and Meta-Analyses. *PLoS ONE* **2013**, *8*, e83138. [CrossRef] [PubMed]
74. Safikhani, S.; Keller, S.; Schweiger, G.; Pirker, J. Immersive Virtual Reality for Extending the Potential of Building Information Modeling in Architecture, Engineering, and Construction Sector: Systematic Review. *Int. J. Digit. Earth* **2022**, *15*, 503–526. [CrossRef]
75. Batista, A.C.; Batista, L.S. Demand Side Management Using a Multi-Criteria ϵ-Constraint Based Exact Approach. *Expert Syst. Appl.* **2018**, *99*, 180–192. [CrossRef]
76. Jafaryeganeh, H.; Ventura, M.; Guedes Soares, C. Robust-Based Optimization of the Hull Internal Layout of Oil Tanker. *Ocean Eng.* **2020**, *216*, 107846. [CrossRef]
77. Kalita, K.; Mukhopadhyay, T.; Dey, P.; Haldar, S. Genetic Programming-Assisted Multi-Scale Optimization for Multi-Objective Dynamic Performance of Laminated Composites: The Advantage of More Elementary-Level Analyses. *Neural Comput. Appl.* **2020**, *32*, 7969–7993. [CrossRef]
78. Reyes-Barquet, L.M.; Rico-Contreras, J.O.; Azzaro-Pantel, C.; Moras-Sánchez, C.G.; González-Huerta, M.A.; Villanueva-Vásquez, D.; Aguilar-Lasserre, A.A. Multi-Objective Optimal Design of a Hydrogen Supply Chain Powered with Agro-Industrial Wastes from the Sugarcane Industry: A Mexican Case Study. *Mathematics* **2022**, *10*, 437. [CrossRef]
79. Xu, X.; Chen, J.; Lin, Z.; Qiao, Y.; Chen, X.; Zhang, Y.; Xu, Y.; Li, Y. Optimization Design for the Planetary Gear Train of an Electric Vehicle under Uncertainties. *Actuators* **2022**, *11*, 49. [CrossRef]
80. Sharma, A.K.; Mukherjee, I. Enhanced Multi-Objective Solution Approach for Multiple Quality Characteristics Optimisation Problems Considering Predictive Uncertainties. *Int. J. Qual. Reliab. Manag.* **2019**, *37*, 112–144. [CrossRef]
81. Wan, C.; Zhang, X.; Zhao, Q.; Yang, K. Operation Loop-Based Optimization Model for Resource Allocation to Military Countermeasures versus Probabilistic Threat. *Appl. Sci.* **2018**, *8*, 214. [CrossRef]
82. Chaturvedi, S.; Rajasekar, E.; Natarajan, S. Multi-Objective Building Design Optimization under Operational Uncertainties Using the NSGA II Algorithm. *Buildings* **2020**, *10*, 88. [CrossRef]
83. Turksen, O. Obtaining Interval Estimates of Nonlinear Model Parameters Based on Combined Soft Computing Tools. *J. Intell. Fuzzy Syst.* **2020**, *38*, 609–618. [CrossRef]
84. Mirghaderi, S.D.; Modiri, M. Application of Meta-Heuristic Algorithm for Multi-Objective Optimization of Sustainable Supply Chain Uncertainty. *Sādhanā* **2021**, *46*, 52. [CrossRef]
85. Srinivas, N.; Deb, K. Muiltiobjective Optimization Using Nondominated Sorting in Genetic Algorithms. *Evol. Comput.* **1994**, *2*, 221–248. [CrossRef]
86. Qu, L.; Zhou, Z.; Zhang, T.; Zhang, H.; Shi, L. An Improved Procedure to Implement NSGA-III in Coordinate Waste Management for Urban Agglomeration. *Waste Manag. Res.* **2019**, *37*, 1161–1169. [CrossRef]
87. Bao, C.; Xu, L.; Goodman, E.D.; Cao, L. A Novel Non-Dominated Sorting Algorithm for Evolutionary Multi-Objective Optimization. *J. Comput. Sci.* **2017**, *23*, 31–43. [CrossRef]
88. Coello, C.A. Evolutionary Multi-Objective Optimization: A Historical View of the Field. *IEEE Comput. Intell. Mag.* **2006**, *1*, 28–36. [CrossRef]
