

An Evolutionary Weight Optimization Framework for Adaptive PROMETHEE-Based Decision Support Systems

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Submitted : Sep 18, 2026 | **Accepted** : Oct, 2026 | **Published** : Oct 8, 2026

Abstract: Multi-Criteria Decision-Making (MCDM) methods are widely employed to support complex decision processes involving multiple alternatives and conflicting evaluation criteria. However, the performance of PROMETHEE-based decision support systems is strongly influenced by the criterion weights, which are commonly predetermined and treated as fixed parameters. Such static weighting may limit the adaptability and discriminatory capability of the resulting decision model. This study proposes an Evolutionary Weight Optimization Framework for Adaptive PROMETHEE-Based Decision Support Systems to address this limitation by integrating evolutionary optimization with the PROMETHEE ranking mechanism. The proposed framework treats criterion weights as optimization variables and iteratively searches for an improved weighting configuration before generating the final PROMETHEE ranking. The experimental evaluation was conducted using a dataset comprising 219 alternatives, with the performance of the proposed optimized PROMETHEE compared against a conventional baseline PROMETHEE model using fixed criterion weights. The evaluation focused on net flow distributions, alternative ranking changes, ranking stability, and the discriminatory behavior of the decision-support models. The results demonstrate that weight optimization substantially modifies the preference structure and produces a broader and more differentiated distribution of net flow values compared with the baseline approach. Several alternatives experienced notable ranking improvements or declines, while some alternatives maintained their positions, indicating different levels of sensitivity to the optimized weighting scheme. These findings demonstrate that evolutionary weight optimization can enhance the adaptability and discriminatory capability of PROMETHEE while preserving its interpretable ranking structure. The proposed framework provides a systematic approach for developing more adaptive, robust, and data-responsive MCDM decision support systems.

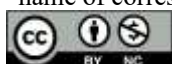
Keywords: Multi-Criteria Decision-Making; PROMETHEE; Evolutionary Optimization; Decision Support System; Adaptive MCDM

INTRODUCTION

The increasing complexity of contemporary decision-making environments has created a growing need for systematic approaches capable of evaluating multiple alternatives across heterogeneous and often conflicting criteria (Higgins, 2023; Naiseh, 2023; Unhelkar, 2022). In practical settings, decision-makers are rarely confronted with a single objective; instead, they must simultaneously consider economic, technical, environmental, social, operational, and strategic dimensions. The presence of conflicting criteria makes intuitive or single-criterion decision-making inadequate because improving one criterion may result in deterioration in another. Multi-Criteria Decision-Making (MCDM), or Multi-Criteria Decision Analysis (MCDA), has therefore become an important methodological paradigm for supporting complex decision processes by providing a structured mechanism for evaluating, comparing, and ranking alternatives according to multiple criteria (Tun, 2025; Wayman, 2024; Xu, 2023).

Among the various MCDM approaches, the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) has received substantial attention because of its ability to represent preference

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relations among alternatives while maintaining an interpretable ranking mechanism (Tiwari, 2022; Tong, 2022; Wątróbski, 2023). The original PROMETHEE methodology was introduced by Brans and Vincke as an outranking approach in which alternatives are compared according to criterion-specific preference functions and relative criterion weights. PROMETHEE I provides a partial ranking, whereas PROMETHEE II produces a complete ranking based on the net preference flow of each alternative. This structure enables decision-makers to analyze alternatives according to their relative preference rather than relying exclusively on aggregated numerical scores (Ahmed, 2024; Lima, 2022; Meng, 2022; Zorlu, 2023).

The methodological relevance of PROMETHEE has been demonstrated by its extensive adoption across different decision-making domains. A comprehensive review by Behzadian et al. identified hundreds of PROMETHEE-related studies covering environmental management, water resources, business and financial management, logistics and transportation, manufacturing, energy management, and other application areas (Kuncova, 2022; Yang, 2022). The broad adoption of PROMETHEE indicates that the method offers a flexible and practically interpretable mechanism for solving ranking and selection problems involving conflicting criteria. However, the extensive application of PROMETHEE does not eliminate an important methodological issue: the reliability of the resulting ranking is highly dependent on how the relative importance of criteria is specified (Li, 2022).

Criterion weighting represents one of the most influential components of an MCDM framework because the weights determine the contribution of each criterion to the final preference structure. In PROMETHEE, the criterion weights are directly incorporated into the preference index and consequently influence the positive, negative, and net preference flows used to rank alternatives. Therefore, even when the underlying alternative-performance matrix remains unchanged, modifications in criterion weights can alter the relative preference between alternatives and potentially change the final ranking. The selection of appropriate criterion weights is consequently not merely a preprocessing step but a fundamental determinant of the behavior and reliability of the decision-support system (Fetanat, 2024; Gonzales, 2022; Ryu, 2023). Recent reviews of MCDM weighting methods similarly emphasize that criterion weighting can substantially influence ranking stability, sensitivity, and robustness (T.R., 2024; Yiğit, 2023).

A fundamental challenge arises because conventional criterion weighting approaches frequently rely either on subjective judgments or on fixed data-driven characteristics. Subjective methods, such as expert-based weighting, are valuable because they incorporate domain knowledge and decision-maker preferences. Nevertheless, they may introduce cognitive bias, inconsistency, and dependence on the expertise of the individuals involved. Conversely, objective weighting techniques derive importance from statistical, informational, or structural properties of the decision matrix, thereby reducing direct dependence on human judgment. However, objective approaches may fail to adequately represent contextual priorities or strategic preferences that are not explicitly observable in the data. The literature consequently distinguishes subjective, objective, and hybrid weighting paradigms, while recent research increasingly considers adaptive and data-driven mechanisms as potential directions for addressing the limitations of static weighting (W. Chen, 2022; Wardropper, 2022; White, 2023).

The problem becomes more critical when a decision-support system is expected to operate under changing decision environments. In many real-world applications, the relative importance of criteria is not necessarily constant over time. Changes in economic conditions, operational requirements, stakeholder priorities, environmental constraints, or strategic objectives can modify the decision context and consequently alter the appropriate balance among criteria. A weighting configuration that produces a reasonable ranking under one decision scenario may therefore become less appropriate when the decision environment changes. This observation challenges the conventional assumption that a single predetermined weight vector is universally optimal for all decision contexts (Fawaz, 2023; Funer, 2024; Sufi, 2022).

