Multi-Objective Optimization in Supply Chain Disruption Risk and Carbon Emissions: A Survey

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Abstract

In the face of increasing supply chain complexities and environmental challenges, multi-objective optimization (MOO) emerges as a crucial tool for balancing competing objectives such as cost reduction, service level maintenance, and carbon emissions mitigation. This survey paper explores the application of the Non-dominated Sorting Genetic Algorithm III (NSGA-III) in the context of supply chain disruption risk and carbon emissions. NSGA-III, an advancement over its predecessor NSGA-II, is particularly proficient in managing high-dimensional data and many-objective optimization problems, which are prevalent in modern supply chains. By utilizing a reference-point-based approach, NSGA-III enhances the generation of diverse Pareto-optimal solutions, providing decision-makers with a comprehensive set of trade-offs among competing objectives. The integration of NSGA-III with surrogate models and advanced techniques, such as the Smooth Tchebycheff Scalarization method and Repulsion Dynamics, further improves the algorithm's efficiency and effectiveness in exploring high-dimensional solution spaces. This survey examines the significance of multi-objective optimization in supply chain management, particularly in balancing disruption risk mitigation, carbon emissions reduction, and manufacturing efficiency. It highlights the transformative potential of NSGA-III and innovative approaches to Pareto front analysis, which support decision-makers in navigating the intricate landscape of supply chain optimization. By offering a robust framework for evaluating and optimizing multiple conflicting objectives, multi-objective optimization facilitates sustainable development and enhances the resilience and competitiveness of global supply chains.

1 Introduction

1.1 Significance of Multi-Objective Optimization

Multi-objective optimization (MOO) is crucial in addressing the complexities of supply chain management, particularly concerning disruption risks and carbon emissions. Supply chains involve multiple conflicting objectives, such as cost reduction, service level maintenance, and environmental impact mitigation, necessitating a balanced approach to optimization [1]. The identification of Pareto-optimal solutions allows decision-makers to navigate trade-offs between competing objectives, although the high-dimensional nature of many supply chain problems complicates the complete mapping of the Pareto front [2, 3]. Innovative methods focusing on the center of the Pareto front have emerged to enhance practical applicability in real-world scenarios [2].

In supply chains, MOO integrates various components, such as production and logistics, to optimize overall performance while minimizing carbon footprints [4]. The capability to model and solve large-scale problems with numerous decision variables and conflicting objectives is exemplified in the Food-Energy-Water Nexus systems [5], emphasizing the need for effective optimization strategies in managing supply chain risks and emissions [6]. Recent advancements, including the Multiobjective

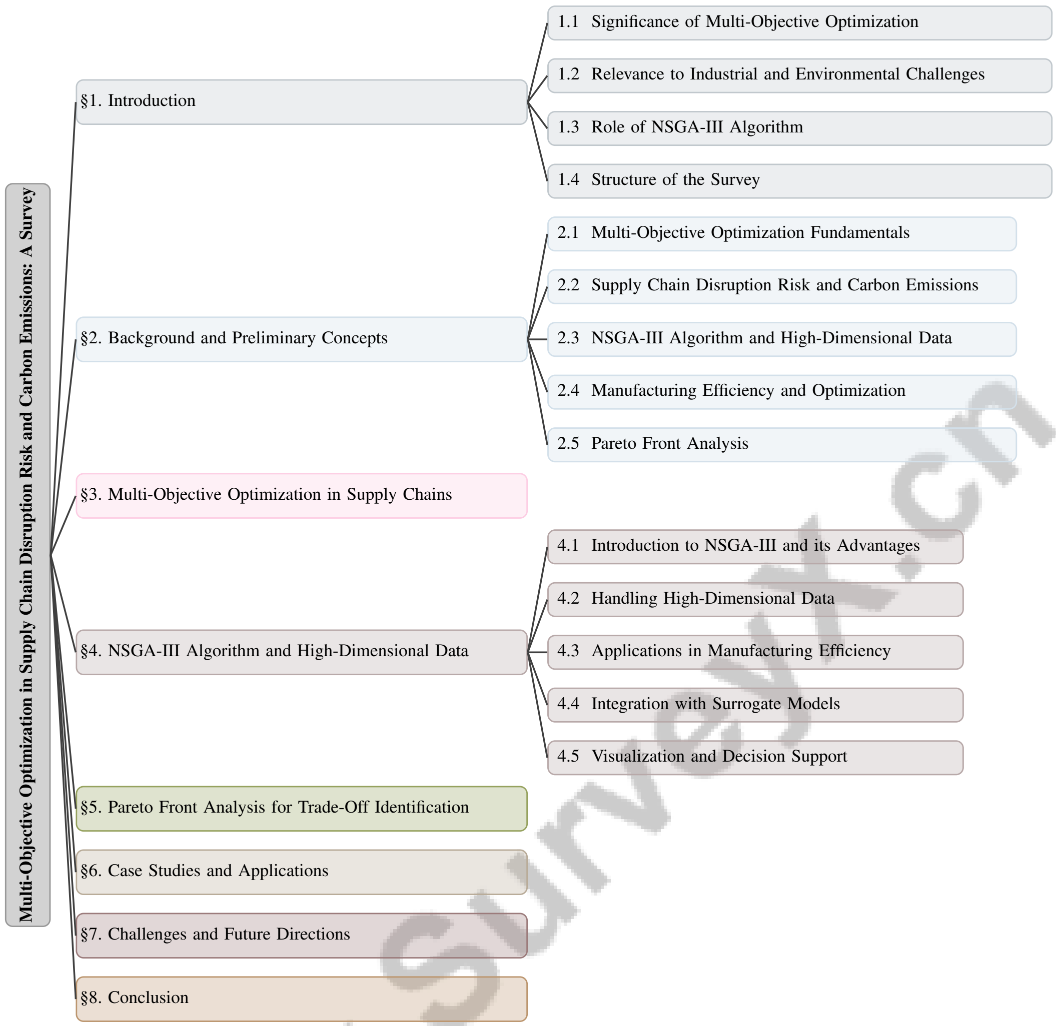

Figure 1: chapter structure

Fractal Decomposition Algorithm (Mo-FDA), demonstrate promise in addressing complexity and scalability challenges in large-scale MOO problems [7]. Thus, MOO serves as an essential tool for decision-makers aiming to optimize supply chain operations, supporting sustainable development by balancing economic viability with environmental concerns [8].

1.2 Relevance to Industrial and Environmental Challenges

MOO is integral in tackling the complex challenges faced by industrial and environmental sectors, where decision-makers must balance competing objectives. Traditional models often inadequately capture the intricacies of modern multi-objective evolutionary algorithms (MOEAs), limiting their applicability in contemporary settings [9]. This gap highlights the necessity for advanced approaches capable of managing multiple conflicting objectives, particularly in supply chains where disruption risks and carbon emissions are significant concerns [10].

Derivative-free optimization methods, as noted by [11], are particularly relevant, addressing real-valued functions under multiple inequality constraints, thus reflecting the complexity of current industrial challenges. The inadequacy of existing algorithms to concurrently manage numerous objectives necessitates the development of new methodologies [12]. This is especially pertinent in the Food-Energy-Water Nexus systems, where sustainability and resource allocation are critical [5].

Innovative techniques, such as the mEI and q-mEI methods, have demonstrated significant improvements in targeting specific regions of the Pareto front, achieving faster convergence and more relevant results within constrained evaluation budgets [2]. These advancements are vital in industrial applications, where optimizing multiple conflicting objectives can be complex and time-consuming [3]. The application of MOO in enhancing system efficiency and performance is evidenced in the optimization of design parameters, addressing current industrial challenges [13]. Thus, MOO serves as a critical tool in navigating industrial and environmental challenges, promoting sustainable development through informed decision-making.

1.3 Role of NSGA-III Algorithm

The NSGA-III algorithm represents a significant advancement in multi-objective optimization, particularly in managing high-dimensional Pareto fronts. Building on its predecessor, NSGA-II, NSGA-III effectively addresses many-objective optimization problems, overcoming earlier algorithms' limitations in handling complexities [14]. A key feature of NSGA-III is its integration with advanced modeling techniques, such as Linear Programming for Multiple-Gradient Descent (LP-MGD), which enhances optimization efficiency through thorough exploration of the solution space [14].

