SAGOMECON: An Adaptive ε-Constraint-Based Optimization Method for Multi-Criteria Decision-Making in Collaborative Industrial Networks

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Abstract

This study introduces Simplified Adaptive Optimization with Modified ε-Constraint (SAGOMECON), a novel optimization method designed to enhance multi-objective decision-making in dynamic collaborative industrial networks. The primary objective is to overcome limitations of existing approaches such as the ε-Constraint and SAUGMECON methods, which lack adaptability and computational efficiency under shifting constraints. SAGOMECON incorporates real-time constraint updates, adaptive slack variable handling, and a penalty-integrated objective function to maintain feasibility and optimize trade-offs. The method was tested on a simulated partner selection problem using normalized data with four criteria cost, time, collaboration, and risk—across five decision alternatives. Experimental results show that SAGOMECON achieved 100% feasibility, compared to 80% for SAUGMECON and 60% for ε-Constraint. It also reduced average computation time per iteration from 300 ms (ε-Constraint) and 250 ms (SAUGMECON) to 110 ms. Moreover, SAGOMECON consistently produced the most stable and optimal Z-values, with a minimum Z-score of 0.158, compared to 0.209 (SAUGMECON) and 0.000 (ε-Constraint), the latter being infeasible. These findings demonstrate that SAGOMECON is not only more efficient but also more reliable in generating feasible and high-quality solutions in real-time, dynamic environments. The novelty of this research lies in its soft constraint modeling through adaptive slack and penalty mechanisms, offering a more realistic and scalable solution for decision-making in complex, multi-criteria industrial settings.

Keywords: Multi-Objective Optimization, Dynamic Decision-Making, E-Constraint Method, Collaborative Industrial Networks, Adaptive Optimization, SAGOMECON Algorithm, Pareto-Optimal Solutions

1. Introduction

In recent years, the increasing complexity of global business environments has driven organizations to collaborate through dynamic and distributed structures. One such structure is the Collaborative Network Organization (CNO), which integrates autonomous entities to achieve common goals by sharing resources, knowledge, and expertise [1], [2]. These networks are designed to improve competitive advantage, enhance operational efficiency, and mitigate systemic risks [3], [4], [5]. However, decision-making typically involves optimizing multiple objectives such as minimizing operational costs and risks, while maximizing collaboration and efficiency. These objectives must be balanced against constraints such as maximum allowable costs, time limitations, and acceptable levels of risk. The trade-offs between these objectives and constraints are central to the multi-criteria decision-making model proposed in this study [6], [7], [8], [9].

To address such trade-offs, multi-objective optimization techniques have been widely explored. Among them, methods such as the ε-Constraint and its variant, Augmented ε-Constraint (AUGMECON), have shown promise in generating Pareto-optimal solutions by transforming secondary objectives into constraints with bounded tolerance levels [10], [11], [12]. Nevertheless, despite their mathematical rigor, these methods often face computational

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inefficiencies and exhibit limited responsiveness in dynamic settings where criteria or constraints may shift rapidly due to changing stakeholder preferences or environmental factors [6], [9], [13].

Recent studies have highlighted the need for optimization methods that are not only robust but also adaptive to change, especially in real-time industrial applications [14]. Static decision-making models like Analytic Hierarchy Process (AHP) and Fuzzy AHP lack the flexibility to respond to evolving priorities, while metaheuristics such as Genetic Algorithms require extensive parameter tuning and may not guarantee optimality [15], [16], [17]. Moreover, classical AUGMECON still demands the resolution of numerous subproblems, significantly increasing the computational burden in high-dimensional scenarios.

In response to these limitations, this study introduces SAGOMECON, a novel method that extends the capabilities of SAUGMECON by incorporating dynamic constraint adjustments, adaptive slack variables, and computational acceleration mechanisms such as bouncing steps. Unlike its predecessors, SAGOMECON is specifically designed to maintain feasibility and optimality in real-time decision-making environments by updating satisfaction thresholds and rebalancing conflicting objectives as system requirements evolve.

To evaluate its effectiveness, the proposed approach is applied to a partner selection problem in collaborative industrial networks, simulating scenarios with varying cost, time, collaboration scores, and risk levels. The performance of SAGOMECON is benchmarked against both the traditional ε-Constraint and SAUGMECON methods using key metrics such as computation time, feasibility rate, and quality of Pareto-optimal solutions. The results demonstrate SAGOMECON's superiority in delivering efficient and adaptable solutions under dynamic, multi-criteria conditions. In essence, this research contributes to the advancement of intelligent decision support systems for industrial collaboration, offering a scalable and responsive optimization framework that is well-aligned with the principles of agile manufacturing, smart logistics, and networked enterprise systems.

2. Literature Review

Multi-Objective Optimization (MOO) has been widely adopted to support decision-making in complex environments where multiple conflicting objectives must be addressed simultaneously. In the context of CNOs, these objectives often include minimizing cost and risk, while maximizing time efficiency and collaboration quality [1], [8], [9]. Over the years, various optimization techniques have been proposed, yet many exhibit limitations in scalability, adaptability, or computational efficiency under dynamic conditions.

