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Towards Integration of Multi Objective Optimization and Multi Criteria Decision Making

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Abstract – Multi Objective Optimization (MOO) is the procedure of arriving at the best solution, where the objectives are in competition with one another. The idea is to classify such solutions that optimize the value of objectives without compromising any of the objectives' performance. Multi-Criteria Decision-Making (MCDM) approaches provide systematic approaches to estimate and rank the options based on the criteria or attributes. This research paper presents a critical review of MOO and MCDM approaches applied in the current literature. Out of the 41 articles that were reviewed, it was identified that 70.7% of the articles that were being used were metaheuristic optimization methods. The first, and the most frequently applied, approach identified in 41.5% of the articles was NSGA-II, which is an evolutionary algorithm. As for MCDM methods, 48.8% of the articles used subjective weights, and the remaining ones were Analytic Hierarchy Process (AHP) and Best-Worst Method (BWM). Besides, the ranking method that was frequently employed was TOPSIS, accounting for approximately 43.9% of the articles. The use of MOO and MCDM was mainly performed sequentially (post-hoc) in 78.1% of the analyzed articles. In addition, uncertainty was accounted for by 80.5% of the MOO models through Monte Carlo Simulation and triangular fuzzy numbers. Conversely, the aspect of uncertainty was addressed in only 29.3% of the MCDM models, where the most common methods were the fuzzy set approach and probability distributions. The ability of the model to be less delicate to the changes in the input parameters was tested in 39% of the analyzed papers through sensitivity analysis.

Keywords – Best-Worst Method (BWM), Non-Dominated Sorting Differential Evolution (NSDE), Non-Dominated Sorting Genetic Algorithm (NSGA), Multi-Objective Optimization (MOO), Multi-Criteria Decision Making (MCDM), Techniques for Order Preference by Similarity to Ideal Solution (TOPSIS), Analytic Hierarchy Process (AHP), Crow Search Algorithm (CSA).

I. INTRODUCTION

Multi-Criteria Decision Making (MCDM) method refers to an approach to decision making that is considered as revolutionary in this field [1, 2]. Benjamin Franklin, who is one of the founding fathers of multi-criteria decision-making research, offered his experimental results on moral arithmetic. Techniques of MCDM have been of interest to empirical and theoretical scientists since 1950s in relation to the capability of mathematical modeling [3]. The goal is to have a notion of how one could build a framework for the representation of decision-making problems and obtaining preferences from the options. It is necessary to perform MCDM methods since it can effectively cope with problems that may arise due to multiple objectives and criteria and, moreover, multiple actors involved in the decision-making process [4]. The relevance of the MCDM methods may be explained by some of the considerations listed in **Table 1**.

The process of optimization can help in defining the ideal value or the best solutions. The optimization problems include the maximization or minimization of the given objective function, single or multiple. Multi-objective optimization (MOO) refers to challenges that involve many goals [15]. This problem type can be met in automotive, engineering, agriculture, mathematics, social studies, finances, aeronautics and many other fields of everyday life. As Emery et al. [16] have described, the MOO application can be used to enhance the efficiency of the fisheries bioeconomic framework. This framework can be useful in assessing the extent of resource exploitation and assessing the viability of a management plan. The exponential growth engineering model, which is based on public property or open access economies, forms the basis of the fisheries biobased model. The goal of Grafton et al. [17] is to create a model for the North Sea fisheries that considers four major objectives: maximizing earnings, sustaining ancient quota shares across nations, maintaining industrial service, and reducing waste.

Table 1. Methods to Consider to Define the Significance of MCDM Methods

Methods	Description	References
Systematic and structured approach	MCDM techniques offer a methodical approach to decision making. Managers are able to break down complex issues into criteria, evaluate various solutions with reference to these criteria, and make rational decisions with the help of clear-cut decision-making rules.	[5, 6, 7]
Incorporation of multiple objectives and criteria	Several practical decisions require the simultaneous consideration of multiple objectives.	[8]
Handling uncertainty and subjectivity	The process of making decisions frequently entails addressing ambiguity and subjectivity.	[9, 10]
Consideration of stakeholder perspectives	Multiple stakeholders with diverse desires and preferences are often involved in many decision contexts.	[11]
Wide range of applications	MCDM methods have been utilized in diverse domains such as business, ecological management, engineering, and others.	[12, 13, 14]

The Niched-Pareto Genetic Algorithm (NPGA) is utilized in the finance field to detect substantial sequences of technical analysis in financial time [18, 19, 20, 21]. Stigler [22] address two main objectives: assessing the matches quality by gauging the trend of finance time series (whether it is an uptrend, head-and-shoulders, or downtrend pattern) and determining the size of the area described by the time series using a linear function and interval length. The NPGA is utilized to ascertain the suitable acute interval for the head-and-shoulders, uptrends, and downtrends patterns. The utilization of MOO in the realm of politics [23] aims to ascertain the primary individuals who gain advantages in political operations. The challenges examined in [24] were the distance among key players in two algorithm models and the average Eigenvector centrality, namely the Prisoners network and the Dolphin Network. Choosing the optimal key player involves considering their ability to contribute effectively both individually and as part of a cohesive unit.