NSGA-III incorporates a dominance-based crossover operator (DBX) to optimize mating strategies within Evolutionary Multi-objective Algorithms (EMAs), improving the search for Pareto-optimal sets [15]. Its adaptability is further demonstrated through interactive frameworks that allow decision-makers (DMs) to incorporate preference information, facilitating a targeted search for preferred solutions [16, 17].

Moreover, NSGA-III's relevance in sustainable supply chains is evident as it integrates with Multi-Objective Genetic Algorithm Optimization Methods (MOGA) to optimize multiple objectives in closed-loop systems [18]. The inclusion of Bayesian optimization techniques, such as those in the Batched Scalable Multi-Objective Bayesian Optimization (BS-MOBO) algorithm, further supports NSGA-III's role in high-dimensional data analysis by incorporating gradient information and facilitating batch evaluations [19].

In game-theoretic frameworks, NSGA-III negotiates satisfactory solutions through concepts like Nash equilibrium and Kalai-Smorodinsky solutions, treating each objective as a player [20]. The Smooth Tchebycheff Scalarization (STCH) method offers a lightweight solution for gradient-based multi-objective optimization, allowing better trade-offs among conflicting objectives, complementing NSGA-III's capabilities [21].

Consequently, NSGA-III stands as a crucial tool in high-dimensional data analysis for multi-objective optimization, significantly enhancing solution accuracy, computational efficiency, and adaptability to complex decision-making processes. This is particularly relevant given the challenges posed by increasing objective numbers in optimization problems, as highlighted by recent studies exploring the implications of many-objective optimization on algorithm design and performance. The integration of Quality Diversity optimization techniques and interactive frameworks for preference elicitation signifies a growing recognition of the need for tailored solutions that address specific decision-maker preferences, expanding MOO's applicability across diverse real-world scenarios [16, 22, 23, 24, 25].

1.4 Structure of the Survey

This survey is structured to provide a comprehensive exploration of multi-objective optimization in the context of supply chain disruption risk and carbon emissions. The elaborates on the significance of MOO, emphasizing its role in addressing complex industrial and environmental challenges. It discusses how MOO techniques deliver solutions that surpass traditional single-objective approaches, particularly in logistics, finance, and environmental management. The introduction sets the stage for exploring the theoretical and empirical implications of increasing objectives, the challenges this presents, and the evolving landscape of algorithms designed to tackle these issues effectively [23, 24, 26, 27, 25]. It also outlines the organization of the survey.

Following the introduction, the **Background and Preliminary Concepts** section provides foundational knowledge necessary for understanding subsequent discussions. It defines key concepts such as multi-objective optimization, supply chain disruption risk, and carbon emissions, emphasizing the NSGA-III algorithm's application in high-dimensional data analysis and its significance in manufacturing efficiency and Pareto front analysis.

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The third section, **Multi-Objective Optimization in Supply Chains**, explores the practical application of optimization techniques in supply chain management, discussing the balance of disruption risk and carbon emissions while maintaining efficiency, supported by existing literature and case studies that illustrate successful implementations and challenges.

The survey then focuses on the **NSGA-III Algorithm and High-Dimensional Data**, detailing the algorithm's suitability for complex optimization problems. This section highlights NSGA-III's advantages over previous algorithms, its role in enhancing manufacturing efficiency, and its integration with surrogate models for improved outcomes.

In the **Pareto Front Analysis for Trade-Off Identification** section, the role of Pareto front analysis in identifying trade-offs among objectives is examined. This section discusses techniques for generating Pareto fronts, innovative analysis approaches, and challenges associated with traditional methods.

The survey also presents **Case Studies and Applications**, showcasing real-world applications of multi-objective optimization in supply chain management. These case studies provide insights into the outcomes and lessons learned from implementing multi-objective optimization strategies across various industrial contexts, emphasizing the importance of aligning decision-making models with the complexities of real-world scenarios characterized by conflicting objectives and the need for sample-efficient exploration of the solution space [22, 28, 29, 30].

Finally, the **Challenges and Future Directions** section identifies challenges in applying MOO to supply chain disruption risk and carbon emissions, discussing potential future research directions and technological advancements that could address these challenges, paving the way for continued exploration and innovation in the field.

The survey concludes by synthesizing key findings and highlighting the critical role of MOO in effectively managing supply chain risks and emissions. It underscores the potential benefits of future research and technological advancements in enhancing supply chain resilience, optimizing cost-efficiency, and minimizing environmental impact, as evidenced by recent models that balance cost minimization with network connectivity and sustainability amid demand uncertainty [18, 31].The following sections are organized as shown in Figure 1.

2 Background and Preliminary Concepts

2.1 Multi-Objective Optimization Fundamentals

Multi-objective optimization (MOO) addresses the simultaneous optimization of conflicting objectives, such as cost reduction, carbon emission minimization, and service level maintenance, which are prevalent in complex systems like supply chain management [6]. Unlike single-objective optimization, MOO identifies a set of Pareto optimal solutions representing trade-offs among competing objectives, where improving one objective typically leads to a decline in another [6]. This challenge is compounded by the need to efficiently optimize multi-objective functions with limited evaluations, aiming for well-balanced solutions near the Pareto front's center [32]. Such optimization is crucial in scenarios with non-convex Pareto fronts, where single solutions cannot simultaneously optimize all objectives.

Recent advancements in decision-support methods have enhanced the identification of relevant solutions along the Pareto front. Techniques like Pareto pruning autonomously generate manageable shortlists from extensive sets of Pareto optimal solutions, enhancing decision-making by reducing complexity [27, 23]. These developments facilitate a better understanding of trade-offs, aiding decision-makers in navigating the complex landscape of supply chain management, where disruption risk and carbon emissions are critical considerations [6].

2.2 Supply Chain Disruption Risk and Carbon Emissions

Supply chains, characterized by intricate interdependencies, face significant disruption risks from events like natural disasters, necessitating strategies that enhance resilience and connectivity while minimizing costs [4]. Concurrently, the global emphasis on sustainability has amplified regulatory pressures to curb carbon emissions across supply chains, which stem from activities such as transportation, production, and logistics. This dual challenge highlights the importance of MOO in balancing economic and environmental goals within supply chain management [18].

Addressing these challenges requires advanced optimization techniques. Bayesian approaches to constrained single-objective optimization focus on approximating solution sets that satisfy multiple inequality constraints while minimizing objectives [11]. The complexity of managing disruption risks and carbon emissions is further compounded by the necessity of optimizing conflicting objectives, as seen in material inventory and transportation problems [33]. Game-theoretic perspectives and Bayesian optimization techniques integrated into MOO frameworks offer promising solutions for improving supply chain resilience and sustainability amidst these challenges [20, 18].

Interactive MOO techniques, such as data-efficient methods, enable precise decision-making under uncertainty by allowing decision-makers to define preferences among conflicting objectives [34]. These advancements underscore MOO's critical role in addressing supply chain disruption risks and carbon emissions, promoting sustainable development and informed decision-making.

2.3 NSGA-III Algorithm and High-Dimensional Data

The Non-dominated Sorting Genetic Algorithm III (NSGA-III) represents a significant advancement in multi-objective optimization, particularly for high-dimensional data. As an evolution of NSGA-II, NSGA-III is designed for many-objective optimization problems, efficiently generating diverse and well-distributed Pareto-optimal solutions [14]. This makes it particularly effective in supply chain optimization, where decision-makers must balance objectives such as minimizing disruption risk, reducing carbon emissions, and maximizing efficiency.

NSGA-III's strength lies in its ability to handle high-dimensional data, a common feature of supply chain optimization problems. The algorithm's effectiveness is enhanced by integrating advanced techniques like Self-Evolutionary Optimization (SEO) and the Distributed Adaptive Processing (DAP) method, which improve the exploration of solution spaces and data processing efficiency in high-dimensional optimization tasks [35, 19].

The algorithm's dominance-based crossover operator (DBX) optimizes mating strategies within Evolutionary Multi-objective Algorithms (EMAs), enhancing the search for Pareto-optimal sets [15]. Additionally, the Smooth Tchebycheff Scalarization (STCH) method supports gradient-based multi-objective optimization, enhancing NSGA-III's robustness and adaptability [21]. This makes NSGA-III a powerful tool for decision-makers navigating the complexities of multi-objective optimization, particularly in supply chain management, where balancing economic viability and ecological sustainability is critical [18, 17].

2.4 Manufacturing Efficiency and Optimization

Optimization plays a crucial role in enhancing manufacturing efficiency by providing a systematic framework for improving processes through optimal solution identification. This is particularly valuable in multi-objective optimization scenarios, where conflicting goals such as production quality and time must be balanced. Recent advancements, including adaptive algorithms and Pareto pruning methods, streamline the optimization process by reducing evaluations and facilitating decision-making [27, 36, 25].