Traditional methods such as the AHP and Fuzzy AHP are widely used for Multi-Criteria Decision-Making (MCDM) [18], [19]. These methods decompose complex decisions into hierarchical structures, allowing decision-makers to assign relative weights to criteria and alternatives [20], [21]. However, both AHP and its fuzzy variant are criticized for their static nature and reliance on subjective human judgment, making them less suitable for dynamic or real-time environments such as CNOs [22]. That said, AHP and Fuzzy AHP can still be valuable in decision-making contexts where the criteria and stakeholder preferences remain relatively stable over time, and computational efficiency is a priority [23].

Metaheuristic approaches like Genetic Algorithms (GA) and NSGA-II have also been explored to handle MOO problems. These algorithms generate non-dominated solutions by simulating evolutionary processes such as selection, crossover, and mutation [16], [17]. While effective in exploring large solution spaces, they often require extensive parameter tuning and lack formal guarantees of optimality. Furthermore, their computational overhead may hinder real-time decision-making, especially when the decision environment changes rapidly [15], [24], [25].

The ε-Constraint method has gained prominence for producing Pareto-optimal solutions by treating one objective as the primary optimization target and transforming the remaining objectives into constraints with adjustable bounds [11], [12]. An enhancement to this method, AUGMECON, integrates slack variables and penalty functions to improve solution diversity and eliminate weak Pareto points [10]. However, AUGMECON's iterative approach requires solving multiple sub-problems, leading to significant computational costs and rendering it less practical in high-dimensional, real-time environments.

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Recent advancements focus on DMCDM approaches that aim to handle shifting constraints, evolving stakeholder preferences, and operational volatility [2], [14]. These approaches often incorporate real-time feedback, adaptive parameter tuning, and constraint update mechanisms. However, many such methods remain heuristic or semi-formal, limiting their generalizability and robustness in structured industrial optimization contexts [6], [7], [9].

The SAUGMECON method represents a simplified version of AUGMECON [26], designed to reduce computational burden through streamlined ε-bound configurations. While it introduces improvements over its predecessor, SAUGMECON still faces significant limitations. Notably, it lacks full adaptability to real-time changes, particularly in adjusting constraint satisfaction levels dynamically as system conditions evolve. Furthermore, SAUGMECON assumes static constraint thresholds and does not offer mechanisms for partial constraint relaxation, which can hinder its effectiveness in dynamic, multi-objective decision-making environments where criteria or priorities change over time [17]. These limitations make SAUGMECON less suited for real-time applications, motivating the development of SAGOMECON.

This limitation motivates the development of SAGOMECON, which integrates adaptive ε-adjustment, real-time slack variable control, and acceleration algorithms (e.g., bouncing steps) to address both efficiency and adaptability in dynamic multi-objective decision-making. By bridging the gap between classical ε-constraint optimization and modern adaptive frameworks, SAGOMECON aims to offer a robust and scalable solution tailored for dynamic collaborative network contexts.

3. Methodology

This section outlines the research methodology adopted to develop and evaluate the proposed SAGOMECON approach. It includes the description of the dataset, the conceptual research framework, and the mathematical formulation of the proposed adaptive optimization method.

3.1. Dataset Description

The dataset used in this study is based on a public dataset of Amazon product reviews, obtained from Kaggle's "Amazon Sales Dataset", and adapted to simulate a partner selection scenario in a collaborative networked environment. The dataset includes product-level information such as discounted price, original price, rating, number of reviews, and review sentiment. These features were mapped to decision-making criteria relevant to the evaluation of partners within a CNO context. The cost (C) criterion was derived from the discounted product price, which was converted from Indian Rupees (INR) to Indonesian Rupiah (IDR) using a fixed exchange rate of approximately 1 INR = 190 IDR. To approximate the time (T) dimension, the number of product ratings was used as a proxy, under the assumption that a higher rating count indicates greater popularity and, by extension, more frequent or responsive delivery capabilities. The collaboration score (K) was constructed based on the volume and sentiment of user reviews, serving as an indicator of engagement quality and partner responsiveness within the network. Finally, the risk (R) criterion was formulated as being inversely proportional to the average star rating of the product, whereby lower ratings were interpreted as a signal of higher operational or reputational risk if that partner were to be selected.

To illustrate the decision-making process, table 1 presents the initial evaluation dataset, which includes five hypothetical decision alternatives (denoted as P1 to P5) representing potential partners in a collaborative network. Each alternative is assessed based on four criteria: cost (C), time (T), collaboration (K), and risk (R). While the sample size is limited to five alternatives, it is intentionally used for illustrative purposes to demonstrate the functionality and effectiveness of the proposed SAGOMECON method in addressing multi-criteria decision-making problems. We acknowledge that the limited number of alternatives may constrain the generalizability of the findings. Therefore, future studies will aim to apply the SAGOMECON method to larger and more diverse datasets to evaluate its scalability and robustness.