Our primary objective is to review and compare the application of MOO and MCDM techniques in modern studies. These methods are important for solving the challenges that are always associated with decision making when several conflicting objectives or criteria have to be met. Through the examination of the applications, integration methods and issues of MOO and MCDM, we present an understanding of the appropriateness and relevance of these methodologies in enhancing the decision-making processes within various fields. This paper has been arranged as follows: Section II presents the data and methods employed in composing the research and obtaining the required results. In Section III and Section IV, a detailed account of the results has been provided, including MOO, MCDM, and integrated MCDM/MOO methods. Moreover, this section highlights the uncertainty and sensitivity analysis of MOO and MCDM. Section V concludes the findings which are illustrated in the research and highlights the usage of the advanced MOO methods as well as the trend to incorporate uncertainty considerations into the models, underlining the significance of these approaches to enhance the multifaceted decision-making processes.

II. DATA AND METHODS

The data for this study was gathered from 41 articles that were published in peer-reviewed journals and which applied MOO and MCDM techniques. These articles were chosen considering the relevance of the articles to the research questions and the scientific quality of the method applied. The reviewed articles were identified from different reputable publishers such as Elsevier, Springer, IEEE, and IOP. The articles cover a broad spectrum of application domains, which gives a broad view of the incorporation of MCDM and MOO systems (see **Table 2**). The general MOO problem can be defined in a mathematical form as presented in the Equation (1).

$$\frac{min}{\max F(x)=[f_1(x),f_2(x),\ldots\ldots,f_k(x)]} \tag{1}$$

Subject to $g(x) \leq 0; h(x) = 0$; and $x_{min} \leq x \leq x_{max}$ where: $F(x)$ is the vector of the key functions, x is the vector of the decision constants, $g(x)$ and $h(x)$ are the vectors of the imbalance and parity constraints. xx_{min} and x_{max} define the range for the decision variables.

As for the metaheuristic methods, the majority of the reviewed articles (70.7%, 29 out of 41) employed these approaches. Among these, Non-dominated Sorting Genetic Algorithm (NSGA) and Genetic Algorithms were the most widely used optimization techniques. In particular, NSGA-II was used in 17 (41.5%) articles among the reviewed ones. The main rationale for adopting these methods was informed by their suitability in solving difficult problems that are non-linear and multi-dimensional. The Crow Search Algorithm (CSA), which is a relatively recent population-based network, was also mentioned for its good computational efficiency and solution accuracy. There were 13 articles that incorporated the use of mathematical models; 12 of which used linear models while the other used the non-linear model. These models were developed to identify Pareto-optimal solution sets with the help of defining multiple objectives and constraints. The ε-constraint and Augmented ε-constraint (AUGMECON) methods were frequently used because they were efficient with small-scale problems and could address multiple objectives.

Table 2. Data Summary of the MOO and MCDM Methods from Pee-Reviewed Sources

Reference ID	MOO Method	MCDM Method	Weighting Method	Ranking Method	Integration Approach	Uncertainty Analysis	Sensitivity Analysis	Publisher	Year
[25, 26, 27]	ε-constraint	TOPSIS	None	TOPSIS	A Posteriori	None	Yes	IOP	2021
[28, 29]	Particle Swarm Optimization (PSO)	PROMETHEE	Subjective (BWM)	PROMETHEE II	A Posteriori	Monte Carlo	No	IEEE	2017
[30, 31]	Crow Search Algorithm	ELECTRE	Objective (Entropy)	ELECTRE	A Priori	Probabilistic	Yes	Springer	2023
[32, 33]	Genetic Algorithm	VIKOR	Subjective (AHP)	VIKOR	A Posteriori	Triangular Fuzzy	Yes	Elsevier	2020
[34, 35]	NSGA-II	TOPSIS	Combination (AHP & Entropy)	TOPSIS	A Posteriori	Monte Carlo	Yes	IOP	2024
[36, 37]	ε-constraint	TOPSIS	None	TOPSIS	A Posteriori	None	Yes	IEEE	2021
[38, 39]	Particle Swarm Optimization	PROMETHEE	Subjective (BWM)	PROMETHEE II	A Posteriori	Monte Carlo	No	Springer	2017
[40, 41]	Crow Search Algorithm	ELECTRE	Objective (Entropy)	ELECTRE	A Priori	Probabilistic	Yes	Elsevier	2018
[42, 43]	Genetic Algorithm	VIKOR	Subjective (AHP)	VIKOR	A Posteriori	Triangular Fuzzy	Yes	IOP	2021
[44, 45]	NSGA-II	TOPSIS	Combination (AHP & Entropy)	TOPSIS	A Posteriori	Monte Carlo	Yes	IEEE	2019
[46, 47]	ε-constraint	TOPSIS	None	TOPSIS	A Posteriori	None	Yes	Springer	2021
[48, 49]	Particle Swarm Optimization	PROMETHEE	Subjective (BWM)	PROMETHEE II	A Posteriori	Monte Carlo	No	Elsevier	2017
[50, 51]	Crow Search Algorithm	ELECTRE	Objective (Entropy)	ELECTRE	A Priori	Probabilistic	Yes	IOP	2022
[52, 53]	Genetic Algorithm	VIKOR	Subjective (AHP)	VIKOR	A Posteriori	Triangular Fuzzy	No	IEEE	2020
[54, 55]	NSGA-II	TOPSIS	Combination (AHP & Entropy)	TOPSIS	A Posteriori	Monte Carlo	Yes	Springer	2019