MOO is particularly valuable in manufacturing, addressing the multifaceted nature of systems where objectives like cost reduction, quality enhancement, and production time minimization frequently conflict. Advanced optimization methods, such as the Improved Multi-Objective Steepest Descent Algorithm, enhance convergence towards Pareto optimal solutions by adaptively adjusting the step size based on objective functions' curvature. This adaptability is crucial in manufacturing, where optimizing multiple objectives demands sophisticated computational approaches [26].

In manufacturing environments, data complexity and volume can present significant challenges. Advanced optimization methods, like the Attention-based Deep Segmentation Network (ADSN), support optimization by focusing on the most informative data parts, improving decision-making and process efficiency [37]. The Multi-Objective Genetic Algorithm Optimization Methods (MOGA) have proven effective in optimizing multiple objectives in sustainable closed-loop systems, supporting sustainable development goals by balancing cost reduction, quality enhancement, and production time minimization [18].

Utilizing exact Pareto optimal search techniques ensures decision-makers can select suitable decision vectors from well-defined trade-offs, enhancing optimization solutions' practical applicability [38].

Integrating interactive MOO algorithms with decision-makers improves data efficiency in exploring the Pareto front, enabling more informed and timely decisions [34]. NSGA-III further enhances manufacturing optimization by efficiently exploring the solution space using advanced modeling techniques like Linear Programming for Multiple-Gradient Descent (LP-MGD), crucial in complex manufacturing environments involving numerous decision variables and constraints [14].

2.5 Pareto Front Analysis

Pareto front analysis is a cornerstone of multi-objective optimization, offering a set of non-dominated solutions where improvements in one objective lead to trade-offs in others [6]. This is particularly vital in supply chain management, where decision-makers balance conflicting objectives such as cost, risk, and environmental impact.

Traditional methods for generating and analyzing Pareto fronts face challenges in high-dimensional spaces, where hypervolume calculations can be computationally expensive, and accurately representing Pareto fronts is difficult [20]. To address these challenges, innovative methods have been developed to enhance Pareto front analysis. The normW method improves solution distribution in the objective space by escaping local optima [39]. The Smooth Tchebycheff Scalarization (STCH) method offers a lightweight and efficient solution for gradient-based multi-objective optimization, complementing NSGA-III capabilities and enabling better trade-offs among conflicting objectives [21].

Enhanced visualization techniques, Pareto pruning, and repulsion dynamics approaches further improve Pareto front approximation uniformity, providing decision-makers with a comprehensive set of optimal trade-offs [23, 40]. These advancements facilitate effective evaluation and comparison of solutions, supporting informed selections that align with individual preferences and broader strategic objectives. This interactive capability enhances decision-making processes, allowing decision-makers to explore different algorithms and their evolutionary processes in a more analytical manner [23, 40]. In supply chain management, where balancing cost, risk, and environmental impact is critical, Pareto front analysis is indispensable for identifying trade-offs and optimizing multiple conflicting objectives [6].

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In recent years, Multi-Objective Optimization (MOO) has gained significant attention within the field of supply chain management due to its potential to enhance efficiency and resilience. A comprehensive understanding of MOO necessitates an exploration of its key concepts and applications, particularly in the context of resilient supply chain network design. As illustrated in Figure 2, this figure categorizes the introduction and recent advancements in MOO, delineating its application in supply chain management. It highlights the critical role of decision-maker preferences and trade-offs, as well as the challenges associated with identifying Pareto-optimal solutions. Each category is further subdivided into essential aspects and methodologies, providing a thorough overview of how MOO contributes to improving supply chain performance. This visual representation not only aids in understanding the complex interrelationships among these concepts but also emphasizes the importance of MOO in addressing contemporary supply chain challenges.

3 Multi-Objective Optimization in Supply Chains

3.1 Introduction to Multi-Objective Optimization in Supply Chains

Multi-objective optimization (MOO) is essential in supply chain management, addressing conflicting goals such as cost efficiency, service enhancement, and environmental impact reduction. The complexity of modern supply chains, characterized by intricate interdependencies and global operations, demands a sophisticated approach to balance these objectives effectively [1]. MOO serves as a structured framework, aiding decision-makers in navigating supply chain challenges, especially amid rising disruption risks and strict carbon emission regulations.

The growing emphasis on sustainability and resilience in industrial operations underscores the relevance of MOO. Organizations are increasingly tasked with minimizing carbon footprints while maintaining competitiveness. Integrating MOO into supply chain management allows decision-

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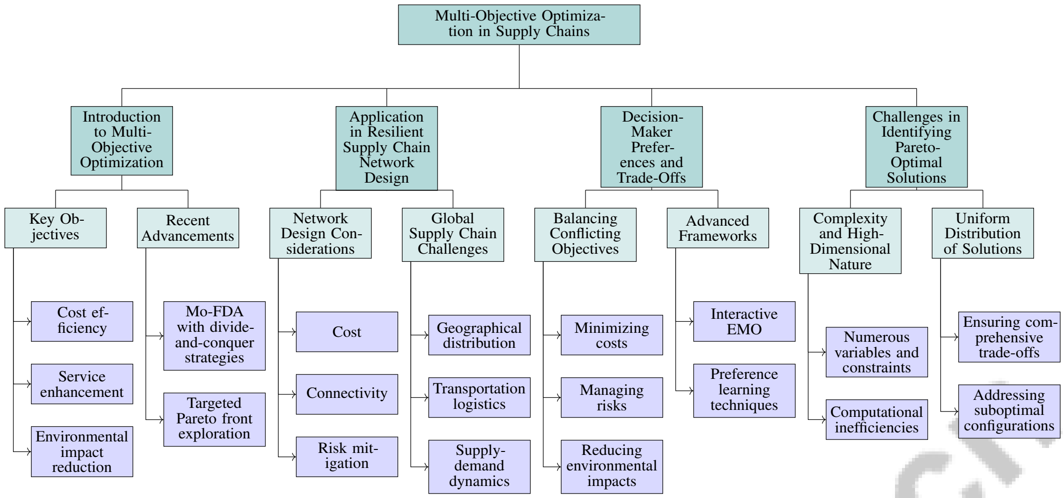

Figure 2: This figure illustrates the key concepts and applications of Multi-Objective Optimization (MOO) in supply chain management. It categorizes the introduction and recent advancements in MOO, its application in resilient supply chain network design, the role of decision-maker preferences and trade-offs, and the challenges in identifying Pareto-optimal solutions. Each category is further divided into subcategories highlighting essential aspects and methodologies, providing a comprehensive overview of MOO's role in enhancing supply chain efficiency and resilience.

makers to identify Pareto-optimal solutions that balance economic and environmental objectives, promoting sustainable and efficient operations [4].

Recent advancements in MOO methodologies, such as the Mo-FDA utilizing divide-and-conquer strategies and hyperspheres, have significantly improved large-scale optimization [7]. These innovations enable more effective navigation of MOO's complex landscape, ensuring supply chain operations remain efficient and environmentally responsible. Moreover, targeted approaches for Pareto front exploration enhance efficiency and user preference alignment, leading to faster convergence than traditional methods [2]. This capability is vital for processing large data volumes and identifying optimal solutions in supply chain management, crucial for maintaining competitive advantages and achieving sustainability goals.

3.2 Application in Resilient Supply Chain Network Design

MOO significantly impacts the design of resilient supply chain networks, engineered to withstand and recover swiftly from disruptions while minimizing service level and cost impacts. The complexity of these networks, with numerous interconnected components and vulnerabilities, necessitates an advanced optimization approach to balance conflicting objectives [31]. Evaluating different configurations based on cost, connectivity, and risk mitigation is crucial. MOO models enable decision-makers to assess various configurations, considering economic and operational factors, aiding in identifying network designs that minimize costs while enhancing robustness and adaptability.

MOO facilitates exploring trade-offs between cost efficiency and network resilience. Advanced optimization techniques help decision-makers identify Pareto-optimal solutions that balance these objectives, ensuring supply chain networks are cost-effective and resilient. Techniques like decision-focused loss functions and interactive visual analytics provide insights into trade-offs associated with design choices, enhancing decision-making in complex scenarios [22, 23, 28, 40, 30].

