Original Research

A Multi-objective Leagile Demand-Driven Optimization Model incorporating a Reliable Omnichannel Retailer: A case Study

Farnaz Javadi Gargari[1], Zahra Saeidi-Mobarakeh[2], Hossein Amoozad Khalili[3*]

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*Corresponding Author, email, Amoozad92@yahoo.com

1. Industrial Engineering Department, Alzahra University, Deh Vanak, Tehran, Iran
2. Department of Industrial Engineering, Central Tehran Branch, Islamic Azad University, Tehran, Iran
3. Department of Industrial Engineering, Sari Branch, Islamic Azad University, Sari, Iran*

Abstract
This research proposes a comprehensive model aimed at optimizing supply chain networks, with a particular focus on leagile demand-driven systems within the context of omnichannel operations. The proposed model integrates various parameters such as total cost, lead time, service level, and residual capacity, addressing the complex interdependencies among retailers in an omnichannel environment. To enhance the reliability of the model, a hybrid meta-heuristic algorithm is employed, leveraging the strengths of MOEA/D-DE (Multi-Objective Evolutionary Algorithm with Differential Evolution), IBEA (Indicator-Based Evolutionary Algorithm), and NSGA-II (Non-dominated Sorting Genetic Algorithm II). This collaborative optimization approach ensures adaptability and efficiency in tackling diverse and intricate optimization challenges inherent in omnichannel networks. Numerical data from a case study on the supply of sanitary masks in Tabriz, Iran, during August 2021 is utilized to validate the model within the specific omnichannel context. The study includes a thorough sensitivity analysis, demonstrating the robustness of the model against disruptions in the omnichannel network. The consistent performance of the model across various disruption scenarios underscores its reliability and efficacy in maintaining the stability of supply chain operations within omnichannel frameworks. This observed resilience significantly enhances the overall robustness of the supply chain, particularly in the face of disruptive events. The model's ability to maintain stability under diverse conditions contributes to fortifying the supply chain against potential disruptions, thereby augmenting its adaptive capabilities in dynamic environments. Managerial and practical implications are discussed, emphasizing the significance of the proposed reliable omnichannel approach in leagile demand-driven systems.

Keywords- Supply Chain Optimization, Hybrid Integrated Meta-heuristic Algorithm, Leagile Demand-Driven Systems, Reliable Omnichannel, Case Study

INTRODUCTION

In the rapidly evolving realm of supply chain management, the fusion of technological advancements, industrial engineering principles, and innovative methodologies has instigated a paradigm shift, fundamentally reshaping the design and orchestration of supply chain networks. This research concentrates on a critical facet of modern supply chain dynamics, specifically examining the intricate interplay among three pivotal elements: reliability, omnichannel strategy, and the amalgamation of lean and agile methodologies within the framework of demand-driven networks. Reliability emerges as a central linchpin, bridging the synergistic implementation of omnichannel strategies and the harmonious integration of lean and agile practices. This underscores the essential role of reliability in unifying and bridging diverse components, emphasizing its critical influence on the successful implementation and cohesion of omnichannel, lean, and agile principles within the research framework.

The conventional supply chain models, characterized by rigid structures and linear processes, encounter significant challenges in adapting to the dynamic and unpredictable nature of contemporary markets [1]. The advent of omnichannel strategies, seamlessly integrating diverse channels like online, offline, and mobile platforms, addresses these challenges by establishing a unified and customer-centric approach [2]. The reliable omnichannel framework necessitates an infrastructure capable of harmonizing intricate elements, including inventory management, order fulfillment, and customer interactions, across a spectrum of channels. This strategic transition reflects a response to the evolving demands of the contemporary market, positioning organizations to address market dynamism challenges and enhance customer satisfaction through a more interconnected and responsive supply chain. Simultaneously, the integration of lean methodologies into supply chain management emphasizes eliminating wasteful practices and optimizing operational processes [3]. The leagile supply chain, a hybrid approach combining elements from both lean and agile strategies, aims to optimize overall performance by reducing costs and enhancing resource utilization and supply chain responsiveness. This integration fosters a supply chain that is not only efficient but also adaptive, responsive, cost-effective, and well-equipped to meet the evolving demands of a dynamic business environment. Additionally, the demand-driven supply chain prioritizes customer demand as the central driver, dynamically responding to real-time fluctuations, and emphasizing customer-centricity through the integration of analytics and AI technologies. This strategic framework enhances customer satisfaction, reduces lead times, optimizes inventory, and improves overall supply chain efficiency by aligning operations with actual customer needs [4].

The research problem addressed in this study revolves around the evolving landscape of supply chain management, where the convergence of technological advancements, industrial engineering principles, and innovative methodologies has led to a paradigm shift in the design and orchestration of supply chain networks. Specifically, the research focuses on the intricate relationship among reliability, omnichannel strategy, and the integration of lean and agile methodologies within the context of demand-driven networks. The research endeavors to offer a comprehensive understanding of the theoretical foundations, practical implications, and potential advancements resulting from the fusion of reliability, omnichannel strategy, and lean-agile methodologies in demand-driven supply chain networks. The paper makes substantial contributions by exploring the intersection of these elements, introducing a reliable omnichannel framework, and addressing gaps in existing literature. Overall, the study provides holistic insights into theoretical and practical dimensions, contributing to the fields of industrial engineering and supply chain management.

Furthermore, the objective is to enhance the dependability of the model through the utilization of a hybrid meta-heuristic algorithm, which draws upon the strengths of MOEA/D-DE (Multi-Objective Evolutionary Algorithm with Differential Evolution), IBEA (Indicator-Based Evolutionary Algorithm), and NSGA-II (Non-dominated Sorting Genetic Algorithm II). By employing this collaborative optimization strategy, flexibility and effectiveness are ensured in addressing the diverse and complex optimization hurdles inherent in omnichannel networks. The chief contributions of the presented paper are summarized as follows:

- The research explores the intersection of reliability, omnichannel strategy, and the integration of lean and agile methodologies. This comprehensive examination enhances our understanding of how these critical elements interact.
- The study presents a reliable omnichannel framework is identified as a crucial factor in unifying diverse components, ensuring successful implementation, and enhancing overall cohesion within the supply chain.
- The research's contributions are rooted in its holistic exploration, innovative framework development, and the bridging of theoretical and practical aspects within the context of demand-driven supply chain networks.
- A new integrated hybrid multi-objective meta-heuristic algorithm (hybrid of MOEA/D-DE, IBEA and NSGA-II) is presented.

The following sections outline the structure of the paper. The subsequent part provides a summary of prior research. In the third section, the mathematical problem is clearly defined. Section four delves into the presentation of solution methods. Moving on to the fifth section, it showcases the numerical results of the case study, including a sensitivity analysis of the proposed model and an assessment of the proposed algorithm's efficiency. The sixth part explores the managerial advantages derived from the research. Lastly, the paper concludes with a summary of the process and results, along with suggestions for future research.

LITERATURE REVIEW

This study is organized into three primary sections to provide a thorough understanding of the specified problem framework. In Section 2.1, the focus is on the topics investigated in supply chain optimization. Section 2.2 delves into the formulation of solution algorithms. The final section highlights the recognized research gaps and emphasizes the specific contributions of this study in advancing developments in this field.

I. Supply Chain Optimization Frameworks

The progression of research topics within supply chain management mirrors the dynamic character of the field. It moves through sequential developments where specific themes become more prominent in varying stages. This evolution highlights the field's adaptability to changing dynamics in global markets, technological advancements, and evolving consumer expectations. Over time, research focus has shifted across areas like lean methodologies, agile practices, sustainability, risk management, and the integration of advanced technologies. Each stage of development signifies a strategic response to emerging challenges and opportunities within the supply chain, showcasing the field's commitment to staying innovative and addressing current issues. In the initial phases, there was a notable focus on the lean concept in the field of supply chain management. Researchers and practitioners recognized the importance of optimizing processes, eliminating inefficiencies, and enhancing overall operational efficiency. This focus originated from lean manufacturing principles and gained prominence as organizations aimed to reduce non-value-added activities like excess inventory, lengthy lead times, and unnecessary costs.

The lean supply chain approach places a strong emphasis on continuous improvement and a customer-centric philosophy. Researchers and practitioners increasingly recognize the significance of these principles in achieving greater responsiveness to customer demands, optimizing resource utilization, and realizing cost savings through streamlined and efficient supply chain operations. This evolution highlights the enduring relevance of lean principles in shaping contemporary supply chain strategies. This emphasis is exemplified by studies conducted by researchers such as, [5], [6], [7], [8] and [9]. Subsequently, the focus shifted to a more holistic approach in supply chain management, incorporating not only lean principles but also embracing agile methodologies. This shift recognized the need for flexibility and adaptability in responding to dynamic market conditions, evolving customer preferences, and unforeseen disruptions. Agile practices, characterized by their responsiveness and quick decision-making, complemented the efficiency-driven nature of lean supply chains. The combination of lean and agile principles has become increasingly recognized as organizations strive to strike a balance between efficiency and flexibility, creating what is often referred to as a "Leagile" supply chain.

This integrated approach aims to harness the strengths of both lean and agile strategies, allowing organizations to navigate the complexities of modern supply chain dynamics with resilience and efficiency. This focus is illustrated by research conducted by scholars like [10], [11], [12], [13], [14] and [15]. Then, companies embraced practices that not only focused on efficiency but also prioritized resilience and adaptability within their supply chain networks. This shift was marked by the integration of robust principles, which emphasize the ability to withstand disruptions and uncertainties. The evolving landscape witnessed the coalescence of these robust practices with the established efficiency of leagile methodologies, forming a dynamic framework known as the "Robust Leagile Supply Chain Networks." This approach enables organizations to navigate the intricacies of contemporary markets by seamlessly blending the efficiency of lean strategies with the flexibility and responsiveness of agile practices. In doing so, companies aim to achieve a balance that not only optimizes resource utilization but also ensures a robust and adaptable supply chain, aligned with the demands of the market and customers. This focus is demonstrated by research carried out by academics like [16], [17], [18] and [19].