89. Nematollahi, B.; Nikoo, M.R.; Gandomi, A.H.; Talebbeydokhti, N.; Rakhshandehroo, G.R. A Multi-Criteria Decision-Making Optimization Model for Flood Management in Reservoirs. *Water Resour. Manag.* **2022**, *36*, 4933–4949. [CrossRef]
90. Yang, Z.; Yang, K.; Wang, Y.; Su, L.; Hu, H. Long-Term Multi-Objective Power Generation Operation for Cascade Reservoirs and Risk Decision Making under Stochastic Uncertainties. *Renew. Energy* **2021**, *164*, 313–330. [CrossRef]
91. Maaroof, B.B.; Rashid, T.A.; Abdulla, J.M.; Hassan, B.A.; Alsadoon, A.; Mohammadi, M.; Khishe, M.; Mirjalili, S. Current Studies and Applications of Shuffled Frog Leaping Algorithm: A Review. *Arch. Comput. Methods Eng.* **2022**, *29*, 3459–3474. [CrossRef]
92. Panah, P.G.; Bornapour, S.M.; Nosratabadi, S.M.; Guerrero, J.M. Hesitant Fuzzy for Conflicting Criteria in Multi-Objective Deployment of Electric Vehicle Charging Stations. *Sustain. Cities Soc.* **2022**, *85*, 104054. [CrossRef]
93. Ebrahimi, S.B.; Bagheri, E. A Multi-Objective Formulation for the Closed-Loop Plastic Supply Chain under Uncertainty. *Oper. Res. Int. J.* **2022**, *22*, 4725–4768. [CrossRef]
94. Mytilinou, V.; Lozano-Minguez, E.; Kolios, A. A Framework for the Selection of Optimum Offshore Wind Farm Locations for Deployment. *Energies* **2018**, *11*, 1855. [CrossRef]
95. Khalilzadeh, M.; Karami, A.; Hajikhani, A. The Multi-Objective Supplier Selection Problem with Fuzzy Parameters and Solving the Order Allocation Problem with Coverage. *J. Model. Manag.* **2020**, *15*, 705–725. [CrossRef]

96. Hasani, A. Resilience Cloud-Based Global Supply Chain Network Design under Uncertainty: Resource-Based Approach. *Comput. Ind. Eng.* **2021**, *158*, 107382. [CrossRef]
97. Zhong, S.; Zhang, J.; He, X.; Liu, S. Sustainable Supply Chain Partner Selection and Order Allocation: A Hybrid Fuzzy PL-TODIM Based MCGDM Approach. *PLoS ONE* **2022**, *17*, e0271194. [CrossRef]
98. Khemiri, R.; Naija, M.; Exposito, E. Dispatching and Rebalancing for Ride-Sharing Autonomous Mobility-on-Demand Systems Based on a Fuzzy Multi-Criteria Approach. *Soft Comput.* **2023**, *27*, 2041–2069. [CrossRef]
99. Mohammed, A.; Setchi, R.; Filip, M.; Harris, I.; Li, X. An Integrated Methodology for a Sustainable Two-Stage Supplier Selection and Order Allocation Problem. *J. Clean. Prod.* **2018**, *192*, 99–114. [CrossRef]
100. Mohammed, A.; Harris, I.; Govindan, K. A Hybrid MCDM-FMOO Approach for Sustainable Supplier Selection and Order Allocation. *Int. J. Prod. Econ.* **2019**, *217*, 171–184. [CrossRef]
101. Ali, S.S.; Paksoy, T.; Torğul, B.; Kaur, R. Reverse Logistics Optimization of an Industrial Air Conditioner Manufacturing Company for Designing Sustainable Supply Chain: A Fuzzy Hybrid Multi-Criteria Decision-Making Approach. *Wirel. Netw.* **2020**, *26*, 5759–5782. [CrossRef]
102. Jaigirdar, S.M.; Das, S.; Chowdhury, A.R.; Ahmed, S.; Chakrabortty, R.K. Multi-Objective Multi-Echelon Distribution Planning for Perishable Goods Supply Chain: A Case Study. *Int. J. Syst. Sci. Oper. Logist.* **2023**, *10*, 2020367. [CrossRef]
103. Medina-González, S.; Espuña, A.; Puigjaner, L. An Efficient Uncertainty Representation for the Design of Sustainable Energy Generation Systems. *Chem. Eng. Res. Des.* **2018**, *131*, 144–159. [CrossRef]
104. Jones, D.; Tamiz, M. *Practical Goal Programming*; International Series in Operations Research & Management Science; Springer: New York, NY, USA, 2010; ISBN 978-1-4419-5770-2.