MOO's application is particularly relevant in global supply chains, where complexity and scale present substantial challenges. This comprehensive approach evaluates interconnected factors, including geographical distribution, transportation logistics, and supply-demand dynamics, enhancing network robustness and adaptability in response to real-world complexities [23, 24].

3.3 Decision-Maker Preferences and Trade-Offs

Incorporating decision-maker preferences in MOO is crucial, particularly in supply chain management. Integrating these preferences into the optimization process ensures solutions align with strategic objectives and operational constraints, yielding mathematically optimal and practically relevant outcomes [41]. Decision-maker preferences significantly guide solution space exploration toward regions reflecting their priorities. In complex systems like supply chains, balancing conflicting objectives—such as minimizing costs, managing risks, and reducing environmental impacts—is essential. The dynamic nature of supply chains, influenced by factors like mergers and disruptions, complicates this balance. MOO models enable decision-makers to evaluate trade-offs between total network costs and overall connectivity, leading to resilient and efficient configurations [4, 31, 42]. Incorporating preference information allows for better navigation of inherent trade-offs, ensuring feasible and desirable solutions.

Advanced frameworks, such as interactive evolutionary multi-objective optimization (EMO), enhance decision-maker preference integration. These frameworks utilize preference learning techniques to dynamically adjust the search process, focusing on Pareto front regions aligning with decision-makers' preferences [43]. This interactive approach improves optimization efficiency and ensures solutions align closely with decision-makers' goals, facilitating more informed and effective decision-making.

3.4 Challenges in Identifying Pareto-Optimal Solutions

Identifying Pareto-optimal solutions in supply chain contexts presents challenges due to the complexity and high-dimensional nature of these systems. Existing mating strategies often fail to enhance solution quality or computational efficiency consistently, hindering effective solution space exploration [44]. This challenge is intensified by the high-dimensional nature of supply chain problems, where numerous variables and constraints can result in computational inefficiencies and convergence difficulties.

Applications like drone delivery scheduling face unpredictability due to events like drone breakdowns and takeoff failures, challenging the maintenance of robust supply chain operations [45]. A key obstacle in existing methods is the inability to ensure a uniform distribution of solutions over the Pareto front, leading to suboptimal configurations, as certain regions may be underrepresented or overlooked. Achieving uniform distribution is crucial for providing decision-makers with comprehensive trade-offs, enabling informed decision-making [44].

In conclusion, developing innovative methods and frameworks that address these challenges is essential for effective supply chain MOO. By overcoming these obstacles, decision-makers can access a more accurate and comprehensive set of Pareto-optimal solutions, facilitating better decision-making in complex supply chain environments.

4 NSGA-III Algorithm and High-Dimensional Data

Category	Feature	Method
Introduction to NSGA-III and its Advantages	Evolutionary Strategies Optimization Techniques	DBX[15] LP-MGD[14], C-EHI[46]
Handling High-Dimensional Data	Efficiency Enhancement Output-Focused Evaluation	PFEA[47], DAP[48] TGP[13]
Applications in Manufacturing Efficiency	Optimization Techniques	RDU-PFA[49], IFSD[50], MIT[33]
Integration with Surrogate Models	Surrogate Model Utilization	BS-MOBO[19], BMOO[11], NSGA-II[4]
Visualization and Decision Support	Optimization Visualization	OSPE[17], STCH[21], MOPOM[6]

Table 1: This table provides a comprehensive overview of various methods and their applications in the context of NSGA-III, focusing on key areas such as evolutionary strategies, optimization techniques, and surrogate model integration. It categorizes methods based on their relevance to handling high-dimensional data, applications in manufacturing efficiency, and visualization and decision support, highlighting the versatility and adaptability of NSGA-III in addressing complex multi-objective optimization challenges.

The Non-dominated Sorting Genetic Algorithm III (NSGA-III) is a critical advancement in multi-objective optimization, particularly adept at addressing the complexities of high-dimensional data. As optimization problems grow in complexity, especially in fields like supply chain management, the

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Visualization and Decision Support	Optimization Visualization	OSPE[17], STCH[21], MOPOM[6]

Table 2: This table provides a comprehensive overview of various methods and their applications in the context of NSGA-III, focusing on key areas such as evolutionary strategies, optimization techniques, and surrogate model integration. It categorizes methods based on their relevance to handling high-dimensional data, applications in manufacturing efficiency, and visualization and decision support, highlighting the versatility and adaptability of NSGA-III in addressing complex multi-objective optimization challenges.

demand for robust methodologies becomes increasingly evident. Table 2 presents a detailed summary of the methods associated with NSGA-III, categorizing them according to their application domains and highlighting their contributions to multi-objective optimization. Additionally, Table 4 presents a comprehensive comparison of methods associated with NSGA-III, detailing their application domains and highlighting the key advantages they offer in multi-objective optimization. This section examines the foundational aspects of NSGA-III, emphasizing its unique advantages and capabilities that position it as a premier approach for navigating many-objective optimization challenges.

4.1 Introduction to NSGA-III and its Advantages

NSGA-III significantly enhances multi-objective optimization (MOO), particularly for many-objective problems where objectives often exceed three. Building on NSGA-II, it employs a reference-point-based approach that improves the generation of diverse and well-distributed Pareto-optimal solutions [14]. This is especially useful in high-dimensional optimization contexts, such as supply chain management, where conflicting objectives—like minimizing disruption risk, reducing carbon emissions, and maximizing operational efficiency—must be simultaneously addressed.

A notable advantage of NSGA-III is its ability to manage many-objective optimization problems effectively through reference points, which guide the search process and ensure diverse solution distributions along the Pareto front [16]. This feature mitigates the common challenge of maintaining diversity among solutions as the number of objectives increases [46].

NSGA-III incorporates several enhancements over its predecessors, including integration with Linear Programming for Multiple-Gradient Descent (LP-MGD), allowing more efficient exploration of high-dimensional solution spaces [14]. It also utilizes a dominance-based crossover operator (DBX), optimizing mating strategies within Evolutionary Multi-objective Algorithms (EMAs) to enhance the search for Pareto-optimal sets [15].

Moreover, NSGA-III's compatibility with machine learning frameworks, such as the Batched Scalable Multi-Objective Bayesian Optimization (BS-MOBO) algorithm, further enhances its proficiency in managing high-dimensional data by incorporating gradient information and facilitating batch evaluations, which reduces computational costs [19]. Techniques like the normW method also improve the diversity and convergence of the Pareto front, offering decision-makers a comprehensive set of optimal trade-offs.

The proposed method introduces tight and moment relaxations to enhance Pareto point detection, demonstrating advantages over traditional scalarization techniques [6]. This capability is vital in complex systems like supply chains, where decision-makers must balance multiple objectives amid various constraints.

4.2 Handling High-Dimensional Data

Managing high-dimensional data in multi-objective optimization presents significant challenges, often leading to computational inefficiencies and convergence difficulties. Recent advancements, such as the Likelihood of Metric Satisfaction (LMS) acquisition function, improve sample efficiency by enabling the exploration of diverse outcomes that meet user-defined performance criteria rather than

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solely focusing on the Pareto frontier. Additionally, dimensionality reduction techniques enhance comparisons between quality diversity and multi-objective optimization frameworks, improving algorithms' ability to maintain diverse populations automatically [22, 25, 30].

Traceless Genetic Programming (TGP) is one technique that evaluates individuals based solely on outputs, allowing rapid convergence towards optimal solutions by focusing on output effectiveness rather than input complexity [13]. This approach is particularly advantageous when data dimensionality obscures the search for optimal solutions.

Parallel processing methods, such as Distributed Adaptive Processing (DAP), further enhance high-dimensional data management by enabling simultaneous data processing, reducing delays caused by bottlenecks [48]. This principle of parallelism is crucial in high-dimensional optimization tasks, where data volume can overwhelm traditional sequential processing.

Iterative methods, like the Improved Steepest Descent Algorithm, utilize refined line search strategies to iteratively update a set of nondominated solutions, systematically improving solution quality and maintaining focus on high-quality Pareto-optimal solutions [50].

Hypervolume and Inverted Generational Distance (IGD) metrics provide robust frameworks for evaluating optimization algorithms' performance in high-dimensional spaces, assessing selected subsets against the true Pareto front and offering insights into optimization efficiency [51]. By emphasizing these performance indicators, decision-makers can better understand trade-offs in high-dimensional optimization.

Systematic search processes that minimize oracle calls while ensuring thorough exploration of potential Pareto points are crucial for managing high-dimensional data, enhancing optimization algorithm efficiency by reducing unnecessary computations and focusing on promising solution space regions [47].