Facilitate a seamless and unified customer experience. This involves the integration of multiple sales channels, such as online platforms, physical stores, and mobile applications, into a cohesive and interconnected supply chain network. The key objective is to break down silos between different channels and create a unified front-end and back-end system that allows customers to browse, purchase, and return products seamlessly, regardless of the channel they choose. This strategy not only meets the evolving expectations of modern consumers who seek convenience and flexibility but also optimizes inventory management and order fulfillment processes for businesses. Ultimately, omnichannel supply chain management aligns with the dynamic nature of contemporary retail, positioning businesses to thrive in an interconnected and customer-centric marketplace. This emphasis is illustrated by studies conducted by scholars such as [20], [21], [22] and [23].

TABLE 1
LITERATURE REVIEW

	Ref.	Research
an Supply Chain	[5]	• Presentation of various common implementation techniques of Lean Supply Chain Management (LSCM) within the healthcare sector. • Examination of factors influencing the selection of target areas and techniques for LSCM implementation by healthcare organizations. • Identification of key areas where lean approaches can enhance healthcare supply chains and development of a standardized language for incorporating lean principles into healthcare management. • Description of practical applications of lean methodologies to improve efficiency in healthcare supply chains. • Provision of valuable insights for healthcare decision-makers regarding the benefits of LSCM implementation, along with highlighting factors such as internal employee dynamics, cost management, medication distribution systems, patient safety, and instrument utilization that affect its application. • Proposal for integrating LSCM principles with healthcare industry objectives to positively impact both healthcare service quality and cost efficiency. • Additionally, suggesting the establishment of standardized terminology for incorporating lean principles into healthcare management practices.
	[6]	• Exploration the impact of lean management on the efficiency of focal firms • Methodology: • Expanding the adoption of lean management throughout the supply chain enhances the operational efficiency of the primary company, in accordance with resource-based theory and the principles of integrated supply chain management. • The internal implementation of lean management within a company boosts its operational efficiency, particularly when it complements the implementation of lean supply chain management practices. • Introducing a structured framework for assessing the operational facets of implementing and planning a lean supply chain strategy. • Adopt a holistic approach to lean supply chain management, utilizing a validated instrument. • Emphasize the need for complementing internal lean practices with those in the supply chain for a comprehensive understanding of factors influencing focal firm efficiency.
	[7]	• Exploration the intersection of lean supply chain management and Industry 4.0 • Develop a conceptual reference model named Lean Supply Chain Planning 4.0 (LSCP 4.0). • LSCP 4.0 integrates Industry 4.0 digital technologies with lean manufacturing tools, with a specific focus on waste reduction and cost minimization in lean supply chain planning. • Offerring valuable insights for decision-makers and researchers to enhance digital supply chain production processes.
	[8]	• Investigate the role of Lean Supply Chain Management (LSCM) as a strategic mechanism for addressing technology uncertainty and enhancing the competitive advantage of organizations. • Utilizing a covariance-based structural equation model (CB-SEM). • Technological uncertainty promotes the adoption of lean practices throughout the supply chain, contributing to stability, improved performance, and a strengthened competitive position for the focal company. • Emphasizing long-term relationships based on trust and commitment to enhance organizational capabilities in responding effectively and flexibly to technological changes.
	[9]	• Examining the impact of both internal and external integration of supply chains on the operational effectiveness of manufacturing firms in Jordan. • Investigating the potential intermediary function of lean operations and practices within this correlation. • Internal and external integration of the supply chain is linked to an increased probability of attaining favorable operational performance, particularly concerning quality metrics. • Identification a positive mediating effect of adopting lean practices among manufacturing companies. • Lean operations play a facilitating role, exerting a positive impact on the connection between the integration of internal and external supply chains, particularly in terms of enhancing the quality dimensions of operational performance.

	Ref.	Research
Leagile Supply Chain	[10]	• Exploration the intersection of Industry 4.0 technologies with lean and agile supply chain management (SCM) strategies • Being the impact and significance of Industry 4.0 technologies on lean and agile practices within SCM operations. • Culmination in a model derived from cross-case analysis, illustrating the technologies influencing lean and agile practices. • Presentation insights into the potential impact of Industry 4.0 technologies on lean and agile practices and their consequent effects on performance. • A substantial impact of these technologies on SCM practices, with varying degrees of influence. • Identification key technologies significantly affecting lean and agile SCM, offering a nuanced understanding of how different digital technologies enable specific sets of practices.
	[11]	• Investigating the correlations among established information technologies (ITs), emerging IT, and the integration of lean and agile supply chain (SC) methodologies. • Highlighting that the utilization of mature IT serves as a catalyst for implementing both lean and agile strategies within the supply chain. • Identifying the moderating role of lean supply chain (LSC) in the association between mature IT and agile supply chain (ASC) when companies adopt both strategies. • Underscoring the necessity for a gradual consolidation process over time to effectively support the advancement of both lean and agile strategies through the implementation of emerging IT.
	[12]	• Investigating the influence of ambidexterity on supply chain performance and exploring how lean and agile supply chains mediate this relationship. • Ambidexterity supports companies in balancing the need to optimize short- and long-term performance while remaining agile and flexible in response to changes in the business environment. • Ambidexterity enhances supply chain performance directly and also magnifies the positive effects of lean and agile supply chain practices. • The importance for companies to enhance operational efficiency, effectiveness, and adaptability to environmental changes and market demands.
	[13]	• Introducuction a leagility assessment framework utilizing the fuzzy quality function. • The paramount capability identified for the automotive supply chain is 'order guidance'. • While 'E-fulfilment logistic' is recognized as the most crucial enabler for achieving supply chain leagility.
	[14]	• Exploration the application of Leagile principles, an integrated lean and agile approach, in software development organizations. • Proposing that Leagile principles generally enhance operational performance, with the exception of the perfection principle. • Emphasizes the importance of enhancing the embracing of Leagile principles in software development organization. • Offering valuable insights for practitioners in the field.
	[15]	• Presentation a comprehensive framework for assessing the impact of lean and agile innovation on lean and agile supply chains within the pharmaceutical industry. • The findings revealed that improvements in lean innovation led to a 97.9% enhancement in lean supply chain performance, while agile innovation contributed to a 97.1% improvement in agile supply chain performance. • Practical implications suggest that pharmaceutical companies should focus on the conceptualization process for lean innovation and emphasize idea generation to enhance their agile supply chain. • The originality of the research lies in its unique approach of selecting and classifying variables, along with the utilization of a positioning matrix before statistical analysis, setting it apart from similar studies in the literature.
Robust Supply Chain	[16]	• Introduction an innovative multi-objective model for addressing closed-loop supply chain problems, incorporating lot sizing and simultaneously considering lean, agility, and sustainability factors. • Integration responsiveness, environmental, social, and economic aspects, incorporating capacity and service-level constraints. • Introduction the strategic and operational backup decisions to enhance system resilience against facility and route disruptions. • Presentation a novel hybrid metaheuristic algorithm is proposed, combining a parallel Multi-Objective Particle Swarm Optimization (PMOPSO) algorithm with a Multi-Objective Social Engineering Optimizer (MOSEO). • Affirmation the effectiveness of the hybrid algorithm through a comparison with the Non-dominated Sorting Genetic Algorithm (NSGA-II).

	Ref.	Research
	[17]	• Presentation a three-objective mathematical model, incorporating economic, environmental, and social aspects. • Confirmation of the model's validity through validation with the NSGA-III metaheuristic algorithm, particularly for large-scale dimensions. • Investigation a case study involving a pharmaceutical supply chain in Iran to assess the model's practical applicability, analyzing critical parameters and evaluating solution results.
	[18]	• Introducing innovative methods aimed at enhancing the efficiency and adaptability of industries. • Creating a decision-making framework to address the challenges associated with selecting viable suppliers. • After identifying key indicators and potential solutions for the research problem, a novel approach known as goal programming-based fuzzy best–worst method (GP-FBWM) is suggested for determining the weights of these indicators. • Implementing the devised method and conducting an analysis of the resulting outcomes. • Offering practical and theoretical insights for managerial consideration.
	[19]	• Introducing a novel framework aimed at establishing a sustainable and environmentally conscious closed-loop supply chain network, encompassing both online and offline channels. • He objective is to provide managers with tools to facilitate economically and environmentally responsible decision-making processes. • The model integrates various factors, including the carbon cap-and-trade policy, regional protection policies of the retailer, and the utilization of multiple modes of transportation. • A robust model is proposed, employing a polyhedral uncertainty set derived from principal component analysis and kernel smoothing techniques. • Addressing the complex and large-scale nature of the supply chain network, a two-stage adaptive genetic algorithm is introduced. • The findings indicate that a rise in online customer activity can help alleviate inventory shortages. However, heightened unpredictability in demand substantially increases overall uncertainty
Omnichannel Supply Chain	[20]	• Presentation an omnichannel services that blend online and offline channels, providing real-time information for enhanced customer engagement. • The integration of healthcare wearable devices has become essential in connecting providers and patients within the omnichannel landscape. • Presentation a framework that combines traditional statistical methods with machine learning approaches to analyze extensive datasets, facilitating the development of a data-driven analytic model for the effective management of omnichannel healthcare supply chain businesses.
	[21]	• Optimization models are developed for the OCLSC system within an omnichannel retail setting. • Implementing BOPS in the manufacturer's dedicated physical store proves advantageous for OCLSC profits. • Investigate the impact of risk attitude on the operational decisions and profits of OCLSC. • Identify the crucial parameters influencing the implementation of the BOPS strategy.
	[22]	• Introduction a two-phase methodology for the selection and demand forecasting of suppliers for omnichannel (OC) retailers. • A comprehensive five-dimension framework is established to assess suppliers, encompassing various aspects. • The optimization model takes into account diverse disruption risks and corresponding strategies. • The geographical location of suppliers is meticulously considered in the analysis.
	[23]	• Concentrating on the internal transformations within a company that impact the function of its supply chain department and its engagements with external entities in the retail sector. • Delving into the specifics of novel business procedures, organizational frameworks, governance structures, and customer engagements, collectively termed as the Retail Business Model (BM). • Recognizing the essential components of the emerging retail BM, constructing a theoretical framework for the BM evolution process, and underscoring the pivotal role of the supply chain department in enabling the adoption and execution of omnichannel strategies.