The dependency of PROMETHEE on its parameterization further strengthens the need for systematic weight optimization. Recent research on PROMETHEE II has demonstrated that changes in preference-function parameters can affect ranking stability and that rank reversal remains an important issue in assessing the reliability of PROMETHEE-based decision models. Sensitivity analysis has consequently become an important component of MCDA because it allows researchers to determine whether the obtained ranking remains stable when model parameters or decision assumptions change. These findings suggest that a decision-support model should not only produce a ranking but should also provide a mechanism for identifying and controlling the parameter configurations that lead to reliable and robust decisions (Li, 2022; Yang, 2022; Zorlu, 2023).

Despite the importance of criterion weighting, a substantial portion of existing PROMETHEE applications still treats criterion weights as externally determined parameters. In such configurations, the decision-support process generally follows a sequential structure in which experts or an independent weighting method first determine the weights, after which PROMETHEE is applied to generate the ranking. Although this approach is computationally straightforward and conceptually transparent, it creates a methodological separation between the weighting process and the ranking objective. The weighting mechanism does not necessarily consider whether a particular weight vector produces stable, discriminative, or decision-relevant rankings within the PROMETHEE model. Consequently, the weight vector may be theoretically plausible but suboptimal with respect to the actual behavior of the decision-support system. This limitation creates an important research opportunity: rather than treating criterion weights as fixed inputs, the weighting process can be formulated as an optimization problem in which

candidate weight vectors are systematically explored to identify configurations that improve the quality and robustness of PROMETHEE-based rankings. Such a formulation transforms the conventional PROMETHEE pipeline from a static decision model into an adaptive decision-support framework. In this perspective, the criterion weights become decision variables, PROMETHEE becomes the ranking engine, and an optimization algorithm becomes the mechanism for searching the weight space (Goudarzi, 2024; Ye, 2022).

Evolutionary optimization provides a promising mechanism for addressing this problem. Evolutionary algorithms are population-based optimization techniques inspired by natural selection and evolutionary processes. Their principal advantage is their ability to explore complex and nonlinear search spaces without requiring the optimization problem to possess a simple analytical structure. This characteristic is particularly relevant to MCDM because the relationship between criterion weights and alternative rankings may be nonlinear, discontinuous, and highly sensitive to small parameter changes. Instead of relying on a single manually determined weight vector, an evolutionary optimizer can generate multiple candidate weight configurations, evaluate their performance through a predefined fitness function, and iteratively improve the candidate solutions through evolutionary operators. Within the proposed research direction, the evolutionary algorithm is not intended to replace PROMETHEE. Instead, the two components perform complementary functions. PROMETHEE provides the preference-based decision mechanism for transforming criterion performances and weights into alternative rankings, while the evolutionary optimization layer searches for a weight configuration that maximizes a predefined decision-quality objective. This integration creates a feedback mechanism between weighting and ranking: candidate weights are evaluated according to their resulting PROMETHEE behavior, and the optimization process continuously updates the weights based on the observed fitness. Such a framework can potentially overcome the limitation of independently determined static weights (Mir, 2024; Yu, 2023).

The formulation of an evolutionary weight optimization mechanism, however, requires careful consideration of the optimization objective. Optimizing weights solely to maximize the score of a predetermined alternative could introduce undesirable bias and may lead to overfitting. Therefore, the fitness function should be designed to capture meaningful properties of a decision-support system, such as ranking stability, discrimination among alternatives, consistency with decision preferences, robustness against perturbations, or agreement with reference decisions. This consideration is particularly important because an optimized weight vector should not simply produce a different ranking; it should produce a ranking that is demonstrably more reliable and robust than that generated by conventional weighting strategies. Ranking stability represents one particularly important criterion for evaluating the quality of an optimized PROMETHEE model. A decision-support system that produces substantial ranking changes in response to small variations in criterion weights may be difficult to trust in practical environments. Sensitivity analysis research in MCDA emphasizes that robustness assessment is essential for determining whether decision outcomes remain consistent under changes in model assumptions and parameters. Therefore, an evolutionary optimization framework can be designed not merely to search for a mathematically optimal weight vector but to identify a weight configuration that provides a desirable balance between discriminatory capability and ranking stability (Huang, 2023; Ning, 2024).

Another important issue concerns the trade-off between data-driven optimization and decision-maker interpretability. Although evolutionary optimization can identify weight configurations that improve a selected objective, decision-support systems should remain understandable to human decision-makers. PROMETHEE possesses an inherent advantage in this regard because its preference functions, criterion weights, and preference flows can be explicitly interpreted. The proposed framework should consequently preserve the interpretability of PROMETHEE while introducing optimization into the weighting layer. Rather than producing an opaque prediction model, the framework can expose the optimized criterion weights and demonstrate how changes in these weights influence the resulting preference flows and rankings. This characteristic distinguishes the proposed approach from conventional machine-learning-based decision systems. Machine learning models are highly effective for prediction and pattern recognition, but their outputs may not always directly represent the relative importance of explicit decision criteria. In contrast, an optimized PROMETHEE framework retains an explicit MCDM structure in which each criterion has a meaningful semantic interpretation. The evolutionary component is used to optimize the parameters of an interpretable decision model rather than replacing the decision model with a black-box predictor. Consequently, the proposed approach occupies an important methodological intersection between optimization, MCDM, and explainable decision support (Brcko, 2023; Y. Chen, 2025).

The concept of adaptive weighting is particularly relevant in this context. Existing weighting research has increasingly explored hybrid, fuzzy, data-driven, and machine-learning-based mechanisms because no single weighting paradigm is universally optimal across all decision contexts. Recent literature explicitly identifies adaptive decision frameworks and machine-learning-based weighting as emerging directions for next-generation MCDM systems. Nevertheless, there remains an opportunity to develop a unified framework in which criterion weights are dynamically optimized according to the behavior of the downstream PROMETHEE ranking process rather than being determined independently from it. Accordingly, the central research problem addressed in this study is the absence of a systematic mechanism for jointly connecting criterion-weight optimization with PROMETHEE-based ranking performance. The conventional approach separates these two stages: weights are determined first, and the ranking is subsequently calculated. Such a separation may result in weight configurations that are locally reasonable from the perspective of the weighting technique but are not necessarily optimal for

producing stable and robust PROMETHEE rankings. The proposed research addresses this problem by conceptualizing criterion weighting as an evolutionary optimization problem embedded within the PROMETHEE decision-support process (Alam, 2023; Oh, 2023).

The proposed framework, termed an Evolutionary Weight Optimization Framework for Adaptive PROMETHEE-Based Decision Support Systems, is therefore designed around three principal components: an MCDM representation of alternatives and criteria, an evolutionary optimization mechanism for searching the criterion-weight space, and a PROMETHEE-based evaluation mechanism for generating and assessing alternative rankings. The optimization process can iteratively generate candidate weight vectors subject to appropriate constraints, normalize them to satisfy the requirements of the MCDM model, execute PROMETHEE ranking, evaluate the resulting decision quality through a fitness function, and evolve the candidate solutions toward improved configurations. This architecture creates an adaptive feedback loop between criterion weighting and decision ranking (Ahmed, 2024; Lima, 2022).