4.3 Applications in Manufacturing Efficiency

Method Name	**Optimization Techniques**	**Manufacturing Contexts**	**Solution Robustness**
RDU-PFA[49]	Repulsive Dynamics	Test Problems	Stochastic Components
IFSD[50]	Improved Steepest Descent	Multi-objective Optimization	Consistent Performance
MIT[33]	Multi-objective Optimization	Dynamic Supply Chain	Effective Under Uncertainty

Table 3: Overview of advanced optimization methods applied in manufacturing contexts, highlighting their respective optimization techniques, application areas, and robustness of solutions. The table compares the methods RDU-PFA, IFSD, and MIT, demonstrating their contributions to enhancing manufacturing efficiency through multi-objective optimization.

NSGA-III's implementation in manufacturing efficiency addresses complex multi-objective optimization challenges, balancing conflicting goals such as cost reduction, quality enhancement, and environmental sustainability. This algorithm is particularly valuable in dynamic manufacturing environments, where production requirements frequently change, necessitating continuous reevaluation of process parameters. By leveraging evolutionary solution adaptation techniques, as demonstrated in metal cutting process optimization, NSGA-III significantly reduces the number of costly simulations required for optimization, enhancing overall efficiency and adaptability [27, 36].

Advanced methods that employ repulsive dynamics among parameters associated with scalarized sub-problems achieve uniform Pareto front approximations, improving manufacturing efficiency [49]. This uniformity provides decision-makers with a comprehensive set of trade-offs essential for optimizing manufacturing objectives.

The Improved Steepest Descent Algorithm (IFSD) demonstrates significant improvements in multi-objective optimization through refined line search strategies that enhance solution set quality and exploration [50]. This adaptability is crucial in manufacturing contexts, where optimizing multiple objectives requires sophisticated computational approaches.

The MIT model exemplifies successful multi-objective optimization application in manufacturing by addressing material transportation between factories, reducing overall production and transportation costs while enhancing supply chain efficiency [33]. Such operational improvements are vital for maintaining competitiveness in the manufacturing sector.

Additionally, robust techniques employing Gaussian Processes in multi-objective Bayesian optimization enhance the identification of robust solutions by inferring Bayes risk and optimizing acquisition functions. This robustness is particularly advantageous in manufacturing environments characterized by uncertainty and variability, ensuring optimization solutions remain effective across various conditions and leading to improved decision-making and efficiency in complex multi-objective optimization scenarios [52, 53]. Table 3 provides a comprehensive comparison of advanced optimization methods utilized in manufacturing efficiency, detailing their optimization techniques, specific manufacturing contexts, and the robustness of their solutions.

4.4 Integration with Surrogate Models

Integrating NSGA-III with surrogate models represents a significant advancement in enhancing multi-objective optimization efficiency and effectiveness. Surrogate models, or metamodels, approximate objective functions and constraints in optimization problems, reducing the computational cost associated with evaluating complex, high-dimensional functions [11]. This integration is particularly beneficial in supply chain management, where decision-makers navigate a landscape of competing objectives, such as minimizing disruption risk, reducing carbon emissions, and maximizing efficiency [4].

NSGA-III's reference-point-based approach facilitates generating a diverse and well-distributed set of Pareto-optimal solutions, enhancing its suitability for integration with surrogate models [16]. The use of surrogate models, like Gaussian processes and Kriging, in conjunction with NSGA-III allows for more efficient exploration of the solution space by approximating objective functions [19]. This is especially advantageous in scenarios involving expensive evaluations, where direct computational burdens can be prohibitive.

The integration of surrogate models with NSGA-III also improves the algorithm's management of high-dimensional data, characteristic of supply chain optimization problems. Techniques such as the Batched Scalable Multi-Objective Bayesian Optimization (BS-MOBO) algorithm, which incorporates gradient information and facilitates batch evaluations, support NSGA-III's role in high-dimensional data analysis [19]. These advancements enable decision-makers to efficiently explore the solution space, identify optimal trade-offs, and make informed decisions amidst complex and competing objectives.

4.5 Visualization and Decision Support

Visualization is crucial for supporting decision-making in multi-objective optimization, especially when employing advanced algorithms like NSGA-III. The complexity of high-dimensional data necessitates effective visualization techniques to help decision-makers understand trade-offs among competing objectives and select suitable solutions. Visualizing the Pareto front, which represents non-dominated solutions, is essential for interpreting multi-objective optimization results and making informed decisions [6].

NSGA-III facilitates generating a well-distributed set of Pareto-optimal solutions that can be effectively visualized, providing a comprehensive overview of the solution space [16]. This is particularly beneficial in supply chain management, where decision-makers must balance objectives such as minimizing disruption risk, reducing carbon emissions, and maximizing efficiency. Visualization techniques, including parallel coordinates and scatter plots, allow decision-makers to explore the Pareto front, identify patterns, and evaluate trade-offs involved in selecting different solutions [2].

Advanced visualization methods, such as the Smooth Tchebycheff Scalarization (STCH) method, enhance decision-making by providing efficient solutions for gradient-based multi-objective optimization, allowing better trade-offs among conflicting objectives and complementing NSGA-III's capabilities in generating diverse Pareto fronts [21]. Additionally, interactive visualization tools enable decision-makers to incorporate their preferences into the optimization process, facilitating a more targeted search for preferred solutions [17].

Integrating visualization techniques with NSGA-III supports the identification of robust solutions amidst uncertainty and variability, as decision-makers can visually assess the impact of different scenarios on the Pareto front. This capability is particularly important in supply chain management, where the dynamic nature of operations requires adaptive and resilient solutions [20].

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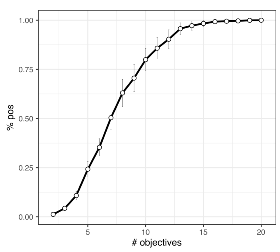
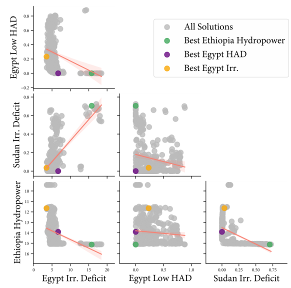
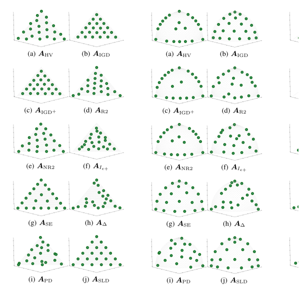


(a) The graph shows the percentage of positive outcomes (pos) as a function of the number of objectives (x-axis) for a dataset.[25]



(b) Comparative Analysis of Solutions for Water Management in Egypt, Sudan, and Ethiopia[23]



(c) Comparison of Different Angle-Based Averages for a Triangle[29]

Figure 3: Examples of Visualization and Decision Support

As illustrated in Figure 3, the NSGA-III algorithm is pivotal in addressing challenges associated with high-dimensional data, particularly in visualization and decision support. The first subfigure highlights the relationship between the number of objectives and the percentage of positive outcomes, demonstrating the algorithm's capacity to handle increasing dimensions while maintaining desirable results. The second subfigure presents a comparative analysis of water management solutions in the geopolitical context of Egypt, Sudan, and Ethiopia, emphasizing the algorithm's utility in evaluating and visualizing multiple competing objectives for decision-making. Lastly, the third subfigure compares different angle-based averages for a triangle, underscoring NSGA-III's versatility in processing and visualizing complex geometric data. Collectively, these examples illustrate the algorithm's robust capabilities in transforming high-dimensional data into actionable insights, providing valuable decision support across diverse fields [25, 23, 29].

Feature	Introduction to NSGA-III and its Advantages	Handling High-Dimensional Data	Applications in Manufacturing Efficiency
Optimization Technique	Reference-point-based	Dimensionality Reduction	Evolutionary Solution Adaptation
Application Domain	High-dimensional Optimization	Multi-objective Optimization	Manufacturing Optimization
Key Advantage	Diverse Solution Generation	Improved Sample Efficiency	Reduces Costly Simulations

Table 4: This table provides a comparative analysis of various optimization techniques related to NSGA-III, focusing on their applications and advantages in handling high-dimensional data and enhancing manufacturing efficiency. It categorizes the methods by their optimization techniques, application domains, and key advantages, offering insights into their effectiveness in multi-objective optimization scenarios.