II. Solution Approaches

In the realm of solution algorithms, notable progress has been observed in the evolutionary trajectory, especially in the fields of industrial engineering, supply chain management, and artificial intelligence. A pivotal moment in this evolution was marked by the introduction of genetic algorithms as a pioneering approach. Following this milestone, researchers undertook the mission to investigate and improve other single-objective algorithms, with the goal of diversifying and optimizing problem-solving methodologies. Prominent contributions to the enhancement of the genetic algorithm can be found in key articles by [24], [25], and [26]. As the discipline advanced, a pivotal evolution surfaced with the advent of multi-objective algorithms, recognizing the inherent intricacy of real-world problems marked by multiple competing objectives. These algorithms aimed to discover solutions that reflect a harmonious balance among diverse objectives, a paramount aspect in fields like supply chain management where varied and conflicting goals are prevalent. Significant strides in this realm are evident in the research by [27], [28], [29] and [30]. A noteworthy transformation in algorithmic design involved recognizing the potential for achieving superior outcomes through the amalgamation of diverse algorithms.

This innovative approach, known as algorithmic hybridization, entails integrating the strengths of various algorithms to augment overall performance. Researchers uncovered that synergistic combinations could harness the individual strengths of algorithms, resulting in enhanced problem-solving capabilities. Illustrative instances of such hybridization endeavors can be found in the works of [31], [32], [33], as well as [34]. The specifics of these articles are detailed in Table 2, providing a comprehensive overview of the evolving research landscape in value chain management.

TABLE 2.
LITERATURE REVIEW OF SOLUTION ALGORITHM

	Ref.	Research
Single Objective Algorithm	[24]	• Proposes an improved real-coded genetic algorithm (RCGA-rdn) addressing poor search ability and population diversity loss. • Integrates specialized operators (RGS, DBX, NM) for enhanced search capabilities. • Compares RCGA-rdn with advanced algorithms on constrained and unconstrained optimization problems, showcasing its effectiveness.
	[25]	• Introduces a new genetic algorithm (GABONST) focusing on balancing exploitation and exploration in optimization problems. • Applies GABONST to language recognition (LID) by integrating it with extreme learning machine (ELM). • Evaluates algorithm performance using statistical measures, demonstrating superiority over conventional algorithms.
	[26]	• Introduces a new algorithm based on simplified crowd optimization. • Focuses on hyperparameter optimization for the LeNet CNN model, achieving higher accuracy on datasets compared to original models. • Demonstrates potential extension to more complex models.
Multi-Objective Algorithm	[27]	• Investigates pool-based and generative approaches in multi-objective molecular discoveries. • Explores pool-based molecular discovery as an extension of multi-objective Bayesian optimization. • Utilizes different generative models for single and multi-objective optimization. • Highlights the integration of Bayesian optimization techniques in de novo multi-objective design.
	[28]	• Introduces the Marine-Predator Multi-Objective Algorithm (MOMPA) based on elitist non-dominated sorting and crowding distance mechanism. • Inspired by the Marine-Predator algorithm, effectively handles optimization problems with multiple conflicting objectives. • Demonstrates MOMPA competence qualitatively and quantitatively.
	[29]	• Introduces improved computational efficiency in Multi-Objective Evolutionary Algorithms (MOEA) through the Pareto Front Network. • Proposes a rare point estimation strategy to reduce computation time. • Validates the effectiveness of PFG-MOEA through performance comparison with other multi-objective evolutionary algorithms.
	[30]	• Introducing a groundbreaking multi-objective cooperation search algorithm (MOCSA) that integrates innovative features such as adjusted team communication, reflective learning mechanisms, and internal competitive strategies to bolster both extensive global exploration and precise local exploitation. • MOCSA undergoes comprehensive evaluation across a spectrum of multi-objective benchmark functions and practical engineering challenges with constraints, exhibiting notably superior performance compared to rival algorithms. • The algorithm showcases remarkable efficacy in search capabilities, particularly in securing feasible solutions for engineering problems constrained by various factors. • Application of MOCSA to a real-world reservoir management system under diverse operational scenarios unveils its effectiveness in furnishing a spectrum of decision alternatives and generating a diverse array of non-dominant solutions within the confines of the feasible solution domain.

	Ref.	Research
Hybrid Algorithm	[31]	• Introduces a hybrid algorithm combining Gray Wolf Optimization (GWO) with Genetic Algorithm (GA). • Utilizes genetic algorithm mutation and crossover operators for timing improvements. • Demonstrates faster convergence of GA-based GWO, especially for large-scale scheduling problems. • Validated using synthetic and real-world datasets, proving its effectiveness.
	[32]	• Presenting a new approach in airport gate allocation through the introduction of the RPIP-GA, a genetic algorithm with innovative features. • Addressing common drawbacks associated with traditional genetic algorithms, such as slow convergence and susceptibility to local optima. • The RPIP-GA integrates multiple strategies in a hybrid approach, including reverse learning, interval probability mutation, and a phagocytosis mechanism. • Experimental validation, conducted on benchmark functions, real-world engineering challenges, and an actual gate allocation scenario, showcases the superior performance of the RPIP-GA in terms of optimality, stability, and convergence accuracy when compared to a variety of algorithms.
	[33]	• Investigates the applicability of a simulated-cuckoo annealing search optimization approach for fine-tuning machine learning algorithms. • Effectively navigates the meta-parameter space to identify optimal configurations. • Achieves a significant improvement in prediction accuracy, particularly in ASR expansion. • Importance for practical engineering scenarios and accurate predictions highlighted.
	[34]	• Introduces a two-phase Multi-Objective Evolutionary Algorithm (MOEA) designed to adeptly handle large-scale multi-objective models. • Through a thorough array of numerical experiments and sensitivity analyses, the proposed model showcases its effectiveness by leveraging the combined advantages of NSGA-II and MOACO. • The conclusive findings from these analyses substantiate the algorithm's proficiency in optimizing the intricate dynamics of efficiency, flexibility, and sustainability in energy consumption profiles throughout the entire value chain. • The algorithm's performance is robustly validated using key indicators such as generation gap (GD), high volume (HV), error ratio (ER), and non-dominant vector generation (ONVG).

III. Research Gap

In conducting a thorough analysis of the existing research landscape in this domain, a conspicuous gap becomes apparent in the background literature. Specifically, there is a conspicuous absence of an integrated approach that comprehensively tackles the interplay between reliability, omnichannel strategy, and the integration of lean and agile methodologies within the context of demand-driven supply chain networks. Although individual studies may delve into one or more of these components, there exists a marked dearth of research systematically exploring their interconnected dynamics. This notable gap underscores the imperative for a holistic framework that takes into account the collective impact of reliability, omnichannel strategy, lean principles, and agile practices on supply chain management. The absence of such an integrated perspective not only constrains the depth of understanding but also impedes the development of comprehensive strategies for contemporary supply chain networks. The research presented herein aims to bridge this gap by furnishing a nuanced analysis and proposing a novel model that addresses these critical elements in a unified manner, thereby making a significant.

Hence, in this research, a multi-objective leagible demand-driven optimization model that incorporates a reliable omnichannel retailer is presented. The primary objectives of the model are to minimize total cost and lead time, while simultaneously maximizing service level and residual capacity within the supply chain networks. The inclusion of a reliable omnichannel retailer in the model enhances its robustness and adaptability to the dynamic demands of the market. This strategic consideration ensures that the optimization efforts are aligned with the evolving landscape of contemporary supply chain dynamics.

In addressing the challenges posed by extensive problems and intricate large-scale multi-objective models, this study introduces an advanced solving algorithm centered on a specialized Multi-Objective Evolutionary Algorithm (MOEA). Recognizing the need for innovation, the integration of Hybrid MOEA/D-DE (Multi-Objective Evolutionary Algorithm with Differential Evolution), IBEA (Indicator-Based Evolutionary Algorithm), and NSGA-II (Non-dominated Sorting Genetic Algorithm II) is presented with significant benefits and deemed necessary for several reasons. Firstly, this integration enables a more robust and versatile approach to solving complex optimization problems, leveraging the unique strengths and perspectives of each algorithm for a comprehensive exploration of the solution space. The hybrid approach ensures adaptability and efficiency in navigating diverse problem characteristics. Secondly, the hybridization strategically utilizes the individual strengths of MOEA/D-DE, IBEA, and NSGA-II in different optimization stages, capitalizing on their complementary features to enhance overall performance.

MOEA/D-DE excels in exploration and convergence speed, IBEA contributes to diversity maintenance and handling Pareto dominance, and NSGA-II aids in non-dominated solutions through its renowned sorting mechanism. This integration effectively addresses limitations inherent in individual algorithms when applied to diverse problem landscapes, resulting in improved convergence, diversity maintenance, and solution quality. In summary, the presentation of the Hybrid integrated MOEA/D-DE, IBEA, and NSGA-II is beneficial and required, offering a versatile, robust, and balanced optimization approach to tackle real-world challenges across various domains.