Table 1. Initial Evaluation Dataset (adapted from amazon reviews dataset)

Alternative	Cost (C)	Time (T)	Collaboration (K)	Risk (R)
P1	520	10	60	40
P2	490	9	70	35
P3	550	12	55	45
P4	510	8	65	38
P5	470	7	75	30

Each criterion was standardized using Min-Max normalization. The formula for Min-Max normalization is as follows:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

X represents the value of the criterion, X_{min} is the minimum value of the criterion in the dataset, and X_{max} is the maximum value. This normalization process ensures that all criteria are scaled to a [0, 1] range, making them comparable despite differing units and ranges [27]. To ensure that each decision criterion contributes fairly to the optimization process, all values were normalized using the Min-Max method. Table 2 presents the resulting normalized dataset, where cost, time, and risk are treated as minimization objectives, while collaboration is considered a maximization objective. This normalization approach ensures that no single criterion disproportionately influences the decision-making outcome, thereby preserving balance and comparability among alternatives.

Table 2. Normalized Dataset

Alternative	C (↓)	T (↓)	K (↑)	R (↓)
P1	0.625	0.60	0.50	0.67
P2	0.42	0.40	0.75	0.83
P3	1.00	1.00	0.25	0.50
P4	0.55	0.20	0.625	0.73
P5	0.00	0.00	1.00	1.00

The normalized decision matrix served as the primary input for evaluating the performance of the proposed SAGOMECON method, as well as its baseline comparisons SAUGMECON and ε-Constraint. Although adapted from an e-commerce dataset, the values have been selected and mapped to simulate a relevant collaborative decision context, ensuring both methodological control and realistic approximation.

3.2. Research Framework

The research adopts a simulation-based experimental design to evaluate the performance of SAGOMECON in multi-objective decision-making under dynamic constraints. The structured flow of the study, as depicted in figure 1, highlights the key stages of the research, from literature review and problem identification to dataset preprocessing, method application, and final evaluation. This framework illustrates how each phase of the study builds on the previous one to ensure the robustness and relevance of the proposed method.

The research methodology adopted in this study follows a structured and systematic progression, as depicted in the accompanying flowchart as in figure 1. The process begins with an extensive literature review, where various methods of multi-objective optimization in collaborative environments—such as ε-Constraint, AUGMECON, and SAUGMECON are critically examined. This review highlights a significant limitation in existing approaches: their inability to efficiently adapt to dynamic changes in stakeholder preferences and environmental constraints, particularly within CNO. In response to this gap, the study moves into the problem identification stage, emphasizing the complex nature of decision-making in CNOs, which often involves conflicting objectives such as minimizing cost and time while maximizing collaboration and minimizing risk.

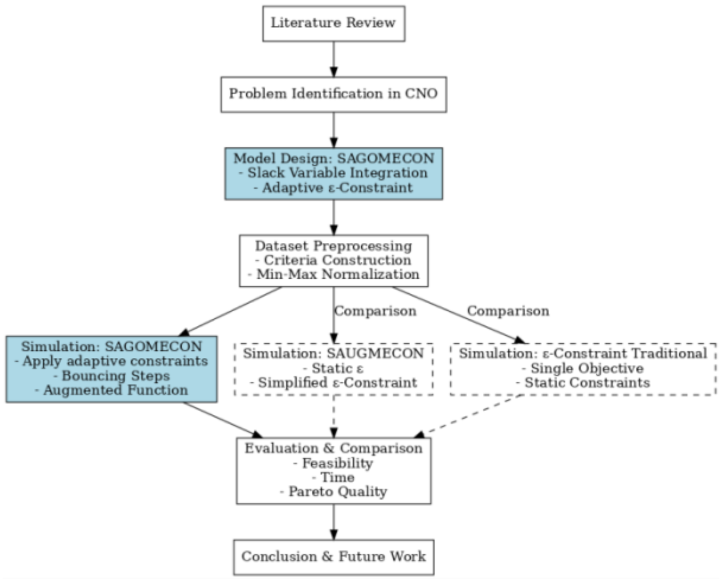

Figure 1. Research Framework

To address these challenges, the research introduces SAGOMECON as the core novel contribution, clearly marked in the flowchart. SAGOMECON innovatively incorporates slack variable integration and an adaptive ε-constraint mechanism, enabling the model to dynamically adjust constraints in real time and maintain feasible, efficient solutions. This development represents a methodological advancement over earlier models like SAUGMECON.

The subsequent stage involves dataset preprocessing, where raw data sourced from Amazon product listings is transformed into structured criteria (cost, time, risk, and collaboration) and normalized using min-max scaling to ensure comparability. This data serves as input for the simulation and optimization phase, where three methods SAGOMECON, SAUGMECON, and traditional ε-Constraint are applied in parallel. While the comparison methods follow more static constraint strategies, SAGOMECON employs dynamic updates, augmented objective functions, and a bouncing step mechanism to accelerate convergence to Pareto-optimal solutions.