The methodological contribution of this framework lies in repositioning criterion weights from static model inputs into optimizable decision variables. Such a transformation enables the system to adapt its weighting structure according to the characteristics of the decision problem and the desired quality of the resulting ranking. In addition, the framework provides an opportunity to evaluate whether evolutionary optimization can improve ranking stability, robustness, discrimination, and consistency compared with conventional PROMETHEE configurations. The research therefore moves beyond the conventional question of “which alternative is ranked first?” toward the more fundamental question of “which weighting configuration produces a reliable and robust ranking under the given decision environment?”. From a scientific perspective, the research contributes to the development of adaptive MCDM by integrating evolutionary search with an established outranking methodology. From a methodological perspective, it provides a systematic mechanism for optimizing criterion weights rather than relying exclusively on manually specified or independently derived weights. From a practical perspective, the framework can support decision-makers who must evaluate alternatives under changing priorities and conflicting criteria while maintaining transparency regarding the factors influencing the final ranking. The approach is also potentially transferable across different application domains because PROMETHEE is not intrinsically restricted to a particular decision context (Li, 2022; Sotiropoulou, 2023).

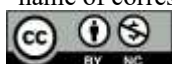
Nevertheless, the proposed integration must be empirically validated against appropriate baseline methods. A credible evaluation should compare the optimized framework with conventional PROMETHEE using fixed weights and, where appropriate, with established subjective, objective, or hybrid weighting approaches. Evaluation should not be limited to the final ranking but should also consider ranking stability, sensitivity to weight perturbations, robustness under data variation, convergence behavior of the evolutionary optimizer, computational efficiency, and consistency of the resulting decision outcomes. Such evaluation is essential to establish whether the proposed evolutionary optimization genuinely improves the decision-support process rather than merely generating alternative weight configurations. Based on these considerations, the research is motivated by the need to develop a decision-support architecture that combines the interpretability of PROMETHEE with the adaptive search capability of evolutionary optimization. The proposed framework addresses a methodological gap between static criterion weighting and adaptive decision support by establishing a feedback-driven optimization process in which criterion weights are iteratively adjusted according to the quality of the resulting PROMETHEE ranking. The expected outcome is a more robust, adaptive, and systematically optimized decision-support mechanism capable of responding to complex multi-criteria environments without sacrificing the interpretability that characterizes PROMETHEE (Bregaglio, 2022; Yigit, 2023).

Therefore, this study proposes “An Evolutionary Weight Optimization Framework for Adaptive PROMETHEE-Based Decision Support Systems” as a methodological framework for integrating evolutionary weight optimization into PROMETHEE. The study specifically investigates whether optimized criterion weights can improve the stability, robustness, and decision quality of PROMETHEE rankings compared with conventional fixed-weight configurations. The research is expected to contribute not only a computational optimization mechanism but also a conceptual framework for developing next-generation adaptive MCDM systems in which weighting and ranking are no longer treated as isolated processes, but as interconnected components of an integrated decision-support architecture (Xu, 2023).

LITERATURE REVIEW

Multi-Criteria Decision-Making (MCDM) is an established methodological approach for supporting decision problems involving multiple alternatives evaluated according to several, often conflicting, criteria. In practical decision environments, the quality of a decision is rarely determined by a single performance indicator; instead, decision-makers must consider a combination of economic, technical, operational, environmental, and strategic factors. Consequently, MCDM methods provide a structured mechanism for transforming heterogeneous evaluation information into preference relations, rankings, or prioritization outcomes. Recent reviews indicate that MCDM continues to expand across engineering, energy, sustainability, supply-chain management, healthcare, and other decision-intensive domains, with PROMETHEE remaining one of the important outranking approaches within this methodological landscape.

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A Decision Support System (DSS) based on MCDM generally consists of alternatives, evaluation criteria, criterion weights, preference mechanisms, and a ranking procedure. The effectiveness of such a system depends not only on the mathematical ranking mechanism but also on the validity of the parameter configuration used to represent decision-maker preferences. Among these parameters, criterion weights are particularly important because they determine the relative contribution of each criterion to the final decision. Consequently, inappropriate or overly rigid weighting can influence ranking outcomes even when the underlying ranking method is theoretically sound. Recent research on MCDM weighting methods distinguishes subjective, objective, and hybrid approaches and emphasizes that weighting selection can substantially affect decision stability, sensitivity, and robustness.

PROMETHEE as an Outranking-Based MCDM Method : The Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) is an outranking-based MCDM method designed to compare and rank alternatives across multiple criteria. Unlike aggregation approaches that directly combine criterion scores into a single utility measure, PROMETHEE establishes preference relations between alternatives using criterion-specific preference functions and relative criterion weights. PROMETHEE I produces a partial ranking, whereas PROMETHEE II produces a complete ranking through the calculation of positive, negative, and net preference flows. This structure provides an interpretable decision mechanism because the contribution of individual criteria and their associated weights can be examined explicitly (Ahmed, 2024; Lima, 2022).

PROMETHEE has been applied extensively in diverse domains, including sustainability, energy, transportation, logistics, supplier selection, environmental management, and resource planning. Recent applications demonstrate that PROMETHEE remains relevant because of its ability to integrate quantitative and qualitative criteria while maintaining an interpretable preference structure. For example, extended PROMETHEE approaches have been employed for sustainable supplier selection, while temporal PROMETHEE has been proposed for decision problems involving changes across time. The continued development of PROMETHEE-based decision-support tools also demonstrates the importance of sensitivity analysis and interactive exploration of weighting configurations. PROMETHEE-Cloud, for instance, incorporates sensitivity analysis, Monte Carlo simulation, and interactive weight analysis to support more robust decision-making (Alam, 2023; Oh, 2023).

Criterion Weighting in PROMETHEE : Criterion weighting constitutes one of the most influential components of a PROMETHEE-based decision model. The weight assigned to a criterion determines the extent to which that criterion contributes to the preference relation and ultimately affects the positive and negative preference flows. Conventional PROMETHEE implementations commonly rely on weights obtained from experts, predefined assumptions, or independent weighting techniques. Although these approaches are practical and interpretable, they may introduce subjectivity or produce a static representation of criterion importance. A weighting configuration that is reasonable from an expert perspective may not necessarily produce the most stable or discriminative ranking when evaluated against the actual decision matrix (Bregaglio, 2022; Yiğit, 2023).