MODEL DESCRIPTION

In the realm of supply chain management, the choice between mathematical modeling and simulation techniques depends on specific objectives, system characteristics, and available data. Mathematical modeling, favored in certain scenarios per [35], offers precise solutions to well-defined problems, particularly when supply chain processes have clear mathematical representations. These deterministic models prove valuable for predicting and understanding aspects of the supply chain. Additionally, mathematical models showcase analytical rigor and optimization capabilities, facilitating the identification of efficient solutions for components like production, distribution, and inventory [36]. Their superior computational efficiency, especially with large datasets, distinguishes them from simulation methodologies. The decision hinges on a nuanced evaluation of goals and data availability, with mathematical modeling proving effective in specific supply chain analysis scenarios, emphasizing the importance of a profound understanding of fundamental metrics for effective management [37].

To effectively manage the supply chain, it is crucial to thoroughly understand these key metrics during the initial stage of modeling.

- Lead Time (LT) is a critical metric that measures the time required to transport products from the moment an order is placed to the point of delivery (Eq. 1) [38].This parameter holds substantial influence over the speed and reliability of the entire supply chain. Efficient management of LT is imperative, as it goes beyond ensuring swift product delivery. By minimizing delays throughout the supply chain, LT management contributes significantly to an overall enhancement in operational efficiency. Swift and reliable product delivery not only meets customer expectations but also enables better planning and coordination within the supply chain [39]. This, in turn, positively impacts various aspects of operations, such as inventory management, production scheduling, and fulfillment, leading to a more streamlined and effective supply chain. Therefore, prioritizing and optimizing Lead Time is essential for achieving operational excellence and customer satisfaction in the dynamic landscape of supply chain management.

$$LT = Time\ of\ Delivery - Time\ of\ Order\ Placement \tag{1}$$

- Service Level (SL) is a fundamental metric that serves as a reflection of the supply chain's effectiveness in meeting customer demand (Eq. 2) [40]. The maximization of service levels, characterized by fulfilling a higher percentage of the total demand, plays a pivotal role in ensuring customer satisfaction and contributing to the overall success of the supply chain. The importance of SL lies in its direct impact on customer experience and loyalty. By striving to fulfill a greater proportion of the total demand, the supply chain demonstrates its commitment to meeting customer expectations in terms of product availability and timely delivery. This, in turn, enhances customer satisfaction and builds trust in the supply chain's ability to reliably meet their needs. Maximizing service levels is not only a key performance indicator but also a strategic approach to creating a positive and lasting impression on customers [41]. As a result, the continuous improvement and optimization of service levels are integral components of successful supply chain management strategies.

$$SL = \frac{Fulfilled\ demand}{Total\ demand} \tag{2}$$

- Residual Capacity (RE) serves as a critical metric in evaluating the remaining capacity at various stages of the supply chain, accounting for the quantities already delivered [42]. The optimization of RE holds paramount importance, as it facilitates effective resource utilization and ensures a delicate equilibrium between supply and demand. By continuously monitoring and fine-tuning this metric, supply chain managers can actively contribute to the establishment of a responsive, consistent, and resource-efficient supply chain. Efficient management of residual capacity involves strategic decision-making regarding the allocation of resources, responding to changing demands, and maintaining optimal operational levels. This process not only enhances overall operational efficiency but also aligns seamlessly with the overarching objectives of contemporary supply chain management. Emphasizing the optimization of Residual Capacity in supply chain strategies fosters the achievement of sustainable and practical goals, reinforcing the adaptability and responsiveness of the supply chain to dynamic market conditions and customer needs [43].

$$RE = Maximum\ Capacity - The\ actual\ quantity\ delivered \tag{3}$$

Achieving these criteria necessitates a data-driven approach, utilizing historical and empirical data to inform and optimize the implemented model. By grounding the model in real-world data, it becomes possible to align it with the intricacies of the actual supply chain dynamics. This data-driven optimization allows the model to reflect the complexities and nuances present in the system, ensuring a more accurate representation of lead time, service levels, and residual capacity. This not only enhances the model's reliability but also positions it as a valuable tool for making informed decisions and improvements within the supply chain. In essence, the integration of past data and empirical insights forms the foundation for a robust and reality-based optimization model [44].

Also, in the context of ensuring a reliable omnichannel, the distribution function of disruption plays a crucial role. The distribution function provides a probabilistic representation of these disruptions, capturing their potential frequency and severity. By incorporating the distribution function into the optimization model, researchers can assess the robustness of the omnichannel system in the face of uncertainties. This involves considering the probabilities associated with different disruption scenarios and their corresponding effects on lead time, service level, and resource utilization. Considering the complexity and multi-objective nature of the optimization model proposed in the title, the choice of distribution function should be able to accommodate various factors such as demand variability, due date uncertainty and inventory management in multiple channels.

The distribution function that can be suitable for such a scenario is the normal distribution, also known as the Gaussian distribution [45]. The normal distribution is widely used in statistical modeling and provides a flexible framework for modeling continuous random variables. It is characterized by a symmetrical bell curve, with parameters such as mean and standard deviation that can capture variability and uncertainty in demand and delivery times.

Furthermore, in the context of omnichannel retailing where reliability is emphasized, it may be necessary to incorporate a distribution function that considers service level agreements and reliability metrics. Forthurmore, ven the dynamic and evolving nature of omnichannel retail environments, a distribution function that allows for adaptation and learning over time may be beneficial. In this regard, Bayesian methods can be explored that allow updating the distribution parameters based on observed data and iterative optimization to improve decision making and performance [46].

By accounting for potential disruptions, the model can generate more resilient and reliable solutions, ensuring that the omnichannel remains responsive even in the presence of unforeseen events. In summary, the distribution function of disruption supports the reliable omnichannel by quantifying and integrating the uncertainties inherent in the supply chain, allowing for the development of strategies that enhance resilience and mitigate the impact of disruptions on overall performance. In the context of Table 3, the process involves delineating and defining identifiers, variables, and parameters to establish a comprehensive foundation for the subsequent model.

TABLE 3
INDEXES, PARAMETERS AND VARIABLES

Indexes	
s= 1,…, S	Suppliers
m=1,…, M	Manufacturers
r= 1, … , R	Retailers
ch= 2, …, CH	Omnichannels of retailers
i= 1, …, I	Customers
t= 1, …, T	Time
Parameters	
D_{it}	Total demand of customer i in time t
$Budget$	Total budget
TC_{smt}	Total cost of a unit product associated with the flow of goods from supplier s to manufacturer m at time t
TC_{mrt}	Total cost of a unit product associated with the flow of goods from manufacturer m to retailer r at time t
TC_{rit}^{ch}	Total cost of a unit product associated with the flow of goods from retailer r to customer I at time t
LT_{sm}	Lead Time of flow s-m
LT_{mr}	Lead Time of flow m-r
LT_{ri}^{ch}	Lead Time of flow r-i in channel ch
SL_{sm}	Service Level of flow s-m
SL_{mr}	Service Level of flow m-r
SL_{ri}^{ch}	Service Level of flow r-i in channel ch
RE_{sm}	Residual Capacity of flow s-m
RE_{mr}	Residual Capacity of flow m-r
RE_{ri}^{ch}	Residual Capacity of flow r-i in channel ch
$Maximum\ Capacity_{st}$	Maximum Available capacity of s in time t
$Maximum\ Capacity_{mt}$	Maximum Available capacity of flow m in time t
$Maximum\ Capacity_{rt}^{ch}$	Maximum Available capacity of flow r for channel ch in time t
$MALT$	Maximum Acceptable Lead Time
$MELR$	Minimum Service Level Requirement
MRU	Maximum Resource Utilization
$\alpha_{ch-ch'}$	Interdependence coefficient between retail omnichannels ch and ch'
σ_t^{ch}	the variability or spread of disruption occurrences of channel ch in time t
μ_t^{ch}	The average or central tendency of disruptions of channel ch in time t
Variables	
x_{smt}	Quantity of product flowing from supplier s to manufacturer m in time t
x_{mrt}	Quantity of product flowing from manufacturer m to retailer r in time t
x_{rit}^{ch}	Quantity of product flowing from retailer r to customer i through channel ch in time t
y_{smt}	Binary decision variable for presence or absence of interaction between s and m, in time t
y_{mrt}	Binary decision variable for presence or absence of interaction between m and r, in time t
y_{rit}^{ch}	Binary decision variable for presence or absence of interaction between r and i by channel ch, in time t