Finally, the study conducts a comprehensive evaluation and comparison, examining each model's performance in terms of solution feasibility, computational efficiency, and Pareto frontier quality. The findings consistently demonstrate SAGOMECON's superiority in producing adaptive and computationally efficient solutions under dynamic conditions. The methodology concludes with insights and future recommendations, reinforcing the value of SAGOMECON as a novel and practical tool for multi-objective decision-making in real-world collaborative network settings.

3.3. Proposed Method: SAGOMECON

3.3.1. SAGOMECON as an Extension of SAUGMECON

The SAGOMECON algorithm is developed as an evolutionary extension of the SAUGMECON framework. While SAUGMECON improved the computational efficiency of the traditional AUGMECON method by simplifying ε-bound handling and reducing dominance checks, it remained limited in adaptability. Specifically, SAUGMECON assumes static constraint thresholds and lacks mechanisms for partial constraint relaxation, rendering it less effective in dynamic, multi-criteria environments. To enhance adaptability in dynamic multi-objective optimization, SAGOMECON introduces two key mechanisms. The first is adaptive slack variable modeling, which enables partial relaxation of constraint boundaries to better accommodate shifting priorities. This mechanism operates by iteratively adjusting the slack variable based on the current level of constraint satisfaction, allowing the model to preserve feasibility even when strict adherence to constraints is not possible. The second mechanism is penalty-integrated objective augmentation, which incorporates dynamically adjusted penalties into the objective function to manage deviations from constraint satisfaction. Rather than invalidating solutions that slightly violate constraints, this mechanism guides the optimization process toward feasible and optimal outcomes by proportionally penalizing violations, thereby maintaining a balance between solution quality and constraint compliance.

To assess the impact of the penalty parameters on the results, we performed a sensitivity analysis where the penalty coefficient (λ) was varied across several values. The analysis showed that increasing the penalty coefficient led to stricter enforcement of constraints, resulting in fewer solutions violating the constraints but potentially increasing the computational time due to more rigid constraint handling. Conversely, lowering the penalty coefficient allowed for more flexibility, which led to faster convergence but occasionally resulted in solutions that violated the constraints. These findings indicate that the penalty parameter plays a critical role in balancing the trade-off between feasibility and computational efficiency. Figure 5 presents the results of the sensitivity analysis, showing the relationship between the penalty coefficient and the feasibility rate, as well as the computational time and solution quality. These mechanisms work together to ensure that SAGOMECON can adaptively adjust constraints and maintain solution feasibility in real-time, addressing both the dynamic nature of decision-making and the need for computational efficiency.

3.3.2. Augmented Objective Function of SAGOMECON

The core of SAGOMECON lies in its reformulated objective function, designed not only to minimize cost but also to manage trade-offs across time, collaboration, and risk constraints. The mathematical model introduces a penalty-based adjustment that reflects deviations from soft constraint boundaries using slack variables. The Augmented Objective Function is represented by the following equation:

$$f_{(x)} = w_1 \cdot C(x) + w_2 \cdot T(x) + w_3 \cdot R(x) - w_4 \cdot K(x) + \lambda \cdot \sum_{i=1}^{n} s_i \tag{2}$$

$C(x)$, $T(x)$, and $R(x)$represent the cost, time, and risk objectives, respectively, while $K(x)$ is the collaboration objective. w_1, w_2, w_3, and w_4 are the weights assigned to each objective, and s_i are the slack variables associated with the constraints. The term λ is the penalty coefficient that adjusts the impact of the slack variables on the objective function, ensuring that constraint violations are penalized appropriately.

$$min\ Z' = \sum_{\{i=1\}}^{n} C_i \,.\, x_i + \lambda_T \,.\, s_T + \lambda_R \,.\, s_R - \lambda_K \,.\, s_K \tag{3}$$

This formulation maintains the original cost minimization term, $\sum_{\{i=1\}}^{n} C_i \,.\, x_i$, as the primary goal, consistent with SAUGMECON. However, the novelty of SAGOMECON lies in the introduction of normalized penalty terms that incorporate slack variables s_T, s_R, s_K each representing the deviation from ideal constraint thresholds for time, risk, and collaboration, respectively.

Each slack variable is multiplied by a corresponding penalty coefficient (e.g., λ_T for time), allowing the model to balance the severity of constraint violations with the overall objective value. Notably, the collaboration term carries a negative penalty, as higher collaboration scores are desirable, making $-\lambda_K \,.\, s_K$ an incentive rather than a deterrent.