The literature on MCDM weighting has therefore developed numerous subjective, objective, and hybrid approaches. Subjective methods rely primarily on expert preferences, whereas objective methods derive weights from the statistical or informational characteristics of the decision matrix. Hybrid approaches attempt to combine both perspectives. A comprehensive review by Ayan et al. identifies the increasing use of advanced weighting techniques, including CILOS, IDOCRIW, FUCOM, LBWA, SAPEVO-M, and MEREC, demonstrating the continuing methodological evolution of criterion weighting. More recent research also identifies machine-learning-based weighting, fuzzy approaches, uncertainty modeling, and adaptive weighting as emerging directions for improving the flexibility and robustness of MCDM systems (Brcko, 2023; Y. Chen, 2025).

Evolutionary Optimization for Decision-Making; Evolutionary optimization provides a promising mechanism for solving complex optimization problems in which conventional analytical approaches may be difficult to apply. Evolutionary algorithms are population-based search techniques inspired by natural selection and evolutionary processes. They iteratively generate candidate solutions, evaluate their fitness, and improve the population through operations such as selection, crossover, mutation, and elitism. Their ability to explore large and nonlinear search spaces makes them particularly suitable for optimization problems in which the relationship between decision variables and the final objective is complex (Huang, 2023; Ning, 2024).

In the context of MCDM, evolutionary algorithms can be used to optimize parameters that directly influence decision outcomes, including criterion weights. This approach differs from conventional weighting because the weights are treated as decision variables rather than fixed inputs. The optimization process can therefore search for a weight vector that maximizes a predefined objective related to ranking quality, discrimination, robustness, or stability. Recent reviews of metaheuristic approaches in MCDA demonstrate the increasing integration of optimization algorithms with multicriteria decision models, reflecting a broader movement toward computationally adaptive decision-support systems. Furthermore, evolutionary optimization research emphasizes the importance of handling constraints and multiple competing objectives when searching complex solution spaces.

Adaptive and Data-Responsive MCDM : The integration of optimization with MCDM represents a transition from static decision-support models toward adaptive and data-responsive frameworks. In a conventional MCDM workflow, criterion weights are generally established before the ranking process and remain unchanged throughout the analysis. This sequential structure separates the weighting problem from the ranking problem. However, the resulting weights may not necessarily be optimal with respect to the downstream ranking behavior. An adaptive framework instead establishes feedback between the weighting and ranking stages: candidate weights are generated, PROMETHEE rankings are calculated, and the resulting ranking characteristics are used to evaluate the quality of the candidate weight configuration (Goudarzi, 2024; Ye, 2022).

This perspective is particularly relevant because recent MCDM research increasingly emphasizes robustness, sensitivity analysis, and stability rather than focusing exclusively on the final ranking. Recent research on PROMETHEE II demonstrates that parameter sensitivity and rank reversal are important issues affecting the reliability of PROMETHEE-based decision models. Similarly, contemporary PROMETHEE tools incorporate sensitivity analysis and Monte Carlo simulation to examine how changes in model parameters influence decision outcomes. These developments support the argument that an effective adaptive PROMETHEE framework should evaluate not only whether an alternative obtains a high rank, but also whether the resulting ranking is sufficiently discriminative, stable, and robust.

Integration of PROMETHEE and Evolutionary Optimization: The combination of PROMETHEE and evolutionary optimization creates complementary methodological roles. PROMETHEE functions as the interpretable ranking engine, transforming alternative performances and criterion weights into preference flows and rankings, while the evolutionary algorithm functions as a search mechanism for identifying improved criterion-weight configurations. This integration retains the transparency of PROMETHEE while providing greater flexibility in determining the relative importance of criteria. Recent work has demonstrated the feasibility of combining PROMETHEE with optimization techniques, including genetic algorithms, for interpretable decision and rule-generation tasks. In one recent study, PROMETHEE II was used to guide a multi-objective genetic algorithm, illustrating how PROMETHEE can serve not only as a ranking technique but also as an evaluation mechanism within an optimization process (Goudarzi, 2024; Ye, 2022).

Another recent development is the integration of PROMETHEE with objective weighting approaches. The EC-PROMETHEE framework, for example, combines Entropy and CRITIC weighting with PROMETHEE and demonstrates how different weighting configurations can be incorporated into a PROMETHEE II decision process. These studies demonstrate that the weighting layer of PROMETHEE can be systematically modified. Nevertheless, most approaches still determine weights through predefined weighting methodologies or external decision-maker specifications. This leaves an important methodological opportunity for directly optimizing criterion weights according to the behavior and quality of the resulting PROMETHEE ranking (Breko, 2023; Y. Chen, 2025).

Research Gap and Positioning of the Present Study Based on the reviewed literature, three major observations can be identified. First, PROMETHEE provides an interpretable and widely applicable framework for multicriteria ranking, but its outcomes remain sensitive to criterion weights and preference-function parameters. Second, extensive research has developed subjective, objective, hybrid, fuzzy, and data-driven weighting approaches; however, these methods generally determine criterion weights independently of the final ranking performance. Third, evolutionary and metaheuristic optimization methods offer an effective mechanism for searching complex solution spaces, but their integration with PROMETHEE has not fully addressed the problem of jointly optimizing criterion weights according to ranking stability, discrimination, and decision quality.

The present study addresses this gap by conceptualizing criterion weighting as an evolutionary optimization problem embedded directly within the PROMETHEE decision-support process. Instead of treating criterion weights as fixed parameters, the proposed framework treats them as optimization variables subject to appropriate constraints, including non-negativity and a total weight equal to one. Candidate weight configurations are iteratively evaluated through the PROMETHEE ranking mechanism, allowing the evolutionary optimizer to search for a configuration that improves the characteristics of the resulting ranking. This positioning extends the conventional PROMETHEE workflow from a static weighting-ranking sequence toward an adaptive feedback-driven architecture. The resulting framework therefore aims to improve the adaptability and discriminatory capability of PROMETHEE while retaining the interpretability of an explicit multicriteria decision model. This research direction is consistent with the broader movement toward adaptive, explainable, and computationally enhanced MCDM systems.

METHOD

This section presents the methodological framework, research design, and technical procedures employed to accomplish the objectives of the study. A well-defined and systematically organized methodology is essential to ensure the validity, reproducibility, and scientific rigor of the research findings. In this study, the methodological framework integrates a Multi-Criteria Decision-Making (MCDM) approach with intelligent optimization

techniques to enhance the effectiveness and adaptability of a PROMETHEE-based decision support system. The proposed methodology is specifically designed to address the limitations associated with fixed criterion weighting by introducing an evolutionary optimization mechanism into the PROMETHEE decision-making process.