The presented mathematical model is as following:

$$Z_1 = Min \sum_s \sum_m \sum_t TC_{smt}\, y_{smt}\, x_{smt} + \sum_m \sum_r \sum_t TC_{mrt}\, y_{mrt}\, x_{mrt} + \sum_r \sum_i \sum_t \sum_{ch} TC_{rit}^{ch}\, y_{rit}^{ch}\, x_{rit}^{ch}\, F(\, r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch}) \sum_{ch\prime \neq ch} y_{rit}^{ch\prime}\, x_{rit}^{ch\prime}\, \alpha_{ch-ch\prime} + (1 - F(\, r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch})) \sum_r \sum_i \sum_t \sum_{ch" \neq ch} TC_{rit}^{ch"}\, y_{rit}^{ch"}\, x_{rit}^{ch"} \sum_{ch\prime \neq ch, ch\prime \neq ch"} y_{rit}^{ch\prime}\, x_{rit}^{ch\prime}\, \alpha_{ch"-ch\prime} \tag{4}$$

$$Z_2 = Min \sum_s \sum_m \sum_t LT_{sm}\, y_{smt} + \sum_m \sum_r \sum_t LT_{mr}\, y_{mrt} + \sum_r \sum_i \sum_t \sum_{ch} LT_{ri}^{ch}\, y_{rit}^{ch}\, F(\, r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch}) \sum_{ch' \neq ch} y_{rit}^{ch'}\, \alpha_{ch-ch'} + (1 - F(\, r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch})) \sum_r \sum_i \sum_t \sum_{ch" \neq ch} LT_{ri}^{ch"}\, y_{rit}^{ch"} \sum_{ch' \neq ch, ch\prime \neq ch"} y_{rit}^{ch'}\, \alpha_{ch"-ch'} \tag{5}$$

$$Z_3 = Max \sum_s \sum_m \sum_t SL_{sm}\, y_{smt} + \sum_m \sum_r \sum_t SL_{mr}\, y_{mrt} + \sum_r \sum_i \sum_t \sum_{ch} SL_{ri}^{ch}\, y_{rit}^{ch}\, F(\, r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch}) \sum_{ch' \neq ch} y_{rit}^{ch'}\, \alpha_{ch-ch'} + (1 - F(\, r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch})) \sum_r \sum_i \sum_t \sum_{ch" \neq ch} SL_{ri}^{ch"}\, y_{rit}^{ch"} \sum_{ch' \neq ch, ch\prime \neq ch"} y_{rit}^{ch\prime}\, \alpha_{ch"-ch\prime} \tag{6}$$

$$Z_4 = Max \sum_s \sum_m \sum_t RE_{sm}\, y_{smt} + \sum_m \sum_r \sum_t RE_{mr}\, y_{mrt} + \sum_r \sum_i \sum_t \sum_{ch} RE_{ri}^{ch}\, y_{rit}^{ch}\, F(\, r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch}) \sum_{ch\prime \neq ch} y_{rit}^{ch\prime}\, \alpha_{ch-ch\prime} + (1 - F(\, r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch})) \sum_r \sum_i \sum_t \sum_{ch"} RE_{ri}^{ch"}\, y_{rit}^{ch"} \sum_{ch' \neq ch, ch\prime \neq ch"} y_{rit}^{ch\prime}\, \alpha_{ch"-ch\prime} \tag{7}$$

The first objective function, Z_1, endeavors to minimize the overall expenses in a supply chain system. This involves optimizing the allocation of resources and reducing costs associated with different aspects of the supply chain, including the movement of products among suppliers, manufacturers, retailers, and customers. The total cost incorporates expenses related to lead time and considers interdependencies between retail omnichannels. Efficient lead time management is crucial for cost minimization and timely product delivery. Additionally, the objective function takes into account the collaborative relationships and potential dependencies between different retail channels, ensuring a holistic and efficient approach to cost reduction. In summary, the objective aims to find an optimal solution that strategically manages the quantity of products moving through the supply chain, addresses lead time considerations, and accounts for interconnections between different retail channels.

The second objective, Z_2, aims to minimize the time it takes for products to traverse the supply chain. This involves optimizing decisions regarding the presence or absence of interactions between suppliers, manufacturers, retailers, and customers. Binary decision variables, denoted as y_{smt} , y_{mrt} and y_{rit}^{ch}, represent these interactions, crucial for determining the flow and timing within the supply chain. Minimizing lead time is essential for efficient operations, and the optimization process strategically manages these interactions, making decisions to initiate or eliminate certain interactions. The objective also considers interdependencies between retail omnichannels, recognizing that the performance of one channel may impact others. In summary, the objective aims to find an optimal solution that minimizes lead time by strategically utilizing binary decision variables and addressing interdependencies between retail omnichannels.

The third objective, Z_3, aims to enhance the overall service level in the supply chain by optimizing decision-making processes related to interactions and fulfillment of customer demand. Binary decision variables (y_{smt} , y_{mrt} and y_{rit}^{ch}) represent the presence or absence of interactions between entities in the supply chain, influencing engagement levels. Maximizing the service level, defined as the ratio of fulfilled demand to total demand, ensures higher customer satisfaction and supply chain efficiency. The objective also considers interdependencies between retail omnichannels, recognizing their collaborative and interconnected nature. In summary, the objective seeks an optimal solution that maximizes the service level by strategically managing binary decision variables and addressing interdependencies between retail omnichannels.

The fourth objective, Z_4, aims to optimize resource utilization across suppliers, manufacturers, retailers, and omnichannels. Binary decision variables (y_{smt} , y_{mrt} and y_{rit}^{ch}) play a crucial role in determining interactions and resource allocation. Interdependencies between retail omnichannels are acknowledged, ensuring a holistic approach that captures synergies or dependencies impacting resource utilization. The objective seeks an optimal solution that maximizes resource utilization by making informed decisions about interactions and efficiently managing interdependencies between retail omnichannels. Overall, this approach contributes to a more streamlined and effective operational process throughout the supply chain.

Subject to:

$$\Big[\sum_s \sum_m \sum_t TC_{smt}\ x_{smt} + \sum_m \sum_r \sum_t TC_{mrt}\ x_{mrt} + \sum_r \sum_i \sum_t \sum_{ch} TC_{rit}^{ch}\ x_{rit}^{ch}\ F(\ r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch}) \sum_{ch' \neq ch} x_{rit}^{ch'}\ \alpha_{ch-ch'} + (1 - F(\ r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch})) \sum_r \sum_i \sum_t \sum_{ch" \neq ch} TC_{rit}^{ch"}\ x_{rit}^{ch"} \sum_{ch' \neq ch, ch' \neq ch"} x_{rit}^{ch'}\ \alpha_{ch"-ch'}\ \Big] \leq Budget \tag{8}$$

$$\Big[\sum_s \sum_m \sum_t LT_{smt}\ y_{smt} + \sum_m \sum_r \sum_t LT_{mrt}\ y_{mrt} + \sum_r \sum_i \sum_t \sum_{ch} LT_{rit}^{ch}\ y_{rit}^{ch}\ F(\ r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch}) \sum_{ch' \neq ch} y_{rit}^{ch'}\ \alpha_{ch-ch'} + (1 - F(\ r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch})) \sum_r \sum_i \sum_t \sum_{ch" \neq ch} LT_{rit}^{ch"}\ y_{rit}^{ch"} \sum_{ch' \neq ch, ch' \neq ch"} y_{rit}^{ch'}\ \alpha_{ch"-ch'} \Big] \leq MALT \tag{9}$$

$$\Big[\sum_s \sum_m \sum_t SL_{smt}\ y_{smt} + \sum_m \sum_r \sum_t SL_{mrt}\ y_{mrt} + \sum_r \sum_i \sum_t \sum_{ch} SL_{rit}^{ch}\ y_{rit}^{ch}\ F(\ r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch}) \sum_{ch' \neq ch} y_{rit}^{ch'}\ \alpha_{ch-ch'} + (1 - F(\ r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch})) \sum_r \sum_i \sum_t \sum_{ch" \neq ch} SL_{rit}^{ch"}\ y_{rit}^{ch"} \sum_{ch' \neq ch, ch' \neq ch"} y_{rit}^{ch'} \alpha_{ch"-ch'} \Big] \geq MELR \tag{10}$$

$$\Big[\sum_s \sum_m \sum_t RE_{smt}\ y_{smt} + \sum_m \sum_r \sum_t RE_{mrt}\ y_{mrt} + \sum_r \sum_i \sum_t \sum_{ch} RE_{rit}^{ch}\ y_{rit}^{ch}\ F(\ r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch}) \sum_{ch' \neq ch} y_{rit}^{ch'} \alpha_{ch-ch'} + (1 - F(\ r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch})) \sum_r \sum_i \sum_t \sum_{ch"} RE_{rit}^{ch"}\ y_{rit}^{ch"} \sum_{ch' \neq ch, ch' \neq ch"} y_{rit}^{ch'} \alpha_{ch"-ch'} \Big] \leq \text{MRU} \tag{11}$$

$$\sum_s \sum_m x_{smt} = \sum_m \sum_r x_{mrt} = \sum_r \sum_{ch} x_{rit}^{ch}\ F(\ r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch}) + (1 - F(\ r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch})) \sum_{ch" \neq ch} x_{rit}^{ch"} = D_{it} \qquad \text{□ i, t} \tag{12}$$

$$\sum_m x_{smt} \leq Maximum\ Capacity_{st} \qquad \text{□ s,m,r,t,ch} \tag{13}$$

$$\sum_r x_{mrt} \leq Maximum\ Capacity_{mt}$$

$$\sum_i x_{rit}^{ch} \leq Maximum\ Capacity_{rt^{ch}}$$

$$F(\ r_t^{ch} | \mu_t^{ch}, \sigma_t^{ch}) = \int_{-\infty}^{r_t^{ch}} f(x | \mu_t^{ch}, \sigma_t^{ch})\ dx \qquad \text{□ r, ch} \tag{14}$$

$$x_{smt}\ ,\ x_{mrt}\ ,\ x_{rit}^{ch} \geq 0 \qquad \text{□ s,m,r,i,t,ch} \tag{15}$$

$$y_{smt}\ , y_{mrt}\ ,\ y_{rit}^{ch} \in \{0, 1\} \qquad \text{□ s,m,r,i,t,ch} \tag{16}$$

$$\sum_s y_{smt} \geq 1\ , \sum_m y_{mrt} \geq 1\ , \sum_r \sum_{ch} y_{rit}^{ch} \geq 1 \qquad \text{□ t, i} \tag{17}$$

Equations (8) to (17) represent the mathematical formulation of the optimization model for the supply chain, introducing various decision variables and constraints.