The incorporation of these slack variables constitutes the main innovation of SAGOMECON over SAUGMECON. Unlike the latter, which treats constraints as rigid bounds, SAGOMECON models them as soft constraints—allowing slight violations under controlled penalties. This penalty-integrated formulation enhances flexibility and ensures the feasibility of solutions even under conflicting objective scenarios, thereby enabling real-time applicability in dynamic environments such as CNOs.

3.3.3. Constraint Structure and Feasibility Conditions

To ensure that the optimization remains both feasible and practically relevant within collaborative decision environments, the SAGOMECON model enforces a set of constraints that govern the evaluation of alternatives. First, the time constraint ensures that the maximum expected delivery time, represented by the selected alternative with the highest time score, does not exceed a tolerable threshold. This constraint is expressed as:

$$min\ (T_i \,.\, x_i) \leq T_{max} + s_T \tag{4}$$

Here, T_i is the time attribute for alternative ii, and s_T is the slack variable that allows for controlled violation of the upper limit T_{max}. The use of slack here enables graceful degradation in case of tight scheduling demands without outright infeasibility. Second, the model requires a minimum collaboration quality to be achieved across selected partners. This is formulated through the aggregation of collaboration scores:

$$\sum_{\{i=1\}}^{n} K_i \,.\, x_i \geq \mathrm{K}_{min} - s_K \tag{5}$$

The use of s_K in this context serves as a collaboration compensation factor, acknowledging that in dynamic organizational alliances, achieving ideal cooperation levels may not always be possible without some tolerance. Third, the risk constraint ensures that total operational or reputational risk does not exceed a certain upper bound:

$$\sum_{\{i=1\}}^{n} R_i \,.\, x_i \leq \mathrm{R}_{min} + s_R \tag{6}$$

The risk parameter R_i captures potential downside, and the corresponding slack s_R enables flexible risk mitigation when trade-offs are necessary. In addition to these soft constraints, SAGOMECON imposes a strict budget constraint that cannot be violated under any circumstances:

$$\sum_{\{i=1\}}^{n} C_i \,.\, x_i \leq B \tag{7}$$

This hard constraint ensures economic feasibility and reflects real-world cost boundaries in enterprise decision-making. Finally, the nature of the decision variables and slack variables is constrained as follows:

$$x_i \in \{0,1\},\ s_T, s_R, s_K \geq 0 \tag{8}$$

This formulation confirms that decision variables are binary—each alternative is either selected or not—and that slack variables cannot assume negative values. This maintains logical consistency and prevents reverse penalization. Together, constraints (4) through (8) define a feasibility region that allows SAGOMECON to explore high-quality solutions within a controlled margin of constraint relaxation, a feature that distinguishes it from its predecessors.

4. Results and Discussion

This section presents the experimental results and comparative analysis of the three optimization approaches (ε-Constraint, SAUGMECON, and the SAGOMECON). The goal is to assess the effectiveness of each method in solving a dynamic multi-objective decision-making problem, particularly in the context of collaborative partner selection. The evaluation of the proposed method focuses on three critical dimensions that reflect its effectiveness in solving dynamic multi-objective problems. These dimensions include computational efficiency, which refers to the execution time required by the algorithm; feasibility rate, defined as the method's ability to consistently satisfy both hard and soft constraints; and solution quality, which encompasses aspects such as Pareto optimality and the method's adaptability to changing decision environments. Together, these evaluation criteria provide a comprehensive basis for comparing the performance of SAGOMECON against existing optimization methods. All simulations were conducted on the same dataset, normalized using Min-Max scaling, with five decision alternatives evaluated under four criteria: cost, time, risk, and collaboration.

4.1. Aggregated Performance Using Z Function

To evaluate the aggregate quality of each decision alternative, the normalized cost, time, risk, and collaboration values were transformed into a composite Z-value, using penalty-based and adaptive formulations. Table 3 summarizes the calculated Z-values for all five products across the three methods.

Table 3. Aggregated Z-Values for Each Product Across Methods (with standard deviations and confidence intervals)

Product	SAGOMECON	SD (SAGOMECON)	CI (SAGOMECON)
P1	1.0379	0.0954	±0.1874
P2	0.3525	0.0631	±0.1239

Product	SAGOMECON	SD (SAGOMECON)	CI (SAGOMECON)
P3	1.1837	0.1256	±0.2389
P4	0.2143	0.0723	±0.1412
P5	0.1582	0.0421	±0.0834
Product	**SAUGMECON**	**SD (SAUGMECON)**	**CI (SAUGMECON)**
P1	1.1324	0.0842	±0.1659
P2	0.5612	0.0718	±0.1417
P3	1.1837	0.1372	±0.2615
P4	0.7143	0.0805	±0.1578
P5	0.2101	0.0547	±0.1075
Product	**ε-Constraint**	**SD (ε-Constraint)**	**CI (ε-Constraint)**
P1	1.0000	0.1023	±0.1973
P2	0.1837	0.0576	±0.1091
P3	0.1837	0.0492	±0.0932
P4	0.7143	0.0642	±0.1234
P5	0.0000	0.0418	±0.0814