5 Pareto Front Analysis for Trade-Off Identification

5.1 Role of Pareto Optimality in Decision-Making

Pareto optimality is fundamental in multi-objective optimization (MOO), providing a framework for decision-makers to address scenarios involving competing objectives, such as cost efficiency, risk mitigation, and carbon emission reduction in supply chain management. It delineates a set of non-dominated solutions, known as the Pareto front, where improving one objective necessitates trade-offs in others. This visualization aids decision-makers in understanding inherent trade-offs, guiding them towards informed and balanced choices [16].

Advanced methodologies like the Pareto front-Diverse Batch Multi-Objective Bayesian Optimization (PDBO) enhance the effectiveness of Pareto front analysis by improving diversity and coverage, crucial for presenting a comprehensive set of trade-offs to decision-makers [54]. Additionally, diversity metrics in multi-objective evolutionary algorithms (MOEAs) emphasize the significance of a well-distributed Pareto front in decision-making processes [9].

Incorporating input uncertainty into optimization enhances Pareto optimality's role further. The Robust Multi-Objective Bayesian Optimization with Input Uncertainty (RMOBO-IU) approach exemplifies this by integrating uncertainties efficiently, yielding more robust solutions suitable for supply chain management, where demand and supply uncertainties are prevalent [10].

The Self-Evolutionary Optimization (SEO) method optimizes hyper-parameters affecting hypervolume, thus improving Pareto front approximation quality [35]. This enhancement is vital for ensuring access to a diverse set of optimal solutions, supporting effective decision-making.

Furthermore, the STCH method achieves efficient convergence and effective trade-offs among conflicting objectives, aligning with Pareto optimality principles and enabling decision-makers to select solutions that are both mathematically optimal and strategically relevant [21].

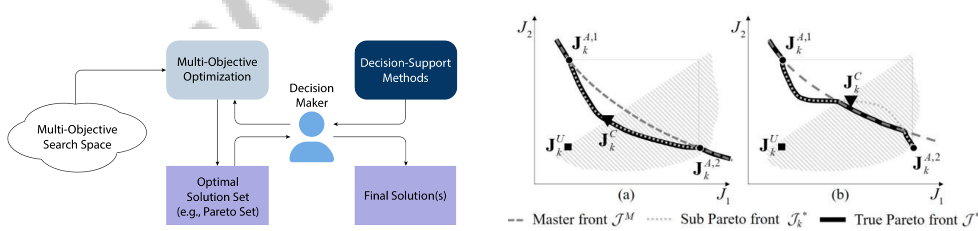
5.2 Techniques for Pareto Front Generation

Generating Pareto fronts is critical in MOO, offering decision-makers a comprehensive array of trade-offs among competing objectives. Innovative techniques have emerged to efficiently generate these fronts, each with unique advantages in solution diversity and computational efficiency. For instance, Pareto HyperNetworks (PHNs) allow simultaneous learning of the entire Pareto front from a single hypernetwork, eliminating the need for separate models for each point. Advanced algorithms for enumerating Pareto fronts optimize oracle calls, enhancing solution identification efficiency. Additionally, frameworks for Controllable Pareto Front Learning integrate scalarization functions, improving accuracy while reducing computational costs compared to traditional methods. Evolutionary diversity optimization techniques leverage multi-objective indicators to ensure a diverse set of solutions that meet quality criteria [55, 22, 56, 57, 47].

The K-Pruning method utilizes knee points as geometrically meaningful references for pruning decisions, effectively generating Pareto fronts by focusing on promising regions of the solution space [58]. This approach ensures that the generated Pareto front is not only diverse but also representative of significant trade-offs.

Another notable method involves factorized approximations, as seen in the study of the mNM landscape, which reveals how variable interactions shape Pareto fronts and employs the Boltzmann distribution to modify these shapes while preserving solution dominance [59]. Such insights enable decision-makers to better understand the solution space structure and identify optimal trade-offs.

These techniques are especially relevant in supply chain management, where the complexity and dimensionality of optimization problems necessitate efficient Pareto front generation methods. By providing decision-makers with diverse optimal solutions from MOO models, these methodologies enhance strategic decision-making, bolstering resilience and sustainability in supply chain operations by balancing trade-offs between cost minimization and network connectivity amid disruptions and evolving market conditions [18, 33, 31, 24, 4].



(a) Multi-Objective Optimization Process[23]

(b) Comparison of Pareto Fronts in Two Different Scenarios[58]

Figure 4: Examples of Techniques for Pareto Front Generation

As illustrated in Figure 4, Pareto Front Analysis is crucial for identifying trade-offs between conflicting objectives in multi-objective optimization. Figure (a) presents a comprehensive optimization process, where a search space is transformed through an optimization algorithm to yield an optimal solution set, subsequently evaluated by a decision-maker using decision-support methods. Figure (b) compares Pareto fronts across two scenarios, highlighting configuration nuances in a two-dimensional space. These visual examples underscore the importance of Pareto Front Analysis in navigating complex multi-objective decision-making landscapes, facilitating informed choices through clear trade-off visualizations [23, 58].

5.3 Innovative Approaches to Pareto Front Analysis

Innovative approaches to Pareto front analysis have significantly advanced multi-objective optimization, enhancing the efficiency and effectiveness of identifying optimal trade-offs among competing objectives. These methods are crucial in high-dimensional optimization problems, particularly in supply chain management, where decision-makers must navigate complex trade-offs among objectives like minimizing disruption risks, reducing carbon emissions, and maximizing operational efficiency amid uncertainties in demand, costs, and lead times. Robust multi-objective optimization techniques, including evolutionary and genetic algorithms, allow for effective exploration of the solution space, identifying configurations that balance these priorities, thereby enhancing supply chain resilience and sustainability [4, 31, 18, 24].

The Repulsion Dynamics approach is one such innovative method, improving the uniformity of Pareto front approximations through a repulsion mechanism among solutions, ensuring an even distribution along the Pareto front and enhancing the robustness of the optimization process [49].

The Smooth Tchebycheff Scalarization (STCH) method provides a lightweight, efficient solution for gradient-based multi-objective optimization, facilitating better trade-offs among conflicting objectives and complementing advanced algorithms like NSGA-III in generating diverse, well-distributed Pareto fronts [21]. This method is particularly beneficial in supply chain management, where the high dimensionality of optimization problems necessitates advanced Pareto front analysis techniques.

Bayesian optimization techniques, such as the Pareto front-Diverse Batch Multi-Objective Bayesian Optimization (PDBO) algorithm, significantly improve the diversity and coverage of the Pareto front through Determinantal Point Processes (DPPs), dynamically selecting acquisition functions to enhance solution efficiency [49].

Moreover, integrating machine learning techniques, such as the Machine Learning-Supported Multiphysics Optimization (ML-MO) approach, allows for approximating outcomes from complex multiphysics simulations, reducing computational burdens and enhancing optimization efficiency, particularly relevant for high-dimensional data analysis [19].

5.4 Challenges and Limitations of Traditional Methods

Traditional methods for Pareto front analysis in multi-objective optimization encounter several challenges, especially in complex real-world scenarios like supply chain disruption risk and carbon emissions management. A primary limitation is the computational complexity involved in generating and analyzing Pareto fronts, particularly in high-dimensional spaces, leading to substantial costs and hindering efficient exploration of the solution space [5].

Many traditional techniques assume a convex Pareto front, which may not hold true in practice, leading to inaccuracies in representation and suboptimal solutions. This misrepresentation obscures true trade-offs, which are often non-linear and inhomogeneous, complicating the identification of optimal solutions [23, 38, 60, 29].

Furthermore, the complexity of real-world applications often involves numerous objectives and constraints, making it challenging to accurately depict the true Pareto front. The unknown nature of this front can affect result interpretability, hindering decision-makers' ability to understand trade-offs among competing objectives [5]. This lack of clarity can impede decision-making, as identifying suitable solutions aligned with strategic goals becomes difficult.

Traditional optimization methods also struggle with adaptability, often failing to integrate decision-maker preferences effectively, which is crucial for addressing specific interests and ensuring alignment with objectives in multi-objective scenarios. This limitation can yield suboptimal solutions, as these methods typically approximate the entire Pareto front rather than focusing on preferred solutions that matter most to decision-makers [22, 16, 41, 23, 28]. Consequently, solutions may be mathematically optimal yet lack practical relevance, failing to align with strategic objectives.