[56, 57]	ε-constraint	TOPSIS	None	TOPSIS	A Posteriori	None	Yes	Elsevier	2021
[58, 59]	Particle Swarm Optimization	PROMETHEE	Subjective (BWM)	PROMETHEE II	A Posteriori	Monte Carlo	Yes	IOP	2020
[60, 61]	Genetic Algorithm	ELECTRE	Combination (AHP & Entropy)	ELECTRE	A Priori	Probabilistic	No	IEEE	2018
[62, 63]	Crow Search Algorithm	VIKOR	Objective (Entropy)	VIKOR	A Posteriori	Triangular Fuzzy	Yes	Springer	2020
[64, 65]	NSGA-II	TOPSIS	Subjective (AHP)	TOPSIS	A Posteriori	Monte Carlo	Yes	Elsevier	2019

Weighting techniques in MCDM can be classified into three types: They include the objective, the subjective, and both objective-subjective. Among the 41 articles, 48.8% (20 articles) used particular weights, mainly AHP and BWM as weight allocation techniques. These methods afford the opportunity of integrating the decision-makers' preferences. A smaller portion of the analyzed papers (14.6%) employed both subjective and objective weights; in such cases, entropy methods were utilized to secure the weighting process. In the ranking methods of MCDM, there were diverse, although TOPSIS was the most frequently applied (43.9%, 18 articles). The TOPSIS method was preferred because of its least number of inputs and the logical framework. The other approaches were VIKOR, ELECTRE, and PROMETHEE, which applied different benefits depending on the multiple criteria and uncertainty factors.

Normalized Decision Matrix (NDM), Positive Ideal Solution (PIS), Relative Closeness to the Ideal Solution (RCIS), Weighted Normalized Decision Matrix (WNDM), Negative Ideal Solution (NIS), Separation Measures (SM) were calculated using the Equations (2), (3), (4), (5) and (6).

$$R_{ij} = \frac{X_{ij}^2}{\sqrt{\sum_{i=1}^{m} X_{ij}^2}} \tag{2}$$

where R_{ij} is the regularized value for i^{th} substitute and j^{th} critierion, X_{ij} is the initial value for the ith substitute and i^{th} criterion, and m represents the number of alternatives.

$$V_{ij} = w_j * R_{ij} \tag{3}$$

where V_{ij} is the weighted regularized value, and w_j is the weight of j^{th} standard.

$$A^+ = \{\max(V_{ij}) \big| j \in J\}, A^- = \{\min(V_{ij}) \big| j \in J'\} \tag{4}$$

whereJ' is the set of cost criteria, A^+ denotes the PIS, J is the set of benefit criteria, and A^- is the negative idea solution.

$$S_i^+ = \sqrt{\sum_{j=1}^{n}\left(V_{ij} - A_j^+\right)^2}, S_i^- = \sqrt{\sum_{j=1}^{n}\left(V_{ij} - A_j^-\right)^2} \tag{5}$$

whereS_i^- is the separation from the NIS and S_i^+ denotes the separation from the PIS.

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-} \tag{6}$$

where C_i^* is the relation nearness to the ideal solution

The most frequently applied integration type was a posteriori, identified in 78.1% (32 articles) of the reviewed articles. This approach entails solving the MOO problem to arrive at the Pareto desirable set, which is followed by the use of MCDM to assess the solutions. Prior integration was employed less frequently; only 14.6% (6 articles) of the studies employed it. In this method, MCDM is applied to determine the best alternatives before going for MOO. Other researches incorporated both integration approaches so as to take merit of the benefits of each method. Uncertainty analysis was another important factor in MOO methods, where 80.5% (33 articles) included it.

Some of the frequently used methods were Monte Carlo Simulation and triangular fuzzy numbers, which assisted in dealing with the uncertainties of design variables, environmental conditions, and model parameters. Concerning uncertainty analysis, it was less frequently incorporated in MCDM methods, with only 20.3% (12 articles) dealing with it. The former was the case if the primary focus was on uncertainties of criteria weights with the help of which fuzzy set theory and probabilistic distributions (PD) were applied. In 39% (16 articles) of the reviewed studies compassion data was accomplished so as to assess the stability of the models when the constraints and weights are changed. It enables one to determine the effects of varying assumptions and inputs on the results.