Overall, the research methodology consists of five interconnected stages: (1) identifying the decision problem, alternatives, and characteristics of the evaluation criteria; (2) establishing the baseline PROMETHEE model using conventional criterion weights; (3) developing an evolutionary optimization mechanism to determine an improved criterion-weight configuration; (4) integrating the optimized weighting mechanism with PROMETHEE within a decision support system framework; and (5) evaluating the performance and robustness of the proposed approach against the conventional PROMETHEE model. These stages are implemented sequentially, with the output of each stage serving as an input to the subsequent stage. This systematic structure ensures that the proposed framework can provide a comprehensive and reproducible solution to the underlying multi-criteria decision-making problem.

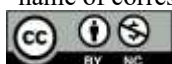
Research Dataset. The research dataset constitutes the primary empirical foundation for developing, implementing, and evaluating the proposed decision support framework. It includes the data source, structural characteristics, and attributes required to formulate the underlying multi-criteria decision-making problem. In this study, the dataset represents a decision environment involving multiple alternatives evaluated according to a predefined set of quantitative criteria. Each alternative is characterized by a collection of measurements representing specific operational or performance conditions relevant to the decision problem. The resulting data are organized into a decision matrix, in which each row corresponds to an alternative or decision condition and each column represents an evaluation criterion. The dataset employed in this study was obtained from InfluxDB for Energy and Utilities, a time-series database commonly utilized for storing and managing operational data generated by energy and utility systems, particularly data obtained from sensors and continuous monitoring processes. Historical observations were extracted from the database and subsequently transformed through data preprocessing into a structured numerical representation suitable for multi-criteria analysis. This transformation was performed to ensure consistency in data representation and to facilitate the subsequent implementation of the PROMETHEE-based decision-making models.

The resulting dataset comprises ten variables, consisting of eight input variables ((X₁-X₈)) and two output variables ((Y₁-Y₂)). The dataset used in this study was obtained from the InfluxDB for Energy and Utilities dataset and consists of 219 observations, which are treated as decision alternatives in the proposed PROMETHEE-based decision support framework. Each observation represents a distinct operational record characterized by a set of quantitative criteria. The input variables characterize the operational parameters and system conditions recorded at specific observation intervals, whereas the output variables represent system performance indicators used to assess and distinguish the decision alternatives. Each observation corresponds to a particular operational condition or decision alternative, while each variable provides its associated quantitative measurement. The dataset primarily consists of numerical and continuous observations, providing a consistent representation of the operational characteristics of the system. This structure makes the data suitable for quantitative comparison within the PROMETHEE framework, where alternatives are evaluated based on their relative performance across multiple criteria. Following preprocessing, the variables are organized into a decision matrix that serves as the principal input for both the conventional PROMETHEE model and the proposed evolutionary weight-optimized PROMETHEE model. The use of the same decision matrix in both models enables a controlled and objective comparison of their decision-making performance and allows the contribution of the proposed weight optimization mechanism to be evaluated systematically.

Table1. Research Dataset Sample

X1	X2	X3	X4	X5	X6	X7	X8	Y1	Y2
0,98	514,50	294,00	110,25	7,00	2	0,00	0	15,55	21,33
0,98	514,50	294,00	110,25	7,00	3	0,00	0	15,55	21,33
0,98	514,50	294,00	110,25	7,00	4	0,00	0	15,55	21,33
0,98	514,50	294,00	110,25	7,00	5	0,00	0	15,55	21,33
0,90	563,50	318,50	122,50	7,00	2	0,00	0	20,84	28,28
0,90	563,50	318,50	122,50	7,00	3	0,00	0	21,46	25,38
0,90	563,50	318,50	122,50	7,00	4	0,00	0	20,71	25,16
0,90	563,50	318,50	122,50	7,00	5	0,00	0	19,68	29,60
0,86	588,00	294,00	147,00	7,00	2	0,00	0	19,50	27,30
0,86	588,00	294,00	147,00	7,00	3	0,00	0	19,95	21,97
0,86	588,00	294,00	147,00	7,00	4	0,00	0	19,34	23,49
0,86	588,00	294,00	147,00	7,00	5	0,00	0	18,31	27,87
0,82	612,50	318,50	147,00	7,00	2	0,00	0	17,05	23,77
0,82	612,50	318,50	147,00	7,00	3	0,00	0	17,41	21,46
...	...	...	...	...	...	...	...	...	...etc

*name of corresponding author



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X1	X2	X3	X4	X5	X6	X7	X8	Y1	Y2
0,82	612,50	318,50	147,00	7,00	4	0,00	0	16,95	21,16
0,82	612,50	318,50	147,00	7,00	5	0,00	0	15,98	24,93

The criteria in the dataset have different characteristics, both benefit-type criteria (higher values are more desirable) and cost-type criteria (lower values are more desirable). Furthermore, the measurement scale between criteria can vary, necessitating a normalization mechanism and preference function, as accommodated by the PROMETHEE method.

- The datasets used in this study can be sourced from:
- Secondary data adapted from MCDM case studies used in the literature,
- Empirical data collected from real-world environments appropriate to the application domain of the decision support system.

To ensure the validity of the experiment, the datasets were selected considering a sufficiently diverse number of criteria and a relatively high level of conflict between them. These characteristics are important for testing the sensitivity and performance of the PROMETHEE system, particularly in the context of optimizing criterion weights. The datasets used are deterministic and contain no missing values, allowing for consistent and controlled evaluation

Baseline PROMETHEE Decision Support Model : This subsection presents the conventional PROMETHEE model used as the baseline for comparison with the proposed evolutionary weight-optimized PROMETHEE model. In the baseline approach, criterion weights are predetermined and treated as fixed parameters throughout the decision-making process. The weights may be assigned using equal weighting or expert-based judgment, representing common practices in conventional PROMETHEE applications. The resulting baseline model provides a reference for evaluating the effectiveness of the proposed evolutionary optimization mechanism in improving PROMETHEE-based decision-making performance.