To address these challenges, innovative methods for Pareto front analysis have been developed, including the Repulsion Dynamics approach, which employs adaptive strategies to achieve a uniform approximation of the Pareto front through a binary repulsive mechanism, and the Smooth Tchebycheff Scalarization (STCH) method, offering a computationally efficient framework for gradient-based optimization while maintaining strong theoretical properties for identifying optimal trade-offs among conflicting objectives [23, 56, 49, 21]. These advancements enhance solution diversity and computational efficiency, equipping decision-makers with a more comprehensive set of optimal trade-offs. By leveraging these innovations, decision-makers can navigate the complexities of multi-objective optimization more effectively, making informed decisions in real-world challenges.

6 Case Studies and Applications

The application of multi-objective optimization (MOO) techniques across various sectors is pivotal in addressing contemporary optimization challenges. This section presents case studies exemplifying MOO's practical applications, demonstrating its effectiveness in solving complex problems across industries. The first case study explores a corporate merger in the food processing industry, where MOO optimizes merger configurations while aligning with economic and environmental objectives.

6.1 Corporate Merger in Food Processing Industry

MOO's application in corporate mergers within the food processing industry underscores its practical implications and efficacy. A significant example involves analyzing a merger, validating MOO's effectiveness with real-world data [31]. Mergers in this sector face challenges like supply chain integration, operational alignment, and environmental policy harmonization, requiring an optimization approach that addresses conflicting objectives such as cost efficiency, service level maintenance, and carbon emissions reduction [31].

The MOO model evaluates various merger configurations, considering economic and operational factors. By identifying Pareto-optimal solutions, decision-makers can explore trade-offs, ensuring the selected merger configuration aligns with strategic and operational constraints [31]. This approach enhances supply chain efficiency and resilience while promoting sustainable development by balancing economic and environmental goals.

Validating the optimization model with real-world data highlights MOO's applicability in addressing complex challenges, supporting decision-makers in navigating corporate mergers and fostering sustainable development and competitive advantage in the food processing industry [31].

6.2 Industrial Wire Drawing Problem

The industrial wire drawing process, a crucial manufacturing component, involves reducing wire diameter through a series of dies while balancing objectives such as energy consumption, production efficiency, and product quality. MOO offers a robust framework for addressing these challenges, enabling the identification of Pareto-optimal solutions that effectively balance these objectives [7].

A case study in the wire drawing sector showcases MOO techniques, employing advanced algorithms like the Non-dominated Sorting Genetic Algorithm III (NSGA-III), which excels in high-dimensional optimization problems [16]. NSGA-III's reference-point-based approach generates diverse Pareto-optimal solutions, offering insights into trade-offs among cost, quality, and efficiency objectives [14].

Integrating machine learning frameworks, such as the Machine Learning-Supported Multiphysics Optimization (ML-MO) approach, enhances optimization by approximating outcomes from complex simulations, reducing computational burdens, and facilitating optimal trade-off identification [19]. Techniques like the Improved Multi-Objective Steepest Descent Algorithm and the Sliding Window Approach for Three-Objective Pareto Optimization improve convergence rates and solution quality, addressing unique challenges in optimizing multiple conflicting objectives in the wire drawing process [27, 61, 26].

This case study emphasizes MOO's critical role in enhancing manufacturing efficiency and product quality. By providing a structured framework for evaluating optimal trade-offs, MOO contributes to developing more efficient and sustainable manufacturing processes, bolstering industrial sector competitiveness across logistics, finance, environmental management, and engineering [23, 24, 27].

6.3 Complex Networks and Human Language Optimization

In multi-objective optimization, complex networks and human language processing present unique challenges and opportunities. These domains involve high-dimensional data and intricate interdependencies, necessitating advanced optimization techniques to navigate the solution space and identify Pareto-optimal solutions. Genetic algorithms, particularly NSGA-III, have shown promise in addressing these complexities [16].

In complex networks, MOO balances objectives such as network efficiency, robustness, and resource utilization. Innovative methods like Repulsion Dynamics improve the uniformity and diversity of Pareto front approximations, providing decision-makers with comprehensive trade-offs [49]. This is crucial for optimizing network structures, where conflicting objectives like minimizing latency and maximizing throughput must be considered.

In human language processing, MOO optimizes aspects of language models, including accuracy, efficiency, and interpretability [19]. The complexity of these tasks necessitates advanced techniques capable of handling high-dimensional data and balancing multiple objectives. Frameworks like ML-MO further enhance optimization efficiency by approximating outcomes from complex simulations, reducing computational burdens, and supporting optimal trade-off identification [19].

The evaluation of MOO techniques in complex networks and human language processing is exemplified by genetic algorithms that approximate the Pareto front, demonstrating their potential in efficiently exploring high-dimensional solution spaces and identifying Pareto-optimal solutions. By offering a comprehensive set of trade-offs, these methods support informed decision-making in complex optimization scenarios [62].

6.4 Performance Evaluation using EAGO

Benchmark	Size	Domain	Task Format	Metric
BM-SS[51]	288	Evolutionary Multi-objective Optimization	Subset Selection	Hypervolume, IGD
EAD[57]	50	Traveling Salesperson Problem	Diversity Optimization	HYP, IGD
MOC-OP[36]	4	Manufacturing Optimization	Multi-Objective Optimization	Hypervolume
FEWN[5]	567	Food-Energy-Water Nexus	Multi-objective Optimization	Hypervolume

Table 5: This table presents a comparative overview of various benchmarks utilized in the domain of multi-objective optimization, highlighting their respective sizes, domains, task formats, and evaluation metrics. The benchmarks include BM-SS, EAD, MOC-OP, and FEWN, each addressing distinct optimization challenges and employing metrics such as Hypervolume and IGD to assess performance.

The Evaluation of Adaptive Global Optimization (EAGO) algorithm marks a significant advancement in the performance evaluation of multi-objective optimization solutions, particularly in supply chain management. EAGO addresses high-dimensional optimization challenges by providing an efficient framework for assessing Pareto-optimal solutions [14]. This is particularly relevant in supply chains, where decision-makers must balance conflicting objectives like minimizing disruption risks, reducing carbon emissions, and maximizing efficiency. Table 5 provides a comprehensive comparison of key benchmarks relevant to the performance evaluation of multi-objective optimization solutions, illustrating the diversity in domains and task formats addressed by these benchmarks.

A key feature of EAGO is its capability to handle non-convex optimization problems, common in real-world applications. By employing a global optimization approach, EAGO effectively explores the solution space, identifying robust and well-distributed Pareto-optimal solutions [6]. This capability is critical for supply chain decision-making, where the complexity and high dimensionality of optimization problems necessitate advanced evaluation methods.

Moreover, employing data-efficient interactive multi-objective optimization techniques, such as the Data-Efficient Interactive Multi-Objective Optimization (DEIMO) approach, significantly enhances the performance evaluation process. This integration enables efficient exploration of the solution space and facilitates optimal trade-off identification among competing objectives, ensuring that decision-makers access high-quality Pareto-optimal solutions that are both mathematically robust and practically relevant [34].

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7 Challenges and Future Directions

The multifaceted challenges of multi-objective optimization (MOO) in supply chain management necessitate a comprehensive examination of computational complexities and innovative methodologies. This section delves into the critical issues of computational complexity and scalability, essential for enhancing the performance and applicability of optimization techniques in real-world scenarios.

7.1 Computational Complexity and Scalability

MOO in supply chain management faces significant computational complexity and scalability issues due to disruption risk mitigation and carbon emissions reduction challenges. The high-dimensional nature of these optimization problems, characterized by numerous objectives and constraints, often leads to computational inefficiencies that impede convergence. As objectives increase, traditional optimization techniques encounter scalability challenges, necessitating innovative methodologies and algorithmic adaptations to manage these complexities effectively [25].

Traditional methods for Pareto front analysis face computational demands in generating and analyzing Pareto fronts in high-dimensional spaces, with hypervolume calculations often proving prohibitively expensive, impacting scalability [5]. This is particularly challenging in supply chain networks, where sophisticated models must balance multiple conflicting objectives [31]. Moreover, traditional approaches may rely on assumptions like the convexity of Pareto fronts, not always valid in practical scenarios, leading to inaccuracies in solution representation and suboptimal outcomes. Advanced MOO methods are required to analyze trade-offs, visualize solutions, and accommodate decision-maker preferences, enhancing the accuracy and relevance of Pareto front representations [23, 60].