III. RESULTS

This section presents a discussion of the derived data from the reviewed articles, focusing on four review questions. These questions include the methods used in Multi-Objective Optimization (MOO) and the reasons behind their selection, the regularly used ranking and weighting methods in Multi-Criteria Decision-Making (MCDM), the integration of MCDM and MOO, and the recent practices of considering ambiguity in these studies.

MOO Methods

Among the 41 articles that were reviewed, 29 (70.7%) of them (as illustrated in **Fig. 1**) employed evolutionary optimization techniques. Out of these, 13 articles utilized mathematical models, with 12 of them being linear and 1 being non-linear [66]. The objective of these models was to identify Pareto-optimal result sets by considering mult-purpose constraints and functions. Out of the various metaheuristic techniques, evolutionary utilization systems such as genetic networks [67]and NSGA (17 articles) were the most frequently employed systems. Seventeen articles, which accounted for 41.5% of the total, employed the NSGA-II version.

Arora et al. [68] proposed a novel population-based technique called CSA, which models the food-hiding behavior of crows [69]. The numerical data of the reserved articles indicates that they originate from a range of reputable publishers, including IOP, IEEE, Springer, Elsevier, and others, as depicted in **Fig. 2**. These publications are distributed in both conference proceedings and academic journals, but Springer appears to be the most frequently utilized dataset. **Fig. 3** displays the spreading of CSA periodicals over the years. There has been a noticeable rise in interest in the study of CSA over the past four years. Since the implementation of CSA in 2016, over 100 papers related to CSA have been issued, with a small increase in 2019. The crow is a highly intelligent avian species capable of facial recognition and alerting its fellow members in the presence of peril. One of the most compelling indications of their intelligence is their ability to conceal food and recall its whereabouts. Furthermore, the study and utilization of CSA can be acquired from the article titled "Exploration and Exploitation of CSA" published in [70].

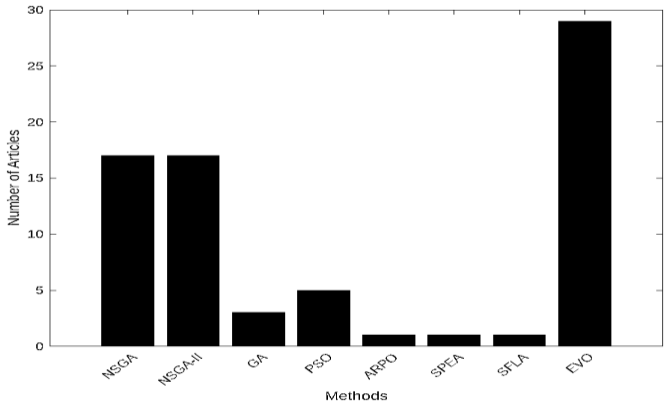

Fig 1. Distribution of Multi-Objective Optimization Methods.

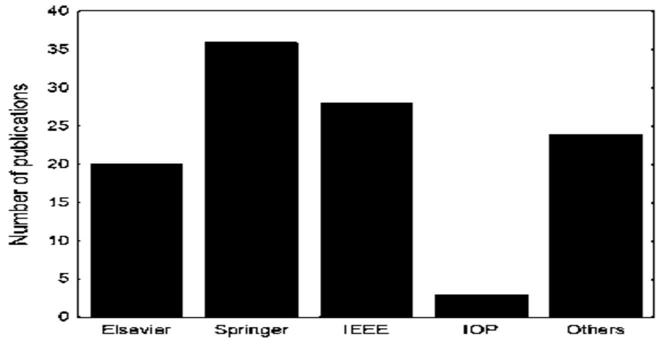

Fig 2. Number of Articles by Scientific Database Pertaining to CSA.

Javidi, Salajegheh, and Salajegheh [71] used the Crow Search Algorithm (CSA) because it provides a balance among the time it takes and the number of calculations needed, while also having a straightforward design. Several researchers reported choosing their optimization methods based on the pertinent literature [72, 73, 74, 75].

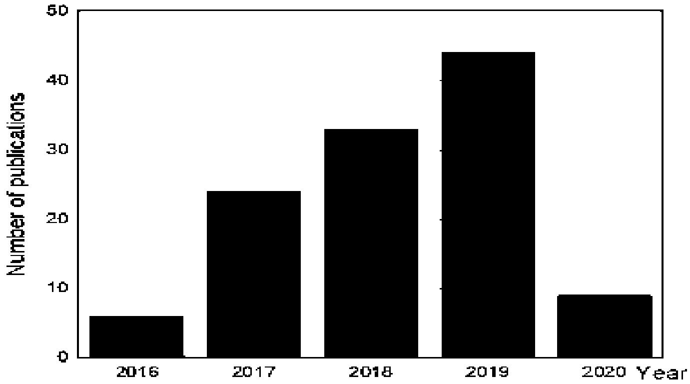

Fig 3. Number of Publications by Year Pertaining to CSA.