105. Lasemi, M.A.; Arabkoohsar, A.; Hajizadeh, A. Stochastic Multi-Objective Scheduling of a Wind Farm Integrated with High-Temperature Heat and Power Storage in Energy Market. *Int. J. Electr. Power Energy Syst.* **2021**, *132*, 107194. [CrossRef]
106. García-Segura, T.; Penadés-Plà, V.; Yepes, V. Sustainable Bridge Design by Metamodel-Assisted Multi-Objective Optimization and Decision-Making under Uncertainty. *J. Clean. Prod.* **2018**, *202*, 904–915. [CrossRef]
107. Taravatrooy, N.; Nikoo, M.R.; Hobbi, S.; Sadegh, M.; Izady, A. A Novel Hybrid Entropy-Clustering Approach for Optimal Placement of Pressure Sensors for Leakage Detection in Water Distribution Systems under Uncertainty. *Urban Water J.* **2020**, *17*, 185–198. [CrossRef]
108. Naserizade, S.S.; Nikoo, M.R.; Montaseri, H. A Risk-Based Multi-Objective Model for Optimal Placement of Sensors in Water Distribution System. *J. Hydrol.* **2018**, *557*, 147–159. [CrossRef]
109. Tayebikhorami, S.; Nikoo, M.R.; Sadegh, M. A Fuzzy Multi-Objective Optimization Approach for Treated Wastewater Allocation. *Environ. Monit. Assess.* **2019**, *191*, 468. [CrossRef] [PubMed]
110. Bahrami, N.; Nikoo, M.R.; Al-Rawas, G.; Al-Jabri, K.; Gandomi, A.H. Optimal Treated Wastewater Allocation Among Stakeholders Based on an Agent-Based Approach. *Water Resour. Manag.* **2023**, *37*, 135–156. [CrossRef]
111. Keisler, J.M. The Value of Assessing Weights in Multi-Criteria Portfolio Decision Analysis: The Value of Assessing Weights. *J. Multi-Criteria Decis. Anal.* **2008**, *15*, 111–123. [CrossRef]
112. Triantaphyllou, E. *Multi-Criteria Decision Making Methods: A Comparative Study*; Applied Optimization; Kluwer: Dordrecht, The Netherlands, 2010; ISBN 978-1-4419-4838-0.
113. Aydin, F.; Gümüş, B. Comparative analysis of multi-criteria decision making methods for the assessment of optimal SVC location. *Bull. Pol. Acad. Sci. Tech. Sci.* **2022**, *70*, 140555. [CrossRef]
114. Gong, Y.-J.; Chen, W.-N.; Zhan, Z.-H.; Zhang, J.; Li, Y.; Zhang, Q.; Li, J.-J. Distributed Evolutionary Algorithms and Their Models: A Survey of the State-of-the-Art. *Appl. Soft Comput.* **2015**, *34*, 286–300. [CrossRef]
115. Mosavi, A. Multiple Criteria Decision-Making Preprocessing Using Data Mining Tools. *IJCSI Int. J. Comput. Sci. Issues* **2010**, *7*, 26–34.