Table 2. Comparison Of Baseline Promethee And Optimized PROMETHEE

Comparative Aspects	PROMETHEE Baseline	Optimized PROMETHEE
General Approach	Conventional PROMETHEE with fixed criterion weights.	PROMETHEE is integrated with a weight optimization algorithm.
Criteria Weight Determination	Determined before the evaluation process (e.g., equal weights or expert judgment).	Treated as decision variables and optimized automatically.
Weight Properties	Static and unchanging during the ranking process.	Dynamic and adaptive to data structures and optimization objectives.
Optimization Methods	Does not use an optimization mechanism.	Uses an evolutionary algorithm to find a global solution.
Subjectivity	Relatively high because it depends on initial assumptions or expert preferences.	Lower because weights are determined through a data-driven computational process.
Weight Sensitivity	High; small changes in weights can significantly change the ranking.	Lower because weights are generated to maximize ranking quality.
Complexity	Limited to simple to medium scenarios.	More effective for complex and high-dimensional problems.
Handling Ability		More stable and consistent across data variations.
Ranking Stability	Tends to be less stable under varying data conditions.	
Solution Quality	Depends on the quality of the initial weights used.	More optimal because weights are obtained through an optimization process.
Computation	Relatively lightweight and fast.	Requires higher computation time due to the iterative process.
Main Outputs	Alternative to conventional net flow-based ranking.	Alternative ranking based on net flow with optimal weights.
Role in Research	Used as a comparison model (baseline).	This is a proposed method.
Limitations	Not adaptive and susceptible to weighting bias.	Requires algorithm parameters and computing resources.
Scientific Contributions	Represents the standard approach in the literature.	Demonstrates improved performance of PROMETHEE-based DSS.

The decision-making process in the baseline model involves several main stages. First, a preference function is determined for each criterion based on data characteristics and the nature of the criteria. This preference function is used to measure the superiority of one alternative over another. Second, preference values between pairs of

alternatives are calculated and aggregated using criterion weights to produce a global preference index. Third, leaving flow and entering flow values are calculated for each alternative as a measure of relative dominance. Finally, a net flow value is obtained as the difference between leaving flow and entering flow, which is then used to determine the final ranking of the alternatives.

1) Decision Matrix

A decision problem is modeled in the form of a decision matrix X , which represents the evaluation of a number of alternatives against a number of criteria:

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{1m} \\ x_{21} & x_{22} & x_{2m} \\ x_{n1} & x_{n2} & x_{nm} \end{bmatrix} \quad (1)$$

where: x_{ij} is the alternative performance value A_i against the criteria C_j , n is the number of alternatives, m is the number of criteria.

2) Preference Function

Untuk setiap kriteria C_j , PROMETHEE menggunakan fungsi preferensi untuk mengukur tingkat keunggulan alternatif A_i terhadap alternatif A_k : For each criterion C_j , PROMETHEE uses a preference function to measure the degree of superiority of alternative A_i over alternative A_k :

For each criterion C_j , PROMETHEE uses a preference function to measure the degree of superiority of alternative A_i over alternative A_k : For each criterion C_j , PROMETHEE uses a preference function to measure the degree of superiority of alternative A_i over alternative A_k :

$$d_j(A_i, A_k) = x_{ij} - x_{kj} \quad (2)$$

The difference value is then mapped into the preference function:

$$p_j(A_i, A_k) = f_j(d_j(A_i, A_k)) \quad (3)$$

with: $p_j(A_i, A_k) \in [0, 1] = f_j$ is the preference function chosen according to the criteria characteristics (e.g. usual, U-shape, V-shape, or linear function)

3) Global Preference Index

The net flow value is used as the basis for the final ranking of alternatives and is calculated as the difference between the leaving flow and the entering flow:

$$\pi(A_i, A_k) = \sum_{j=1}^m w_j \cdot P_{j(A_i, A_k)} \quad (4)$$

with weight constraints:

$$\sum_{j=1}^m w_j = 1, w_j \geq 0 \quad (5)$$

In the baseline model, the weights w_j are determined conventionally (e.g., equal weights or based on expert judgment) and do not change during the evaluation process.

4) Net Flow and Alternative Ranking

The net flow value is used as the basis for the final ranking of alternatives and is calculated as the difference between the leaving flow and the entering flow:

$$\phi(A_i) = \phi^{(+)}(A_i) - \phi^{(-)}(A_i) \quad (6)$$

Alternatives with larger $\phi(A_i)$ values have higher preference levels and are placed in better rankings. In the baseline model, the ranking results are entirely determined by the data structure and the static criterion weights used.

This baseline model serves as a benchmark to evaluate the extent to which criterion weight optimization improves the performance of the decision support system. By comparing ranking results, decision stability, and other evaluation values between the baseline and proposed models, this study can objectively measure the contribution of the developed optimization approach.

Research Design: The overall research design includes the workflow, experimental stages, and the relationships between the methodological components used. The research design was developed using an experimental and comparative approach, with the primary objective of evaluating the effectiveness of the optimized PROMETHEE model compared to the baseline model. The research begins with identifying the problem and determining the research objectives, followed by a literature study to obtain relevant theoretical and methodological foundations.