MCDM Methods

To elucidate the methodological decisions employed in the revised articles that documented the utilization of MCDM approaches, data was collected for the ranking and weighting approaches individually.

Weighting Methods

There are three main categories of weighting in MCDM methods: subjective weights based on decision makers' partialities; objective weights derived from input data; and combined subjective and objective weights. Twenty publications (48.8%) out of the assessed articles solely used subjective weights to account for DMs' partialities. The most commonly used methods for this were AHP (55%) and BWM (20%) (**Fig. 4**).

Ranking Methods

The reviewed articles utilized various outranking techniques, as well as reference and goal level methods, for MCDM. The TOPSIS method was used in the majority of cases, accounting for 18 articles, which represents 43.9% of the total (**Fig. 4**). TOPSIS is a technique that needs a small number of inputs and produces outputs that are easy to understand. It also allows for the inclusion of subjective and/or purpose weights without difficulty [76]. Furthermore, it guarantees minimal loss of information and offers a resilient logical framework with a powerful computational capacity, as evidenced in [77]. As opposed to VIKOR, which only deliberates the detachment from the ideal that is positive [78].

TOPSIS examines optimal solutions that are both negative and positive. A limited number of articles employed the VIKOR technique to select the optimal choice from the Pareto set [79]. Figuera et al. [80] and Govindan and Jepsen [81] employed the ELECTRE method. Out of the 41 articles, only 6 utilized the PROMETHEE position technique, while 3 employed PROMETHEE II (**Fig. 4**). PROMETHEE II is preferable because it can perform a comprehensive ranking using global total flows, unlike PROMETHEE I which only supports an incomplete ranking according to global negative and global positive flows [82]. PROMETHEE II is a reliable and straightforward method that can handle both scaled and numerical values, including uncertainty [83]. Processing original data is not necessary. Instead, it employs various preference functions [84]. The system can analyze the differences between options and evaluate various criteria using different scales [85].

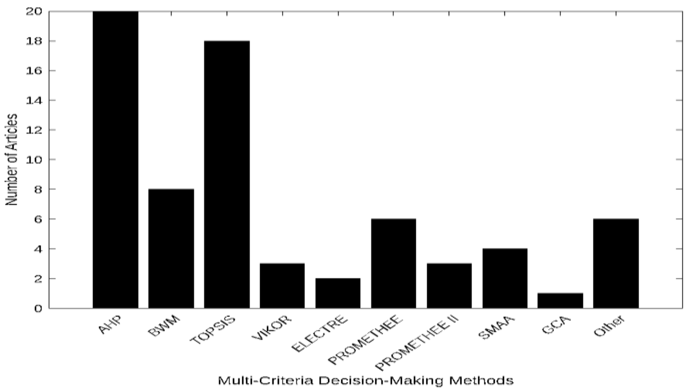

Fig 4. Distribution of MCDM Methods.

Integrated MCDM/MOO Techniques

MCDM approaches can be used with MOO techniques in two manners: a posteriori and a priori. The incorporation approach that was most frequently utilized was a posteriori, which was employed in 32 papers, accounting for 78.1% of the total. A posteriori integration refers to the process of initially solving the MOO issue to provide Pareto-optimal solutions. These solutions are subsequently used as alternatives for the MCDM problem, as shown in **Fig. 5**. The utilization of various weighing and ranking techniques enables the identification of the most effective solutions for the system under study. Prior to integration, a process known as a priori integration involves using MCDM methodologies to find the most optimal system alternative and then optimizing that system [86].

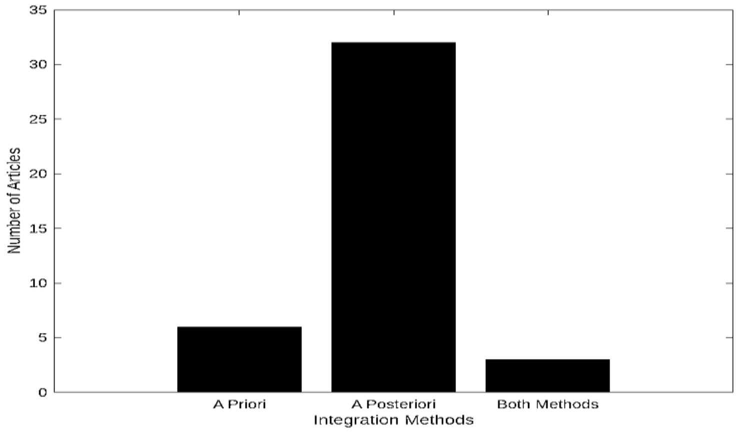

Fig 5. Integration Methods.