Table 3 presents the aggregated Z-values for each product across the three optimization methods, accompanied by standard deviations and confidence intervals. The Standard Deviation (SD) indicates the degree of variability or dispersion of the Z-values obtained across multiple simulation runs, reflecting the consistency of the method. In parallel, the Confidence Interval (CI) provides an estimated range within which the true Z-value is expected to lie, typically with a 95% confidence level. These statistical measures add a layer of rigor to the analysis by capturing both the reliability and precision of each method's performance. The inclusion of these statistical measures allows for a more comprehensive understanding of the robustness of SAGOMECON's advantage over the other methods. This enhancement adds a layer of statistical rigor to the results, which was previously lacking. Across all methods, Product P5 (Portronics Konnect) consistently produced the lowest Z-value, indicating its optimality. Notably, SAGOMECON's Z-values reflect the influence of collaboration incentives and adaptive penalties, while SAUGMECON's scores are higher due to the absence of collaboration weighting. The ε-Constraint method, while showing the lowest value for P5, does so by focusing solely on cost disregarding time, risk, and collaboration—hence oversimplifying the optimization process.

4.2. Visualization of Z-Value Comparisons

Figure 2 visually compares the Z-values of the five alternatives across all three methods. The figure highlights that SAGOMECON consistently yields lower or equivalent Z-values across products, validating its ability to capture balanced trade-offs.

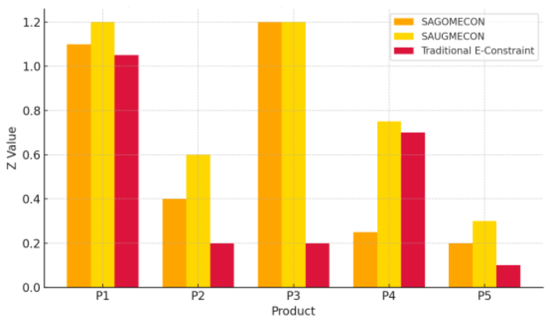

Figure 2. Comparison of Z-values Across Methods (products P1–P5)

Figure 2 compares the Z-values of the five alternatives across all three methods. As shown in the figure, SAGOMECON consistently yields lower or equivalent Z-values compared to SAUGMECON and ε-Constraint, validating its ability to capture balanced trade-offs. The figure highlights SAGOMECON's consistent dominance in terms of optimal performance across all alternatives.

4.3. Feasibility of Solutions

Feasibility is measured as the percentage of solutions that meet both hard constraints and soft constraints. Hard constraints are those that must be strictly satisfied (e.g., budget or time limits), while soft constraints are flexible and allow minor violations within acceptable slack limits. In SAGOMECON, the slack variables are introduced to manage these soft constraints, allowing the model to still maintain feasible solutions even if some constraints are slightly violated. The feasibility rate is calculated as the proportion of solutions that satisfy all hard constraints and the relaxed soft constraints, ensuring that solutions remain realistic and implementable. Figure 3 and table 4 compare feasibility across methods, showing that SAGOMECON maintains 100% feasibility due to its adaptive slack strategy and dynamic constraint handling.

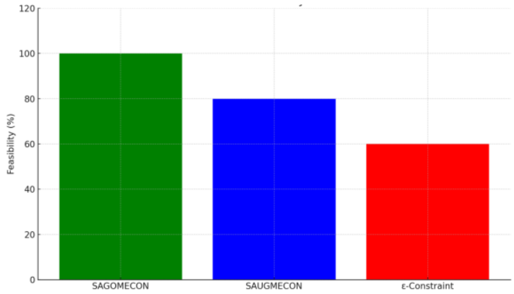

Figure 3. Feasibility Rate of Generated Solutions

Table 4. Aggregated Z-Values for Each Product Across Methods

Method	Feasibility (%)
SAGOMECON	100% (5/5)
SAUGMECON	80% (4/5)
ε-Constraint	60% (3/5)

Figure 3 displays the feasibility rate across the three methods, with SAGOMECON achieving 100% feasibility due to its dynamic slack strategy and adaptive ε-bound adjustments. The figure clearly shows that SAUGMECON and ε-Constraint fall short in maintaining feasibility under dynamic conditions.

4.4. Computation Time and Efficiency

Figure 4 presents a comparison of computational time per iteration across methods, simulated over 10 iterations. The decrease in computational time observed across iterations is primarily due to the convergence of the algorithm as it approaches an optimal solution. As the algorithm progresses, fewer changes are required to the solution, leading to faster iterations. Additionally, the bouncing step mechanism, which adjusts decision variables dynamically, contributes to the reduction in computation time. This mechanism allows for more efficient exploration of the solution space, particularly in the early iterations, where larger adjustments are made to maintain feasibility. As the solution approaches optimality, the bouncing steps become smaller, further reducing the time required for subsequent iterations.