Innovative methodologies such as the Incremental Multi-Objective Optimization (IMO) approach enhance performance by incorporating decision-maker preferences into the optimization process, improving solution quality and computational efficiency [50]. Advancements like Repulsion Dynamics enhance the uniformity and convergence of Pareto front approximations, providing decision-makers with a comprehensive set of optimal trade-offs [49]. The Attention-based Deep Segmentation Network (ADSN) supports optimization by focusing on the most informative data parts, although the complexity introduced may hinder real-time applications.

The choice of hyper-parameters in methods like the Improved Multi-Objective Steepest Descent Algorithm (IFSD) and the Smooth Tchebycheff Scalarization (STCH) method significantly impacts performance, highlighting the need for precise parameter tuning for effective optimization outcomes. The reliance on accurate real-time data, as demonstrated in the MIT model for material inventory and transportation problems, underscores the importance of precise data for effective optimization [33].

Integrating game-theoretic perspectives and Bayesian optimization techniques into MOO frameworks presents promising avenues for addressing these challenges [20]. These advanced methods enable the incorporation of decision-maker preferences and facilitate more efficient decision-making processes, enhancing the resilience and sustainability of supply chains in the face of disruption risks and carbon emission challenges. Furthermore, applying MOO in sustainable closed-loop systems exemplifies how these approaches can effectively address both economic and environmental objectives in supply chain management [18].

Data-efficient interactive multi-objective optimization techniques offer potential solutions to these challenges, enabling more precise and efficient decision-making processes amid uncertainty [34]. By leveraging such advanced methods, supply chain managers can navigate the trade-offs between disruption risk and carbon emissions, ultimately contributing to the sustainable development of global supply chains.

7.2 Preference Modeling and Decision-Maker Integration

Preference modeling and integrating decision-maker preferences into MOO models are crucial for achieving solutions that align with strategic objectives and operational realities. These methods ensure that solutions are not only mathematically optimal but also practically relevant, reflecting decision-makers' goals and realities [43].

Interactive evolutionary multi-objective optimization (EMO) frameworks enhance the integration of decision-maker preferences by leveraging preference learning techniques that dynamically adjust

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the search process, focusing on regions of the Pareto front aligned with decision-maker preferences. This approach improves optimization efficiency and ensures that identified solutions are more aligned with decision-makers' goals, leading to informed and effective decision-making [43].

The effectiveness of these models hinges on the accuracy of decision-maker feedback. Inconsistent or erroneous preferences can adversely affect optimization results, leading to suboptimal solutions that do not align with strategic objectives [43]. Developing robust preference elicitation techniques that can accurately capture decision-maker preferences is essential for maintaining the effectiveness and relevance of the optimization process.

Integrating decision-maker preferences into MOO models is particularly crucial in supply chain management, where stakeholders must balance conflicting objectives—such as minimizing costs, mitigating risks, and reducing environmental impacts—while adapting to dynamic conditions influenced by unforeseen events [23, 24, 27, 31]. By incorporating preference information, decision-makers can navigate the trade-offs inherent in MOO, ensuring that identified solutions are both feasible and desirable.

7.3 Algorithm Adaptability and Robustness

The adaptability and robustness of MOO algorithms are crucial for addressing the complexities of supply chain management problems. With increasingly intricate supply chains and multiple conflicting objectives—such as cost efficiency, risk mitigation, and carbon emission reduction—advanced optimization algorithms capable of adapting to varying conditions and maintaining robustness across diverse scenarios are essential [6].

Efficiently managing high-dimensional data and exploring complex solution spaces is a significant challenge in developing adaptable MOO algorithms. Traditional methods often struggle with the computational demands of high-dimensional optimization problems, complicating convergence and the identification of optimal trade-offs among competing objectives [6]. Enhancing the adaptability and robustness of optimization algorithms is crucial.

The Repulsion Dynamics approach improves the uniformity of Pareto front approximations through a repulsion mechanism among solutions. This ensures a more even distribution of solutions along the Pareto front, enhancing the robustness of the optimization process and providing decision-makers with a comprehensive set of trade-offs [49]. This capability is particularly valuable in high-dimensional optimization problems, such as those encountered in supply chain management, where decision-makers must balance multiple objectives.

The CWS method has demonstrated strengths in managing multiple objectives and reducing computational complexity in MOO scenarios [32]. This method provides a robust framework for decision-makers to navigate the intricate landscape of multiple objectives, particularly in supply chain management, where the complexity and high dimensionality of optimization problems necessitate advanced techniques for effective Pareto front analysis.

Future research should focus on in-depth parametric analysis and exploring theoretical foundations related to dynamic systems or Markov chains, as suggested by [62]. Exploring methods to manage non-convexities and extending proposed methods to more general classes of optimization problems will be crucial for enhancing the adaptability and robustness of MOO algorithms [6].

7.4 Integration with Emerging Technologies

Integrating emerging technologies with MOO methods presents significant opportunities for enhancing optimization outcomes, particularly in complex systems like supply chain management. As global disruptions and stringent environmental regulations challenge supply chains, adopting advanced technologies—such as MOO models and genetic algorithms—empowers decision-makers to develop strategies that enhance service levels while addressing uncertainties in demand and environmental impacts [4, 31, 18].

Future research should focus on integrating various distribution functions into the mapping process, enhancing optimization outcomes by providing a comprehensive representation of the solution space. This enables decision-makers to identify optimal trade-offs [43]. Developing flexible frameworks for preference adaptation and learning user preferences is critical for tailoring solutions that align with decision-makers' goals and priorities, including advanced preference elicitation techniques that dynamically adjust to changing preferences [63].

Moreover, integrating advanced human-computer interaction methods and enhancing visual exploration techniques are crucial for improving the explainability of obtained solutions. Providing decision-makers with a clear view of the solution space significantly enhances the optimization process, enabling more informed and strategic decision-making [40].

Refining pruning techniques and exploring emerging trends in MOO are essential for enhancing optimization outcomes. By focusing on these areas, future research can address challenges associated with computational complexity and scalability, ultimately supporting the development of more efficient and effective optimization methods [27].

Validating benchmark methods with more realistic simulations is another important avenue for future research. Integrating proposed methods into other optimization frameworks allows researchers to assess their effectiveness in real-world scenarios, ensuring their practical applicability [36].

8 Conclusion

The investigation of multi-objective optimization (MOO) within supply chain disruption risk and carbon emissions management underscores its pivotal role in contemporary industrial challenges. By enabling the concurrent optimization of conflicting objectives such as cost efficiency, service level, and environmental sustainability, MOO emerges as an indispensable strategy for modern supply chain management. The transition of traditional optimization problems into multi-objective frameworks illustrates MOO's capacity to bolster resilience and sustainability in global supply chains.

Central to MOO is the Pareto front analysis, which elucidates optimal trade-offs among competing objectives. Advanced methodologies, like the Pareto front-Diverse Batch Multi-Objective Bayesian Optimization (PDBO) algorithm, have enhanced the diversity and comprehensiveness of Pareto fronts, equipping decision-makers with a broad spectrum of strategic options. The incorporation of input uncertainty, as demonstrated by the Robust Multi-Objective Bayesian Optimization with Input Uncertainty (RMOBO-IU) approach, further fortifies solution robustness, crucial for navigating uncertainties in supply chain management.

The NSGA-III algorithm is particularly notable for its adeptness in handling high-dimensional data, a frequent characteristic of supply chain optimization challenges. Its reference-point-based strategy, coupled with techniques such as the Smooth Tchebycheff Scalarization (STCH) method and Repulsion Dynamics, ensures a diverse and well-distributed set of Pareto-optimal solutions. This robust framework aids decision-makers in managing the intricacies of multiple objectives, significantly enhancing the efficacy of Pareto front analysis for informed strategic decisions.

The integration of machine learning frameworks, exemplified by the Machine Learning-Supported Multiphysics Optimization (ML-MO) approach, has markedly improved optimization efficiency by mitigating the computational demands of high-dimensional data analysis. The proficiency of these advanced methodologies in efficiently sourcing solution candidates highlights their applicability across diverse engineering domains, reinforcing the importance of MOO in addressing complex optimization issues.

Despite these advancements, traditional Pareto front analysis methods face challenges, particularly in high-dimensional contexts, necessitating continued innovation in MOO methodologies. The development of novel approaches, such as the Incremental Multi-Objective Optimization (IMO) and the extension of the NISE algorithm through the MONISE method, offers promising research directions. These innovations are vital for tackling the computational complexity and scalability challenges inherent in high-dimensional optimization problems, especially within supply chain management.

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