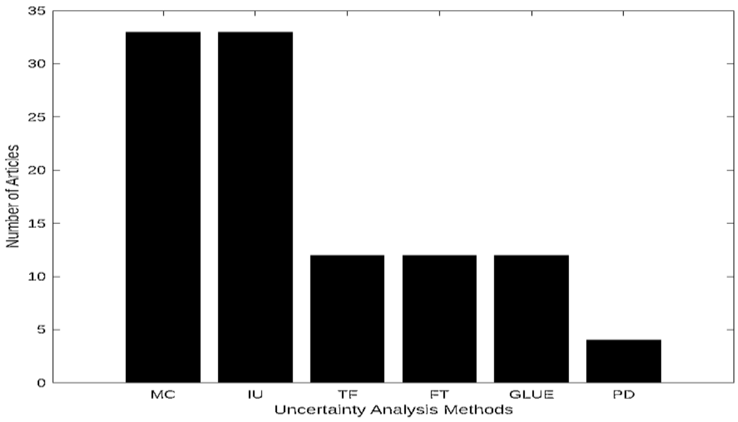

Fig 6. Uncertainty Analysis Methods.

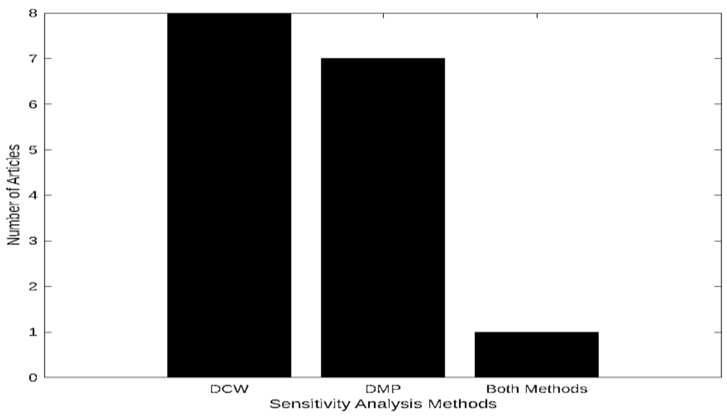

Fig 7. Sensitivity Analysis Methods.

Uncertainty Analysis

Uncertainty considerations can be conducted using two methods: the MOO model and the MCDM model. MOO challenges primarily take into account uncertainties related to design factors, model parameters, and objective functions. However, the presence of uncertainty in the weights of criteria and/or the partialities of verdict makers is a significant worry in MCDM situations. The subsequent sections delineate the prevailing methodologies identified in the examined literature for incorporating uncertainty ideas in MOO and MCDM situations.

Uncertainty in MOO

Uncertainties in MOO challenges arise from several factors such as environmental aspects (e.g., flood flow for reservoir-related challenges, design constants [87], and model constraints. Incorporating uncertainty into MOO challenges is a widely practiced approach. Out of a total of 41 studies, 33 (80.5%) included uncertainty concerns in their MOO models, as shown in **Fig. 6**. Various uncertainty propagation methods were documented, such as Monte Carlo (MC) Simulation, triangular fuzzy (TF) numbers [88], the interval uncertainty (IU) method [89], the fuzzy set theory/fuzzy transformation (FT) method [90], generalised likelihood uncertainty estimation (GLUE) [91], and others. The triangular fuzzy numbers and the MC Simulation approaches were the most prevalent among them. MC Replication is capable of managing intricate systems that involve several sources of uncertainty. The system generates a variety of potential results and their corresponding likelihoods using a substantial collection of random data samples [92]. The use of triangular fuzzy numbers for uncertainty analysis is prevalent because of its simplicity, interpretability, and ease of mathematical manipulation [93]. According to the evaluated studies [94, 95, 96], there are currently no established standards that priorities the adoption of any one technique for uncertainty data.

Uncertainty in MCDM

Criteria weights are the primary sources of ambiguity in MCDM situations. Although uncertainty analysis is not commonly integrated with MCDM methodologies, the same is true for MOO problems. Out of the total of 41 studies, only 12 (29.3%) have taken into account uncertainty in MCDM approaches. This is mostly done to address uncertainty related to subjective weights, as seen in **Fig. 6**. Six of the publications used fuzzy set theory or triangular fuzzy numbers, and the other four used PD to deal with the ambiguity in the standard weights.

Sensitivity Analysis

Due to the variability in model parameters, other researchers have produced numerous scenarios and conducted sensitivity analysis to assess the model's reliability. When there is uncertainty in the weights assigned to criteria, sensitivity data is conducted for MCDM procedures using various weights. The examined studies equally employed sensitivity assessments using various model scenarios/parameters and varying weights in MCDM approaches. A total of 16 out of 41 (39%) studies performed compassion data. Among these, 8 articles utilized different criteria weights (DCW) for the sensitivity check, while 7 articles used alternative model parameters in MOO issues. Only one individual utilized both strategies, as depicted in **Fig. 7**.