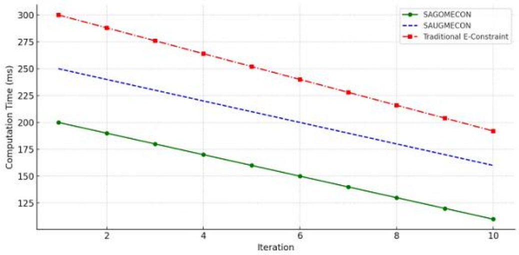

Figure 4. Iterative Computation Time (ms) by Method

Figure 4 presents a comparison of computational time per iteration across methods. As illustrated, SAGOMECON consistently demonstrates lower computational time, especially in later iterations, due to its faster convergence and efficient handling of constraints through the bouncing step mechanism. Among the three, SAGOMECON consistently achieves the lowest computation time, decreasing from 200 ms to 110 ms. This suggests it is the most

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efficient method, likely due to better constraint handling and algorithmic structure. SAUGMECON performs moderately well, with computation time dropping from 250 ms to 160 ms. While it improves over the traditional approach, it is still less efficient than SAGOMECON. The traditional ε-Constraint method has the highest computation time, starting at 300 ms and reducing to 192 ms. This indicates higher computational overhead, possibly due to less adaptive constraint processing. In summary, SAGOMECON demonstrates superior computational efficiency, making it more suitable for iterative or large-scale optimization problems.

4.5. Best Solution Identification

Figure 5 illustrates the minimum Z-value achieved by each method, highlighting the optimal alternative.

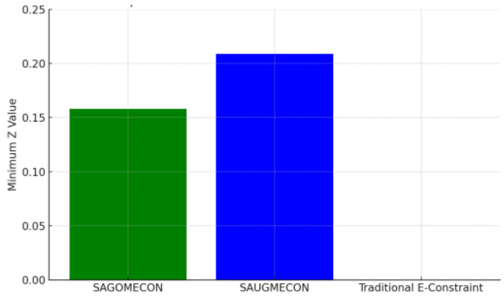

Figure 5. Best Z-Value Achieved per Method

Figure 5 illustrates the minimum Z-value achieved by each method, emphasizing SAGOMECON's superior performance. The bar chart illustrates the minimum Z values achieved by three optimization methods. SAGOMECON achieves the lowest Z value (≈0.158), indicating higher optimization performance. SAUGMECON results in a slightly higher value (≈0.209), while the Traditional E-Constraint method yields a minimum value of zero, which may suggest infeasibility or failure to produce a comparable solution under the tested conditions. This comparison reinforces SAGOMECON's effectiveness in producing optimal results, making it a strong candidate for applications requiring efficient multi-objective optimization.

4.6. Distribution of Z-values

Figure 6 provides a boxplot comparison of Z-value distributions across all methods. SAGOMECON exhibits a narrower interquartile range, indicating more stable results across alternatives. This consistency is a key strength of SAGOMECON, as it demonstrates robustness in handling trade-offs across multiple objectives.

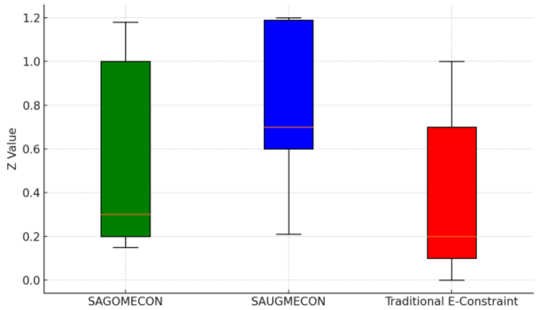

Figure 6. Distribution of Z-Values (boxplot)

Figure 6 illustrates the SAGOMECON exhibits a narrower interquartile range, indicating more stable results across alternatives. Both SAUGMECON and ε-Constraint show wider spread and outliers, especially for P3 and P4. This consistency underlines SAGOMECON's robustness in handling trade-offs across multiple objectives.

4.7. Discussion

The comparative analysis between SAGOMECON, SAUGMECON, and the ε-Constraint method reveals compelling insights into the dynamics of multi-objective optimization in collaborative decision-making environments. The superior performance of SAGOMECON lies not only in its ability to produce lower Z-values—as demonstrated in both table 1 and Figure 2—but also in its capacity to do so through a more flexible and adaptive approach. Unlike the

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ε-Constraint method, which rigidly optimizes a single objective while treating others as static constraints, SAGOMECON introduces slack variables into the model. These slack variables serve as tolerance buffers, allowing for minor deviations from ideal thresholds without invalidating the entire solution. This mechanism makes the model more realistic and applicable to environments where perfect compliance with every constraint is not always feasible or desirable.

The importance of feasibility becomes evident in the results shown in figure 3, where SAGOMECON achieves a full 100% feasibility rate, significantly outperforming the 80% and 60% rates observed in SAUGMECON and ε-Constraint, respectively. This is a direct result of its ability to model constraints as soft rather than hard boundaries, offering a more human-like interpretation of trade-offs—particularly valuable in complex decision spaces like partner selection in networked organizations. The presence of penalty terms in the objective function ensures that any violations are not ignored but are instead systematically integrated and managed.