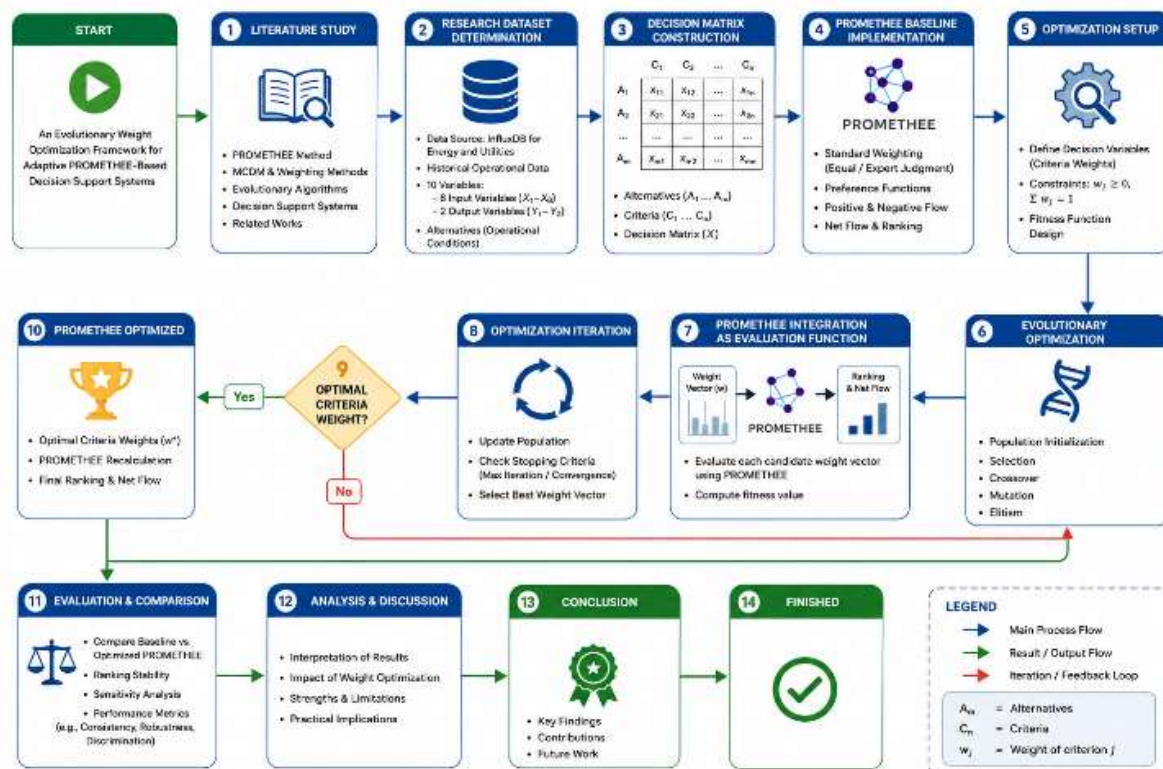


Fig 1. Research Design

The figure 1 illustrates the research workflow for "An Evolutionary Weight Optimization Framework for Adaptive PROMETHEE-Based Decision Support Systems," beginning with a literature review to identify concepts related to PROMETHEE, MCDM, weighting methods, and evolutionary algorithms. This is followed by selecting a dataset from InfluxDB for Energy and Utilities and constructing a decision matrix based on the relevant alternatives and criteria. Next, a baseline PROMETHEE model is established using predetermined criteria weights, followed by an optimization setup where criteria weights serve as decision variables subject to non-negativity constraints and a requirement that the sum of weights equals one. The process proceeds with evolutionary optimization—encompassing population initialization, selection, crossover, mutation, and elitism—where each weight candidate is evaluated using PROMETHEE as the evaluation function to determine its fitness value. Optimization is performed iteratively until termination criteria are met or optimal criteria weights are obtained. The best weights are then used to generate the optimized PROMETHEE model and the final ranking of alternatives. Subsequently, the baseline and optimized models are compared based on ranking stability, sensitivity, and performance metrics such as consistency, robustness, and discriminative power. Finally, the results are analyzed and discussed to identify the impact of weight optimization on decision quality, leading to the formulation of conclusions, research contributions, limitations, and directions for future research.

RESULT

This section presents the results obtained from the implementation and evaluation of the baseline and evolutionary weight-optimized PROMETHEE decision support models. The analysis emphasizes differences in net flow values, changes in alternative rankings, and ranking stability following criterion-weight optimization. Both models were evaluated using the same dataset containing 219 alternatives, enabling a consistent and objective comparison between conventional and optimized weighting schemes. The primary analyses include the distribution of net flow values, the highest- and lowest-ranked alternatives, ranking changes between the two approaches, and net flow variance as an indicator of model sensitivity and discriminatory capability. These results provide the basis for assessing whether the proposed optimization mechanism improves the quality, stability, and reliability of PROMETHEE-based decision-making.

Comparison of Net Flow Values and Alternative Rankings : This subsection compares the net flow values and alternative rankings produced by the baseline and optimized PROMETHEE models. The analysis examines how evolutionary optimization of criterion weights influences the preference scores and resulting ranking structure of the 219 alternatives. The comparison is presented through tabulated results to clearly illustrate the magnitude

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of changes in net flow values and rankings between the two approaches. These findings are subsequently used to assess the impact of weight optimization on the consistency and quality of the resulting decision outcomes.

Table 3. Comparison Of Net Flow And Ranking Results Between Baseline And Optimized

	Applicant Name (Alternative)	Net Flow Baseline	Net Flow Optimized
0	A1	1,1625	1,5116
1	A2	0,8755	1,4896
2	A3	0,8755	1,4860
3	A4	0,8755	1,4854
4	A5	0,7320	1,4805
...	...	...	...
215	A216	-0,8467	-1,4414
216	A217	-0,8467	-1,4457
217	A218	-0,9902	-1,4474
218	A219	-0,9902	-1,4512

Table 3 presents a direct comparison of the net flow values and alternative rankings generated by baseline PROMETHEE and optimized PROMETHEE. The results show that weight optimization resulted in significant changes in the net flow values of most alternatives. For example, alternative A152 maintained its first-ranking position in both methods, but experienced an increase in its net flow value from 1.1625 to 1.5116, indicating a strengthening of its dominance relative to other alternatives. Conversely, several alternatives, such as A2 and A5, experienced a drastic decrease in ranking after optimization, indicating that the optimal weights placed different emphasis on the evaluation criteria.

This phenomenon indicates that baseline PROMETHEE tends to produce more concentrated net flow values, while optimized PROMETHEE is able to broaden the range of net flow values, thus making the differences between the alternatives more pronounced.

Analysis of the Best and Lowest-Ranked Alternatives: The highest and lowest-ranked alternatives generated by both approaches. The discussion focuses on the consistency and differences in results between baseline PROMETHEE and optimized PROMETHEE at the extreme alternatives. This analysis is important for assessing decision stability and ensuring that weight optimization does not alter the identification of significantly superior or inferior alternatives.

This table 4 presents the highest and lowest-ranked alternatives based on both methods. The results show that in the best alternative group, optimized PROMETHEE produces higher net flow values and a clearer distance between ranks compared to the baseline. Conversely, in the lowest-performing alternative group, both methods are relatively consistent in identifying the worst-performing alternative, although the optimized method's net flow values show greater dispersion. The consistency across the extreme alternatives (best and worst) indicates that weight optimization does not disrupt the underlying decision structure but rather improves the resolution and clarity of rankings among intermediate alternatives.

Changes in Alternative Rankings : The ranking changes experienced by each alternative after optimizing the criteria weights. The discussion focuses on the magnitude of the ranking shifts and the patterns of changes that emerge due to the weight adjustments. This ranking change analysis is used to evaluate the sensitivity of the decision support system and identify the alternatives most affected by the optimization process.

Table 4. Ranking Changes Between Baseline And Optimized PROMETHEE.

Alternatif	Rank Baseline	Rank Optimized	Rank Change
A152	1.0	1.0	0.0
A121	6.0	2.0	4.0
A131	4.5	3.0	1.5
A40	2.0	4.0	-2.0
A117	9.0	5.0	4.0
...	...	...	...
A176	215.0	215.0	0.0
A80	215.0	216.0	-1.0
A128	217.0	217.0	0.0
A96	218.0	218.0	0.0
A17	219.0	219.0	0.0

Table 4 presents the rank change experienced by each alternative after weight optimization. The results show that most alternatives experienced a shift in ranking, either up or down. For example, alternative A121 experienced a rank increase from position 6 to position 2, while A40 experienced a decrease from position 2 to position 4. These changes indicate that weight optimization was able to correct the initial weighting bias and produce rankings that better fit the data structure. Alternatives that did not experience a rank change were generally at the extremes, indicating decision stability in cases of very strong or very weak dominance.