Equation (8) represents the total cost constraint, where the objective is to minimize the overall expenses within the supply chain. The total cost includes the expenses associated with the movement of products between suppliers, manufacturers, retailers, and customers. The terms within the summations account for the cost components at different stages, considering interactions between entities and the distribution function of disruptions. The constraint ensures that the total cost does not exceed the specified budget. Equation (9) constrains the lead time (LT) in the supply chain. The goal is to minimize lead time by optimizing the decision variables denoted as y_{smt}, y_{mrt}, and y_{rit}^{ch}, representing the presence or absence of interactions between suppliers, manufacturers, retailers, and customers through specific retail omnichannels. The constraint ensures that the Mean Average Lead Time (MALT) does not exceed a predefined threshold. Equation (10) imposes a service level constraint. The objective is to maximize the service level, defined as the ratio of fulfilled demand to total demand. The decision variables y_{smt}, y_{mrt}, and y_{rit}^{ch} represent the interactions, and the constraint ensures that the Mean Effective Lead Ratio (MELR) is greater than or equal to a specified threshold.

Equation (11) limits the residual capacity (RE) in the supply chain. The decision variables y_{smt}, y_{mrt}, and y_{rit}^{ch} represent the interactions, and the constraint ensures that the Maximum Residual Utilization (MRU) does not exceed a predefined limit. Equation (12) guarantees that the total demand at each stage equals the delivered quantity, considering the distribution function of disruptions (D_{it}). Equations (13) set maximum capacity constraints for suppliers, manufacturers, and retail omnichannels. Equation (14) defines the cumulative distribution function for disruptions, integrating the probability density function within the specified range. Equations (15) specify non-negativity constraints for the decision variables x_{smt}, x_{mrt}, and x_{rit}^{ch}. Equation (16) restricts the decision variables y_{smt}, y_{mrt}, and y_{rit}^{ch} to binary values (0 or 1), representing the presence or absence of interactions. Equation (17) ensures that at least one interaction occurs in each time period for suppliers, manufacturers, and retail omnichannels.

The set of equations presented together form a comprehensive mathematical model for supply chain optimization. By systematically addressing the equations related to minimizing costs, reducing lead time, maximizing service levels, and optimizing resource utilization, the model explicitly considers the unique challenges and requirements associated with maintaining a dependable omnichannel network. This inclusion reflects a strategic commitment to creating a supply chain that not only achieves cost efficiency, timely delivery, and high customer satisfaction but also fosters resilience and reliability in the interconnected web of retail channels. As a result, the model contributes to the establishment of a robust and responsive supply chain that thrives in the dynamic landscape of modern business, where the reliability of omnichannel interactions is paramount to sustained success.

SOLUTION APPROACH

In this section, a novel hybrid Multi-Objective Evolutionary Algorithm (MOEA) is proposed. The hybrid integrated algorithm combines MOEA/D-DE (Multi-Objective Evolutionary Algorithm with Differential Evolution), IBEA (Indicator-Based Evolutionary Algorithm), and NSGA-II (Non-dominated Sorting Genetic Algorithm II) with the aim of leveraging the distinct strengths of each algorithm in a collaborative manner, ultimately enhancing overall optimization performance. MOEA/D-DE specializes in decomposing multi-objective problems using Differential Evolution, providing efficiency in navigating complex and non-linear landscapes, particularly beneficial in intricate optimization scenarios. IBEA focuses on diversity maintenance through an indicator-based approach, proving advantageous for problems featuring a large number of objectives and complex Pareto fronts, fostering a diverse set of solutions. NSGA-II excels in efficient non-dominated sorting, making it well-suited for problems with a moderate number of objectives and diverse Pareto fronts, showcasing rapid convergence.

The integration of these algorithms occurs collaboratively across various stages of the optimization process, including initialization, evolutionary steps, information exchange, and solution integration. This collaborative approach aims to capitalize on the unique strengths of each algorithm, addressing individual limitations and creating a balanced and effective hybrid algorithm. The presented hybrid integrated algorithm is anticipated to offer advantages in adaptability, efficiency, and solution quality across a wide range of optimization problems, establishing itself as a valuable tool for tackling the complexities of real-world optimization challenges. Fine-tuning and experimentation play a crucial role in optimizing collaboration points to achieve desired performance in specific problem domains. In following, in Section 4.1 each single algorithm is disclosed. In Section 4.2 the proposed hybrid MOEA algorithm to solve the problem is expressed.

I.MOEA/D-DE, IBEA and NSGA-II

- MOEA/D-DE Algorithm [47]

  MOEA/D-DE, which stands for Multi-Objective Evolutionary Algorithm based on Decomposition with Differential Evolution, is an optimization algorithm designed for solving multi-objective problems. This algorithm falls under the category of evolutionary algorithms, specifically focusing on evolutionary strategies for multi-objective optimization. Key Features of MOEA/D-DE:

1. Decomposition-based Approach: MOEA/D-DE decomposes a multi-objective problem into several single-objective subproblems. This decomposition allows the algorithm to handle each subproblem independently, simplifying the overall optimization process.
2. Differential Evolution (DE): Differential Evolution is employed as the evolutionary strategy within MOEA/D-DE. DE is a heuristic optimization algorithm known for its efficiency in exploring solution spaces, particularly in the presence of complex and non-linear relationships.
3. Efficient Exploration-Exploitation Balance: MOEA/D-DE aims to strike a balance between exploration (searching for new solutions) and exploitation (improving known solutions). This balance is crucial for adapting to intricate and challenging optimization landscapes.
4. Versatility: The algorithm is versatile and can be applied to a wide range of multi-objective optimization problems, making it suitable for scenarios where the objectives may conflict with each other.

Overall, MOEA/D-DE provides an effective approach to address complex optimization challenges by breaking them down into more manageable subproblems and leveraging the exploration capabilities of Differential Evolution.

- IBEA Algorithm [48]

IBEA, which stands for Indicator-Based Evolutionary Algorithm, is an optimization algorithm designed for solving multi-objective optimization problems. IBEA falls under the category of evolutionary algorithms and is specifically tailored for scenarios where multiple conflicting objectives need to be considered simultaneously. Key Features of IBEA:

1. Indicator-Based Approach: IBEA employs an indicator-based approach to evaluate the quality of solutions in the population. Common indicators include hypervolume and additive epsilon indicators. These indicators provide a quantitative measure of how well a set of solutions covers the Pareto front, which represents the trade-off between conflicting objectives.
2. Diversity Maintenance: IBEA places a strong emphasis on maintaining diversity within the population. Diversity is crucial in multi-objective optimization to ensure a broad exploration of the solution space and capture a diverse set of trade-off solutions.
3. Pareto Dominance: Like many multi-objective algorithms, IBEA uses Pareto dominance to compare and rank solutions. A solution is considered superior if it is not dominated by any other solution in terms of all objectives.
4. Handling Complex Pareto Fronts: IBEA is particularly effective when dealing with optimization problems that exhibit complex Pareto fronts, where the trade-offs between objectives are intricate and challenging.
5. Versatility: The algorithm is versatile and can be applied to a wide range of multi-objective optimization problems, making it suitable for scenarios where maintaining diversity and exploring the Pareto front are critical.

In summary, IBEA is a powerful tool for addressing multi-objective optimization problems by using indicator-based measures to guide the evolutionary process, emphasizing diversity maintenance, and effectively handling complex Pareto fronts.

- NSGA-II Algorithm [49]

NSGA-II, or Non-Dominated Sorting Genetic Algorithm II, is a multi-objective optimization algorithm used to solve complex optimization problems with multiple conflicting objectives. Developed to address the challenges posed by multi-objective optimization, NSGA-II belongs to the family of evolutionary algorithms. Key Features of NSGA-II:

1. Non-Dominated Sorting: NSGA-II uses a non-dominated sorting technique to classify solutions into different fronts based on their Pareto dominance relationships. This allows the algorithm to identify and maintain a diverse set of non-dominated solutions, forming the Pareto front.
2. Crowding Distance: To maintain diversity within the Pareto front, NSGA-II introduces the concept of crowding distance. Crowding distance measures, the density of solutions around each solution in the front. Solutions with greater crowding distances are given priority to ensure a well-distributed set of non-dominated solutions.

3. Elitism: NSGA-II incorporates elitism by preserving the best solutions from one generation to the next. Elitism helps maintain high-quality solutions throughout the optimization process.
4. Genetic Operators: The algorithm employs standard genetic operators such as crossover and mutation to create new offspring solutions. These operators facilitate the exploration of the solution space and contribute to the generation of diverse solutions.
5. Fast Convergence: NSGA-II is known for its fast convergence properties, meaning it efficiently reaches a diverse and high-quality set of solutions in a relatively small number of generations.
6. Selection Mechanism: Solutions are selected based on a combination of non-dominated sorting and crowding distance. This selection mechanism ensures a balanced representation of solutions with respect to both quality and diversity.
7. Applicability: NSGA-II is widely applicable to various optimization problems, especially those characterized by multiple conflicting objectives. It has been successfully employed in fields such as engineering, finance, and operations research.

In summary, NSGA-II is a robust and widely used algorithm for solving multi-objective optimization problems. Its ability to efficiently explore and maintain diversity in the Pareto front makes it a valuable tool for addressing real-world problems with multiple conflicting objectives.

II. Proposed Solution Approach

Generally, hybrid meta-heuristics algorithms are developed in order to leverage the individual advantages of each algorithm and attenuate their negative individual points. The hybrid integrated algorithm is a collaborative optimization approach that combines the strengths of three distinct algorithms: MOEA/D-DE (Multi-Objective Evolutionary Algorithm with Differential Evolution), IBEA (Indicator-Based Evolutionary Algorithm), and NSGA-II (Non-dominated Sorting Genetic Algorithm II). This integration is designed to create a versatile and robust optimization tool that can address a wide range of complex problems with multiple conflicting objectives.

1. MOEA/D-DE (Multi-Objective Evolutionary Algorithm with Differential Evolution):

Focus: MOEA/D-DE emphasizes decomposing multi-objective problems using Differential Evolution.

Strengths: Efficient exploration of complex and non-linear relationships; Effectiveness in intricate and challenging optimization landscapes.