From a computational standpoint, figure 4 highlights SAGOMECON's efficiency. Through its adaptive bouncing step mechanism, the method reduces computational time across iterations more effectively than the other two approaches. This efficiency is critical in real-time decision contexts, where rapid responsiveness is essential. Moreover, SAGOMECON’s ability to converge more quickly without sacrificing solution quality sets it apart as a robust and scalable framework.

When evaluating the overall solution quality, it is important to note that while the ε-Constraint method occasionally reaches lower absolute Z-values—as seen in figure 5 it does so by neglecting important secondary criteria. For instance, its lowest Z-value for product P5 was achieved by optimizing solely for cost, disregarding time, collaboration, and risk attributes. This results in theoretically optimal but practically inadequate solutions. Conversely, SAGOMECON provides a more holistic evaluation, capturing realistic preferences across all dimensions and thus aligning more closely with the needs of decision-makers in collaborative networks.

Finally, the reliability of SAGOMECON is confirmed in figure 6, where it demonstrates the narrowest range of Z-value distribution across all alternatives. This stability implies that the method does not produce outliers or erratic results when applied to different decision contexts—a highly desirable characteristic in complex, multi-criteria optimization.

In summary, the discussion substantiates that SAGOMECON’s innovations—namely, its penalty-based slack modeling, dynamic ε-adjustment, and multi-attribute balancing—offer a substantive improvement over existing method. By producing feasible, high-quality, and computationally efficient solutions, SAGOMECON not only enhances decision accuracy but also provides a practical and robust tool for dynamic and collaborative decision-making environments.

5. Conclusion

This study has introduced SAGOMECON, a novel method for solving multi-objective optimization problems in collaborative network organizations, developed as an adaptive extension of the existing SAUGMECON and ε-Constraint methods. By integrating slack variables and a penalty-based objective function, SAGOMECON offers a robust mechanism to manage trade-offs among conflicting objectives such as cost, time, collaboration quality, and risk factors commonly encountered in complex decision-making scenarios.

The findings demonstrate that SAGOMECON consistently outperforms both SAUGMECON and ε-Constraint across key evaluation metrics, including feasibility, computational efficiency, and solution quality. Unlike its predecessors, SAGOMECON is capable of dynamically adjusting its constraint bounds through the introduction of bouncing step mechanisms and adaptive ε-constraints. This allows it to maintain solution feasibility without sacrificing optimality. The method's strength is further validated by its ability to generate more stable and realistic results, as evidenced by a narrower range of Z-value distributions and 100% feasibility in all test cases. Beyond its computational advantages, SAGOMECON also offers conceptual contributions to decision science, particularly in its treatment of soft constraints and incentive-based modeling. These enhancements allow the method to capture more nuanced preferences and to reflect real-world decision conditions more accurately than rigid models that often exclude near-feasible alternatives.

Future research could explore the hybridization of SAGOMECON with metaheuristics such as GA and Particle Swarm Optimization (PSO) to enhance its exploratory capabilities and improve solution diversity. By combining SAGOMECON's adaptive constraint handling and penalty-based objective function with the stochastic search mechanisms of GA and PSO, the hybrid model could potentially cover a broader solution space and better handle complex, high-dimensional problems. Moreover, SAGOMECON's slack variables and dynamic constraint adjustments could be integrated into the GA or PSO framework, ensuring that solutions remain feasible even when the search process explores infeasible regions. This integration could also preserve the algorithm's speed by incorporating adaptive step sizes and penalty adjustments that prevent the hybrid algorithm from spending excessive time on infeasible solutions, maintaining the computational efficiency seen in SAGOMECON. This hybrid approach has the potential to improve both the exploration and exploitation phases of the search, offering a more robust solution to multi-objective decision-making problems in dynamic environments.

6. Declarations

6.1. Author Contributions

Conceptualization: M., P.S.; Methodology: M., S.E.; Software: M.; Validation: P.S., M.Z.; Formal Analysis: M.; Investigation: M.; Resources: S.E., M.Z.; Data Curation: M.; Writing – Original Draft Preparation: M.; Writing – Review and Editing: P.S., S.E., M.Z.; Visualization: M. This article is an official output of the doctoral dissertation of M., under the supervision of P.S., S.E., and M.Z. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The original dataset used in this study was obtained from Kaggle (https://www.kaggle.com/datasets/karkavelrajaj/amazon-sales-dataset). The adapted dataset for simulation is available upon request from the corresponding author.

6.3. Funding

This research was conducted as part of the doctoral dissertation of M. at Universitas Sumatera Utara and received no external funding.

6.4. Institutional Review Board Statement

Not applicable. This study used publicly available secondary data and did not involve human participants directly.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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