DISCUSSIONS

This subsection provides an integrated interpretation of the experimental findings, focusing on the effects of criterion-weight optimization on PROMETHEE performance and its broader methodological implications for multi-criteria decision support systems. The discussion examines how the optimized weighting scheme changes the distribution of preference values and the ranking structure of alternatives, while also highlighting the theoretical and practical significance of the proposed approach.

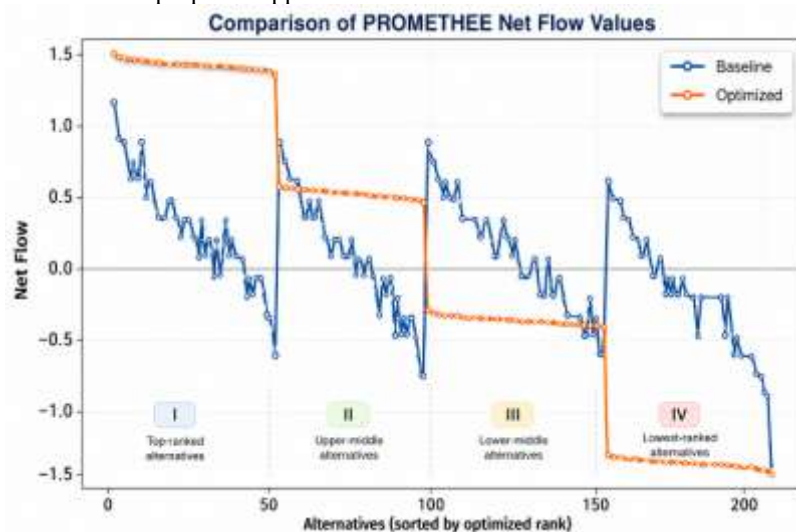


Fig 2. Comparison of Promethee Net Flow Values

Figure 2 compares the net flow values obtained from the baseline and optimized PROMETHEE models across all alternatives according to their optimized ranking. The optimized model exhibits a broader range and more clearly differentiated distribution of net flow values, whereas the baseline model shows a comparatively less structured pattern. Higher-ranked alternatives generally demonstrate stronger positive net flow values, while lower-ranked alternatives tend to exhibit more pronounced negative values under the optimized model. This distribution suggests that the optimized weighting scheme enhances the model's ability to distinguish differences in alternative performance, thereby providing a clearer representation of preference intensity within the decision-making process.

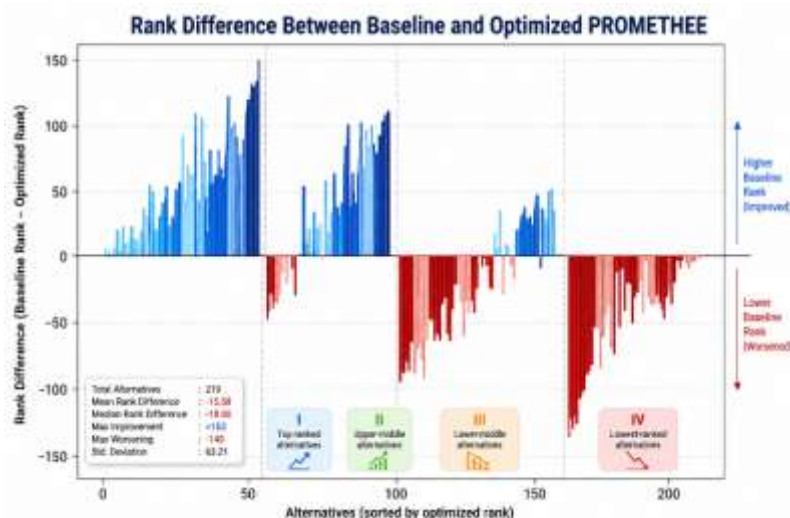


Fig 3. Rank Difference Between Baseline and Optimized Promethee

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Figure 3 illustrates the differences in alternative rankings between the baseline and optimized PROMETHEE models. Positive values represent improvements in ranking following weight optimization, whereas negative values indicate a decline in ranking position. The results reveal substantial variation in ranking changes across the alternatives, with some alternatives moving considerably upward or downward. This variation demonstrates that criterion-weight optimization has a direct influence on the relative preference structure generated by PROMETHEE. The observed changes further indicate that the optimized weighting mechanism can adapt the ranking process more effectively to the underlying characteristics of the decision data.

Overall, the experimental findings demonstrate that evolutionary criterion-weight optimization can substantially modify and enhance the behavior of the PROMETHEE-based decision support system. Compared with the baseline configuration, the optimized model generates a wider differentiation of net flow values and produces a more responsive ranking structure, enabling clearer distinctions among alternatives. The observed ranking changes also confirm that criterion weights play a critical role in determining PROMETHEE outcomes and that fixed weighting schemes may not adequately capture the characteristics of a particular decision environment. By treating criterion weights as optimizable variables, the proposed framework provides a more adaptive and systematic mechanism for configuring PROMETHEE, thereby strengthening its potential to deliver more informative and context-sensitive decision outcomes. These findings support the methodological contribution of evolutionary weight optimization as an effective strategy for enhancing multi-criteria decision support systems

CONCLUSION

This study demonstrates that the proposed evolutionary weight optimization framework can substantially influence the decision outcomes of the PROMETHEE-based decision support system by adapting the criterion weights to improve the resulting ranking structure. Using 219 alternatives, the comparison between baseline and optimized PROMETHEE shows notable changes in alternative positions, including substantial improvements for several alternatives, such as A121, which moved from rank 6 to rank 2, while A117 improved from rank 9 to rank 5. At the same time, several alternatives experienced downward movements, indicating that the optimized weighting scheme altered the relative importance of criteria and consequently redistributed the preference among alternatives. Nevertheless, some alternatives, including A152 at rank 1 and A17 at rank 219, maintained their positions across both approaches, suggesting that their relative performance remained robust despite changes in criterion weights. Overall, these findings indicate that evolutionary optimization provides a meaningful mechanism for adapting PROMETHEE criterion weights and generating a more responsive decision-support model. The proposed framework therefore offers a systematic alternative to conventional fixed-weight PROMETHEE and provides a foundation for developing more adaptive, robust, and context-sensitive multi-criteria decision-making systems

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