2. IBEA (Indicator-Based Evolutionary Algorithm):

Focus: IBEA centers on diversity maintenance through an indicator-based approach.

Strengths: Well-suited for problems with a large number of objectives and complex Pareto fronts; Promotes a diverse set of solutions, contributing to a comprehensive exploration of the solution space.

3. NSGA-II (Non-dominated Sorting Genetic Algorithm II):

Focus: NSGA-II efficiently handles non-dominated sorting for maintaining Pareto fronts.

Strengths: Well-suited for problems with a moderate number of objectives and diverse Pareto fronts; Rapid convergence during subsequent generations, enhancing overall performance.

4. Collaborative Approach:

- Initialization Phase: Each algorithm contributes to initializing subsets of the population. MOEA/D-DE, IBEA, and NSGA-II each initialize a portion of the population.
- Evolutionary Steps: MOEA/D-DE focuses on decomposition-based evolution with differential evolution. IBEA is applied for diversity maintenance. NSGA-II performs non-dominated sorting and genetic operators.
- Information Exchange: Between MOEA/D-DE and IBEA: Exchange of a subset of promising individuals.
- Between NSGA-II and MOEA/D-DE: Information exchange on non-dominated solutions.
- Integration of Solutions: Solutions from MOEA/D-DE, IBEA, and NSGA-II are combined into a unified population. Selection mechanisms are applied to maintain diversity.

- Performance Evaluation: The integrated population's performance is evaluated, monitoring key metrics (e.g., hypervolume, generational distance).
- Termination Conditions: Termination conditions are defined, monitoring convergence across all cooperating algorithms and setting a maximum number of generations or iterations.

The Figure 1 presents a depiction of the algorithm described in Python.

```
class MOEADDE:
    def __init__(self, population_size):
      # Initialization Phase
      self.population_moea_dde = self.initialize_moea_dde_population(population_size)

    def initialize_moea_dde_population(self, size):
      # Initialize subsets of the population for MOEA/D-DE
      # Each algorithm initializes a specific portion of the population
      # Implementation details for initialization can be added as needed
      pass

    def evolutionary_steps(self):
      # Evolutionary Steps
      # MOEA/D-DE focuses on decomposition-based evolution using differential evolution
      # IBEA is applied for diversity maintenance during the evolutionary process
      # NSGA-II performs non-dominated sorting and genetic operators for evolution
      pass

    def information_exchange(self, other_algorithm_population):
      # Information Exchange
      # Between MOEA/D-DE and IBEA: Exchange a subset of promising individuals between the two algorithms
      # Between NSGA-II and MOEA/D-DE: Exchange information on non-dominated solutions between the algorithms
      pass

    def integrate_solutions(self, population_ibea, population_nsga_ii):
      # Integration of Solutions
      # Combine solutions from MOEA/D-DE, IBEA, and NSGA-II into a unified population
      # Apply selection mechanisms to maintain diversity within the integrated population
      pass

    def performance_evaluation(self):
      # Performance Evaluation
      # Evaluate the performance of the integrated population
      # Monitor key metrics such as hypervolume and generational distance
      pass

    def termination_conditions(self):
      # Termination Conditions
      # Define termination conditions for convergence across all cooperating algorithms
      # Set a maximum number of generations or iterations as a termination criterion
      pass
```

FIGURE 1
REPRESENTATION OF THE PRESENTED ALGORITHM IN PYTHON

This collaborative framework leverages the unique strengths of each algorithm, addressing their individual limitations and creating a balanced and effective hybrid algorithm. The collaboration occurs at different stages of the optimization process, including initialization, evolutionary steps, information exchange, and solution integration. The resulting hybrid integrated algorithm is expected to offer advantages in terms of adaptability, efficiency, and solution quality across a broad spectrum of optimization problems. Fine-tuning and experimentation are crucial for optimizing the collaboration points and achieving the desired performance in specific problem domains. The parameters of algorithms are presented in Table 4.

TABLE 4
THE PARAMETERS OF ALGORITHMS

MOEA/D-DE			IBEA			NSGA-II		
Population Size (N)	Definition	The total number of solutions (individuals) in the population.	Population Size (N)	Definition	The total number of solutions (individuals) in the population.	Population Size (N)	Definition	The total number of solutions (individuals) in the population.
	Purpose	Influences the diversity and exploration capability of the algorithm.		Purpose	Influences the diversity and exploration capability of the algorithm.		Purpose	Influences the diversity and exploration capability of the algorithm.
Decomposition Method	Definition	MOEA/D-DE decomposes the multi-objective problem into subproblems.	Archive Size (k)	Definition	The number of solutions maintained in the external archive.	Crossover Probability (pc)	Definition	The probability of crossover occurring between two parent solutions.
	Purpose	Determines how the objectives are decomposed, affecting the exploration of the solution space.		Purpose	Controls the size of the archive, where non-dominated solutions are stored for diversity maintenance.		Purpose	Controls the rate of recombination to produce new solutions in the population.
Neighborhood Size (T)	Definition	The number of neighboring subproblems considered for each solution.	Indicator Function	Definition	The performance metric used to assess the dominance relationship between solutions.	Mutation Probability (pm)	Definition	The probability of mutation for an individual solution.
	Purpose	Influences the interaction between solutions and subproblems during the evolution.		Purpose	Determines how solutions are ranked and selected based on their contribution to diversity.		Purpose	Controls the rate at which random changes are applied to individual solutions for diversification.
Crossover Rate (CR):	Definition	Probability of crossover during the differential evolution operation.	Update Interval	Definition	Specifies how often the external archive is updated.	Tournament Selection Parameter (η)	Definition	The size of the tournament selection group.
	Purpose	Controls the balance between exploration and exploitation in the search space.		Purpose	Influences the frequency at which non-dominated solutions are added to or removed from the archive.		Purpose	Influences the selection pressure in the algorithm.
Mutation Scaling Factor (F)	Definition	Scaling factor for the differential evolution mutation.	Termination Criteria	Definition	Conditions for stopping the optimization process (e.g., maximum number of generations, reaching a satisfactory solution).	Maximum Generations	Definition	he maximum number of generations or iterations the algorithm will run.
	Purpose	Influences the step size of the mutation, affecting the diversity of the population.		Purpose	Controls the overall duration and convergence of the algorithm.		Purpose	Specifies the termination condition for the optimization process.

MOEA/D-DE			IBEA			NSGA-II		
Update Frequency	Definition	Specifies how often the subproblems are updated.	Crossover and Mutation Operators	Definition	Genetic operators applied during the evolution process (e.g., crossover and mutation)	Crowding Distance Archive Size (σ)	Definition	The size of the archive used for crowding distance calculation.
	Purpose	Determines the frequency at which subproblems are adapted to the evolving population.		Purpose	Determines how new solutions are generated and diversified in the population.		Purpose	Controls the diversity preservation mechanism by maintaining a set of non-dominated solutions.
Termination Criteria	Definition	Conditions for stopping the optimization process (e.g., maximum number of generations, reaching a satisfactory solution).	Initialization Method	Definition	Strategy for initializing the population.	Crowding Distance Archive Update Interval	Definition	How often the crowding distance archive is updated.
	Purpose	Controls the overall duration and convergence of the algorithm.		Purpose	Influences the starting point of the optimization process.		Purpose	Influences the frequency of archive updates to adapt to changes in the population.
Weight Vectors	Definition	Vectors representing weights assigned to each objective during the decomposition process.	Fitness Assignment Method	Definition	Approach for assigning fitness values to solutions based on the chosen indicator.	Termination Criteria	Definition	Conditions for stopping the optimization process (e.g., maximum number of generations, reaching a satisfactory solution).
	Purpose	Defines the trade-offs between objectives and guides the search toward the Pareto front.		Purpose	Guides the selection of solutions for reproduction and survival in the population.		Purpose	Controls the overall duration and convergence of the algorithm.
Initialization Method:	Definition	Strategy for initializing the population.				Crossover and Mutation Operators	Definition	Genetic operators applied during the evolution process (e.g., crossover and mutation).
	Purpose	Influences the starting point of the optimization process.					Purpose	Determines how new solutions are generated and diversified in the population.
						Initialization Method	Definition	Strategy for initializing the population.
							Purpose	Influences the starting point of the optimization process

III. Preferences of Proposed Algorithm

The hybrid integrated algorithm, which incorporates MOEA/D-DE, IBEA, and NSGA-II, strategically leverages the unique strengths of each constituent algorithm, thereby facilitating diversity, efficient convergence, and balanced optimization. MOEA/D-DE, renowned for its emphasis on Differential Evolution, demonstrates proficiency in navigating intricate landscapes and effectively addressing challenges posed by complex relationships in optimization problems. On the other hand, IBEA's indicator-based approach prioritizes the maintenance of diversity, proving particularly advantageous in scenarios characterized by numerous objectives and complex Pareto fronts. Meanwhile, NSGA-II's efficient non-dominated sorting mechanism significantly contributes to rapid convergence. This collaborative framework intelligently harnesses these complementary strengths at different stages of the optimization process, fostering the development of a well-rounded and effective hybrid algorithm capable of adapting across diverse problem domains. Fine-tuning and experimentation are pivotal in optimizing the collaboration points, ensuring the algorithm's versatility and optimal performance in addressing real-world optimization challenges.