IV. DISCUSSION

Verma et al. [97] and Ramesh et al. [98] introduced enhanced approaches for NSGA-II. The NSGA-II technique is commonly employed in multi-objective optimization issues. However, the classic NSGA-II algorithm has many drawbacks, including high processing expenses and inadequate convergence in complex practical applications. In order to address the aforementioned shortcomings, a refined NSGA-II method is suggested in [99]. Initially, the crossover and mutation operators are specifically built. Additionally, a fresh elitist strategy is also created. Next, the simulations of the standard test functions are conducted, and the results demonstrate that the enhanced strategies can significantly increase the confluence and operational efficacy of the conventional system. In [100], a multi-purpose mathematical model is built to examine the feasibility of the algorithm in planning the charge for steelmaking. The simulation is conducted using authentic industry data. The results demonstrate the algorithm's feasibility for charge scheduling. The technique known as Non-dominated Sorting Differential Evolution (NSDE) was created by Li, Sansavini, and Zio [101] by combining NSGA-II with disparity evolution. The researchers selected NSGA-II mainly due to the higher calculation speed and better ability to sustain the assortment of Pareto-optimal solutions and higher confluence rate [102, 103, 104]. Berrichi et al. [105] applied SPEA to classify an efficient and maintainable supply chain for creation resources. They concluded that this technique is much more efficient than Pareto Envelope-Based Selection and NSGA-II Systems to solve real-world problems.

Another aspect of NSGA-II is the use of the non-domination notion which permits for the identification of solutions that are non-dominant to any other solutions with reference to all objectives [106, 107]. Evolutionary-based MOO approaches were widely used because of their capability of searching for many objectives at a time, encouraging the spread of results and enhancing the possibility of finding the worldwide optima. They are ideal for solving non-linear and more complicated challenges where the objective functions are nondifferentiable and/or discontinuous [108]. Reddy and Bijwe [109] describe a new and more effective evolutionary-based algorithm for resolving the OPF challenge. This approach uses the incremental load flow model according to sensitivity and heuristic. This document is useful to the system operator in making sound and credible decisions. The primary disadvantage of applying a meta-heuristic-based MOO strategy is that it calls for a large amount of computer resources. Through the application of the efficient MOO approach being proposed in this paper, the overall number of load flows needed is greatly reduced, which is indicative of a vast enhancement in the rate at which solutions are obtained.

Five articles (12.2%) utilized the PSO approach. The PSO approach was chosen for its notable characteristics, including its minimal parameter requirements, user-friendly operation, rapid convergence, high search speed, and superior global optimization capabilities, even for intricate models [110, 111]. Abraham et al. [112] utilized the Shuffled Frog-Leaping method (SFLA), a population-based metaheuristic method that combines Particle Swarm Optimization and memetics [113]. The reason they selected SFLA is because it can integrate stochastic and deterministic techniques to achieve more accurate and high-standard trade-off results that are both disparate and evenly circulated. Additionally, SFLA is capable of handling difficult and high-dimensional problems [114]. Among the instances of ε-constraint-based utilization approaches (namely, AUGMECON and ε-constraint), mathematical modelling was utilized in six papers. The ϵ-constraint technique is a commonly employed methodology for solving MOO issues. The authors enhanced this approach by including stringent dimensionality reduction techniques and pseudo/quasi-random sequences. Empirical evidence demonstrates that the improved algorithm surpasses the conventional ϵ-constraint technique in both the amount and quality of the Pareto points generated by the algorithm. The methodology proposed by Hua et al. [115] is well-suited for addressing environmental problems that often involve multiple redundant objectives. It enables the handling of complex MOO models with numerous objectives. Balaman et al. [116] argued that the ε-constraint technique is particularly suitable for small-scale scenarios. The ε-constraint approach converts all key purposes into restraints, except for the purpose function with the maximum priority. An epsilon is a predetermined value that represents the maximum permissible boundary for each of the key purposes. By adjusting the value of epsilon, the Pareto set can be located [117].

Mavrotas and Florios [118] and Bouziaren and Aghezzaf [119] also utilized an enhanced ε-constraint method called AUGMECON. The robust augmented ε-constraint algorithm, AUGMECON-R, is provided by the authors to address multi-purpose linear programming issues. This new approach addresses the limitations of AUGMECON 2, which is a popular enhancement of the ε-constraint technique. The drawbacks can be characterized as the inefficient management of the lowest points of the goal functions and, particularly, the substantial time needed to implement it when additional objective functions are introduced to a problem. Nikas et al. [120] utilize AUGMECON-R to compare it with its previous version, by examining a collection of benchmark problems from existing literature as well as a set of considerably more intricate problems with four to six objective functions. The authors propose that the technique surpasses its predecessor by solving far fewer models in a considerably shorter amount of time. It also enables the straightforward and timely resolution of challenging or practically infeasible issues related to multiple objective functions, particularly in terms of time and processing requirements.