116. Hafiz, F.; Swain, A.; Mendes, E. Multi-Objective Evolutionary Framework for Non-Linear System Identification: A Comprehensive Investigation. *Neurocomputing* **2020**, *386*, 257–280. [CrossRef]
117. Ramos, M.A.; Boix, M.; Aussel, D.; Montastruc, L.; Domenech, S. Water Integration in Eco-Industrial Parks Using a Multi-Leader-Follower Approach. *Comput. Chem. Eng.* **2016**, *87*, 190–207. [CrossRef]
118. Mooselu, M.G.; Nikoo, M.R.; Rayani, N.B.; Izady, A. Fuzzy Multi-Objective Simulation-Optimization of Stepped Spillways Considering Flood Uncertainty. *Water Resour. Manag.* **2019**, *33*, 2261–2275. [CrossRef]
119. Hong, Z.; Feng, Y.; Li, Z.; Wang, Y.; Zheng, H.; Li, Z.; Tan, J. An Integrated Approach for Multi-Objective Optimisation and MCDM of Energy Internet under Uncertainty. *Future Gener. Comput. Syst.* **2019**, *97*, 90–104. [CrossRef]
120. Latifi, M.; Rakhshandehroo, G.; Nikoo, M.R.; Sadegh, M. A Game Theoretical Low Impact Development Optimization Model for Urban Storm Water Management. *J. Clean. Prod.* **2019**, *241*, 118323. [CrossRef]
121. Carpitella, S.; Brentan, B.; Montalvo, I.; Izquierdo, J.; Certa, A. Multi-Criteria Analysis Applied to Multi-Objective Optimal Pump Scheduling in Water Systems. *Water Supply* **2019**, *19*, 2338–2346. [CrossRef]
122. Han, J.; Yang, C.; Lim, C.-C.; Zhou, X.; Shi, P.; Gui, W. Power Scheduling Optimization under Single-Valued Neutrosophic Uncertainty. *Neurocomputing* **2020**, *382*, 12–20. [CrossRef]
123. Ehteram, M.; Ahmed, A.N.; Fai, C.M.; Afan, H.A.; El-Shafie, A. Accuracy Enhancement for Zone Mapping of a Solar Radiation Forecasting Based Multi-Objective Model for Better Management of the Generation of Renewable Energy. *Energies* **2019**, *12*, 2730. [CrossRef]

124. Farrance, I.; Frenkel, R. Uncertainty in Measurement: A Review of Monte Carlo Simulation Using Microsoft Excel for the Calculation of Uncertainties through Functional Relationships, Including Uncertainties in Empirically Derived Constants. *Clin. Biochem. Rev.* **2014**, *35*, 37–61. [PubMed]
125. Fu, S.; Zhou, H. Triangular Fuzzy Number Multi-Attribute Decision-Making Method Based on Set-Pair Analysis. *J. Softw. Eng.* **2016**, *11*, 116–122. [CrossRef]
126. Turner, I.; Bamber, N.; Andrews, J.; Pelletier, N. Systematic Review of the Life Cycle Optimization Literature, and Development of General Recommendations for Performance of Life Cycle Optimization Studies. *Renew. Sustain. Energy Rev.* **2024**. *under review*.