Additional mathematical programming techniques employed in the examined studies were Mixed Integer Linear Programming [121], LP metrics [122], and Weighted Goal Programming (WGP) [123]. WGP enables the inclusion of decision makers' partialities for each key purpose to a greater extent than traditional goal programming. It also transforms all incompatible constants into a regularized weighted single-objective purpose [124]. Goal programming (GP) is a highly utilized and efficient approach for tackling practical multi-purpose decision-making challenges. The phrase “Multi-Objective Transportation Problem” (MOTP) refers to a particular category of vector maximum (minimum) linear programming challenge that usually involves many, conflicting, and discordant objective purposes. The summary of GP and Weighted Goal Programming (WGP) may be found in MOTP, as shown in [125]. In summation, the use of WGP allows for the articulation of a solution technique for MOTP, as described in [126].

Incorporation of preferences from many decision makers and stakeholders is done through BWM and AHP. While both methods involve pairwise comparison principles, BWM mainly employs the reference comparisons, which leads to a decrease in the figure of pairwise contrast matrices by a large margin [127]. At times, the presentation of AHP was further improved by applying fuzzification which uses a different perception matrix to the mutual one [128]. Fuzzy AHP does not allow the weight of a feature to change due to other elements, thus preserving the physical meaning of weight distribution [129]. Out of the research papers included in the study, six papers (14.6%) employed an integration of both quantitative and qualitative weights. From the main weighting methods that were used, only entropy was used. It has been established that the use of this elaborate weighing approach is more effective and standardized [130]. A small number of studies excluded subjective weighing altogether and based their calculations solely on objective weights, albeit in a limited number of cases [131, 132, 133]. From the sampled articles, 11 did not use any form of weighing methodology at all, and these comprised 26.8% of the total.

Prior to conducting MOO, weighting systems are employed to allocate weights to the main purposes. Occasionally, these weights could be employed to transform the MOO challenge into a solitary-objective optimization problem [134]. Only 6 out of the 41 papers adhered to the a priori procedure. Three other articles incorporated both a posteriori and a priori approaches to merge MCDM and MOO, as shown in **Fig. 5**. Prior to executing MOO, they employed weighting methods to rank the Pareto-optimal results [135, 136, 137]. However, after conducting MOO, they switched to using ranking methods for the same purpose. The selection of the incorporation method (either a posteriori, a priori, or a mixture of both) is entirely determined by the decision maker (DM). Several contemporary tools and software can be employed to incorporate MOO and MCDM. These include MATLAB [138], Python (utilizing libraries such as SciPy, Scikit-Criteria, PyDecision Tree, Distributed Evolutionary Algorithms, etc.) [139], the General Algebraic Modelling System (GAMS) [140], machine learning [141], Multi-Objective Evolutionary Algorithms (MOEA) Models in R and Java [142], data mining [143].

Sensitivity analysis (SA) is generally considered as an integral part of uncertainty analysis (UA). SA and UA are considered mandatory for constructing models in any discipline that employs models. The UA is a tool that allows the uncertainty assessment linked with the framework output and the uncertainties of its inputs. SA analyses how various changes within the model output can be accredited to variances in inputs and how the behavior of the model depends on the data it has been fed. The results in [144, 145, 146, 147], defining the building energy performance simulation, show that UA is more effective approach than deterministic methods to control the level of uncertainty in building design processes. The main sources of variability that affect the accuracy of predicting building energy consumption are: fluctuations in weather temperature, deterioration of the building envelope material properties, and unpredictable behavior of occupants. The UA is linked to the SA to find the inputs that create the highest impacts on the uncertainties of the energy consumption of the building [148, 149]. The authors have elucidated a comparatively novel method to create a simulation of building energy performance that includes both the UA and SA. The energy performance calculations are based on thermal models of the building that consider the resistance and capacitance values.

V. CONCLUSION

In our review of MOO and MCDM methods, we have highlighted their applications, interaction, and strategies of dealing with uncertainty in decision-making. There was a highly frequent use of metaheuristic optimization techniques, especially EA such as NSGA-II, which demonstrated the ability of metaheuristic algorithms to search and find Pareto-optimal solutions in large problem spaces. Furthermore, the application of MCDM approaches like TOPSIS and AHP highlights the importance of these approaches in providing a structured manner of analyzing options and arriving at a decision in line with the policymaker`s objectives. The fact that most of the integration methods are a posteriori indicates the sequential problem-solving approach, whereby the MOO solutions are used as inputs in MCDM, thus improving decision-making. Besides, the treatment of uncertainty by tools such as Monte Carlo Simulation and fuzzy set theory shows that robustness analysis is a significant aspect of decision-making in an uncertain world. The present work also helps the progress of decision science by providing information about the interaction between MOO and MCDM methodologies and their application for solving actual decision challenges. In the future, the improvement of integration approaches, the advancement of better uncertainty frameworks, and the expansion of the application area for these approaches to other fields are suggested to improve the effectiveness and reliability of decision making.

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