127. Aschemann-Witzel, J.; Gantriis, R.F.; Fraga, P.; Perez-Cueto, F.J.A. Plant-Based Food and Protein Trend from a Business Perspective: Markets, Consumers, and the Challenges and Opportunities in the Future. *Crit. Rev. Food Sci. Nutr.* **2021**, *61*, 3119–3128. [CrossRef]
128. Potter, H.K.; Röös, E. Multi-Criteria Evaluation of Plant-Based Foods—Use of Environmental Footprint and LCA Data for Consumer Guidance. *J. Clean. Prod.* **2021**, *280*, 124721. [CrossRef]
129. Rust, N.A.; Ridding, L.; Ward, C.; Clark, B.; Kehoe, L.; Dora, M.; Whittingham, M.J.; McGowan, P.; Chaudhary, A.; Reynolds, C.J.; et al. How to Transition to Reduced-Meat Diets That Benefit People and the Planet. *Sci. Total Environ.* **2020**, *718*, 137208. [CrossRef]
130. Zhubi-Bakija, F.; Bajraktari, G.; Bytyçi, I.; Mikhailidis, D.P.; Henein, M.Y.; Latkovskis, G.; Rexhaj, Z.; Zhubi, E.; Banach, M.; Alnouri, F.; et al. The Impact of Type of Dietary Protein, Animal versus Vegetable, in Modifying Cardiometabolic Risk Factors: A Position Paper from the International Lipid Expert Panel (ILEP). *Clin. Nutr.* **2021**, *40*, 255–276. [CrossRef] [PubMed]
131. Saget, S.; Costa, M.; Santos, C.S.; Vasconcelos, M.W.; Gibbons, J.; Styles, D.; Williams, M. Substitution of Beef with Pea Protein Reduces the Environmental Footprint of Meat Balls Whilst Supporting Health and Climate Stabilisation Goals. *J. Clean. Prod.* **2021**, *297*, 126447. [CrossRef]
132. Tziva, M.; Negro, S.O.; Kalfagianni, A.; Hekkert, M.P. Understanding the Protein Transition: The Rise of Plant-Based Meat Substitutes. *Environ. Innov. Soc. Transit.* **2020**, *35*, 217–231. [CrossRef]
133. MacWilliam, S.; Parker, D.; Marinangeli, C.P.F.; Trémorin, D. A Meta-Analysis Approach to Examining the Greenhouse Gas Implications of Including Dry Peas (*Pisum sativum* L.) and Lentils (*Lens culinaris M.*) in Crop Rotations in Western Canada. *Agric. Syst.* **2018**, *166*, 101–110. [CrossRef]
134. Marinangeli, C.P.F.; Curran, J.; Barr, S.I.; Slavin, J.; Puri, S.; Swaminathan, S.; Tapsell, L.; Patterson, C.A. Enhancing Nutrition with Pulses: Defining a Recommended Serving Size for Adults. *Nutr. Rev.* **2017**, *75*, 990–1006. [CrossRef]
135. Peoples, M.B.; Hauggaard-Nielsen, H.; Huguenin-Elie, O.; Jensen, E.S.; Justes, E.; Williams, M. The Contributions of Legumes to Reducing the Environmental Risk of Agricultural Production. In *Agroecosystem Diversity*; Elsevier: Amsterdam, The Netherlands, 2019; pp. 123–143; ISBN 978-0-12-811050-8.
136. Vogelsang-O'Dwyer, M.; Zannini, E.; Arendt, E.K. Production of Pulse Protein Ingredients and Their Application in Plant-Based Milk Alternatives. *Trends Food Sci. Technol.* **2021**, *110*, 364–374. [CrossRef]
137. Fernando, S. Production of Protein-Rich Pulse Ingredients through Dry Fractionation: A Review. *LWT* **2021**, *141*, 110961. [CrossRef]
138. Rivera, J.; Siliveru, K.; Li, Y. A Comprehensive Review on Pulse Protein Fractionation and Extraction: Processes, Functionality, and Food Applications. *Crit. Rev. Food Sci. Nutr.* **2022**, 1–23. [CrossRef]
139. Dumoulin, L.; Jacquet, N.; Malumba, P.; Richel, A.; Blecker, C. Dry and Wet Fractionation of Plant Proteins: How a Hybrid Process Increases Yield and Impacts Nutritional Value of Faba Beans Proteins. *Innov. Food Sci. Emerg. Technol.* **2021**, *72*, 102747. [CrossRef]
140. Milani, A.S.; Shanian, A.; El-Lahham, C. A decision-based approach for measuring human behavioral resistance to organizational change in strategic planning. *Math. Comput. Model.* **2008**, *48*, 1765–1774. [CrossRef]