COMPUTATIONAL EVALUATION AND STATISTICAL EXPERIMENTATIONS

The review of the presented model as well as the proposed algorithm with the numerical data of the case study of the supply of sanitary masks in August 2021 in two regions of Tabriz, Iran have been investigated. The selection of the case study on the supply of sanitary masks in Tabriz, Iran, in August 2021 is highly appropriate for this paper due to its temporal relevance during the global COVID-19 pandemic. This specific timeframe captures the unique challenges and dynamics associated with the surge in demand for sanitary masks. The geographical focus on Tabriz adds granularity, allowing for a nuanced understanding of how local conditions and regulations influence supply chain dynamics. Furthermore, the study's emphasis on the intersection of supply chain management aligns with the need for advanced modeling and algorithmic approaches to address real-world challenges in the critical domain of public health. The findings from this case study are poised to contribute valuable insights for optimizing supply chain operations and addressing challenges related to essential goods during pandemics. The independent parameters relevant to the case study are detailed in Table 5. To tune the parameters of the proposed hybrid integrated MOEA, a Trial and Error process was completed. The utilization of numerical data from the case study in Tabriz, Iran, not only enhances the empirical validity of the research but also facilitates the extraction of actionable insights.

It is necessary to mention that the presented algorithm is solved model using PPGMO library of Python: PyGMO (Python Parallel Global Multi-objective optimization) stands out as a robust choice for solving multi-objective optimization problems due to its combination of algorithmic diversity, efficiency, and customization capabilities [50]. With a wide range of optimization algorithms specifically tailored for multi-objective scenarios, PyGMO provides users with the flexibility to choose the most suitable algorithm for their problem. The library's parallel computing capabilities enhance efficiency, enabling faster convergence and better exploration of the search space. Additionally, PyGMO's modular design allows users to easily extend and customize algorithms, adapting them to the unique characteristics of their optimization tasks. Its integration with popular scientific computing libraries like NumPy and Scipy further enhances its usability, making PyGMO a comprehensive and powerful tool for addressing multi-objective optimization challenges in the Python ecosystem. Then, the presented algorithm is solved model using PPGMO of Python: PyGMO (Python Parallel Global Multi-objective optimization) stands out as a robust choice for solving multi-objective optimization problems due to its combination of algorithmic diversity, efficiency, and customization capabilities.

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TABLE 5
PARAMETERS VALUE OF THE MODEL AND THE ALGORITHM

S= 5	*M=8*	*R= 25*	*I=65*	*T=30*
D_{it}	*[10000, 50000]*	LT_{sm}	*[15, 20]*	
$Budget$	3×10^{10}	LT_{mr}	*[5,12]*	
TC_{smt}	*[1000,1500]*	LT_{ri}^{ch}	*[2,8]*	
TC_{mrt}	*[1200,1800]*	RE_{sm}	*[500,700]*	
TC_{rit}^{ch}	*[1500, 2200]*	RE_{mr}	*[400,600]*	
SL_{sm}	*[80%, 92%]*	RE_{ri}^{ch}	*[150,240]*	
SL_{mr}	*[78%, 89%]*	$Maximum\ Capacity_{st}$	$[10^5, 3\times10^5]$	
SL_{ri}^{ch}	*[90%, 98%]*	$Maximum\ Capacity_{mt}$	$[10^5, 2\times10^5]$	
$MALT$	5×10^2	$Maximum\ Capacity_{rt}^{ch}$	$[10^3, 3\times10^3]$	
$MELR$	*85%*	$\alpha_{ch-ch'}$	*[0,1]*	
MRU	4×10^3	μ_t^{ch}	*[0.1,03]*	
σ_t^{ch}	*[1.5,2.5]*	*Population*	*100*	
Mutation rate	*0.2*	*Crossover rate*	*0.8*	
(IBEA) Neighborhood	*10*	*Maximum number of generations*	*100*	
	Generational distance for termination		*0.1*	

In consideration of the case parameters, the outcomes derived from the application of the presented hybrid algorithm to solve the model are succinctly presented in Table 6. Moreover, the case study has been systematically addressed using each individual algorithm to validate and affirm the potential of the newly presented hybrid algorithm. This comparative analysis ensures a comprehensive understanding of the proposed solution's efficacy by benchmarking its performance against established algorithms. Also, to facilitate straightforward comparison, the results are presented in Figure 2.

TABLE 6
RESULTS

MOEAD/D-DE		IBEA		NSGA-II		The Presented Hybrid Integrated MOEA	
Z_1	265×10^6	Z_1	281×10^6	Z_1	253×10^6	Z_1	216×10^6
Z_2	1611	Z_2	1706	Z_2	1658	Z_2	1503
Z_3	89%	Z_3	87%	Z_3	89%	Z_3	92%
Z_4	7125	Z_4	7584	Z_4	7983	Z_4	8547
CPU Time(S)	210	**CPU Time(S)**	227	**CPU Time(S)**	220	**CPU Time(S)**	192

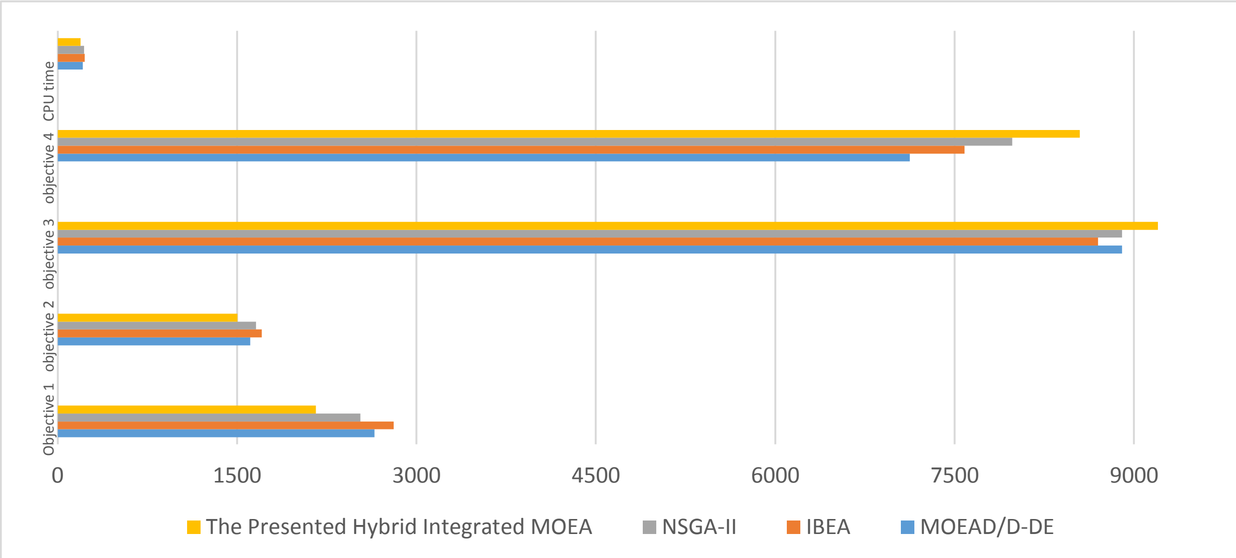

FIGURE 2
RESULTS OF CASE STUDY

Table 6 presents a comparative analysis of the performance of four algorithms: MOEAD/D-DE, IBEA, NSGA-II, and the newly introduced Hybrid Integrated Multi-Objective Evolutionary Algorithm (MOEA). When considering the objective functions Z_1 and Z_2, the Hybrid Integrated MOEA exhibits superior performance compared to its counterparts. Notably, the values for Z_1 are significantly lower, signifying more effective minimization, with the presented MOEA achieving the lowest value at 216×10^6. Similarly, for Z_2, the Hybrid MOEA outperforms other algorithms with a value of 1503. In terms of maximizing functions Z_3 and Z_4, higher percentages are preferable. The proposed Hybrid Integrated MOEA excels in maximizing Z_3 with a percentage of 92%, surpassing other algorithms. For Z_4, the presented MOEA demonstrates effectiveness by achieving the highest value at 8547. In terms of computational efficiency, measured by CPU time (in seconds), the Hybrid Integrated MOEA performs optimally with the lowest time consumption at 192 seconds. This underscores the efficiency of the proposed algorithm in addressing the multi-objective optimization problem within the specified case study. In summary, the presented model, implemented through the Hybrid Integrated MOEA, demonstrates superior performance across various metrics, including minimizing and maximizing functions, as well as computational efficiency. The subsequent sub-sections will delve into scrutinizing performance, evaluating the functionality of the suggested algorithm, and assessing the sensitivity of the proposed model.

II. Multi-objective Evaluation Metrics

Analyzing multi-objective evaluation metrics is crucial for comparing the performance of optimization algorithms, assisting in algorithm selection, parameter fine-tuning, and benchmarking. These metrics offer a standardized approach to assess an algorithm's capability to approximate the true Pareto front. Insights derived from this analysis contribute to advancing research, providing researchers and practitioners with a foundation for making informed decisions, comprehending algorithm behavior, and ultimately enhancing the effectiveness of optimization solutions in real-world applications [52]. To evaluate the performance of the proposed algorithm and compare its efficiency with single-objective algorithms, it is imperative to assess optimization using multi-objective evaluation metrics. These metrics provide insights into how well the algorithm can achieve a balance between conflicting objectives [53]. In this paper, Generational Distance (GD), Hypervolume (HV), Error Ratio (ER), and Overall Non-Dominated Vector Generation (ONVG) are analyzed.

- ***Generational Distance (GD)***

Generational Distance (GD) serves as a metric to gauge the average distance between each solution in the obtained Pareto front and the true Pareto front [54]. It is commonly expressed mathematically as follows:

$$GD = \sqrt{\frac{1}{|PF_{true}|} \sum_{i=1}^{|PF_{true}|} d_i^2} \quad (18)$$

Where d_i represents the Euclidean distance from each solution in the true Pareto front to its nearest neighbor in the obtained Pareto front.

In this equation, $|PF_{true}|$ signifies the number of solutions in the true Pareto front. The Euclidean distance d_i is computed between each solution in the true Pareto front and its nearest neighbor in the obtained Pareto front. The inclusion of the square root and normalization ensures that Generational Distance (GD) provides a meaningful measure of the average distance. A lower GD value indicates a better convergence of the obtained Pareto front to the true Pareto front.

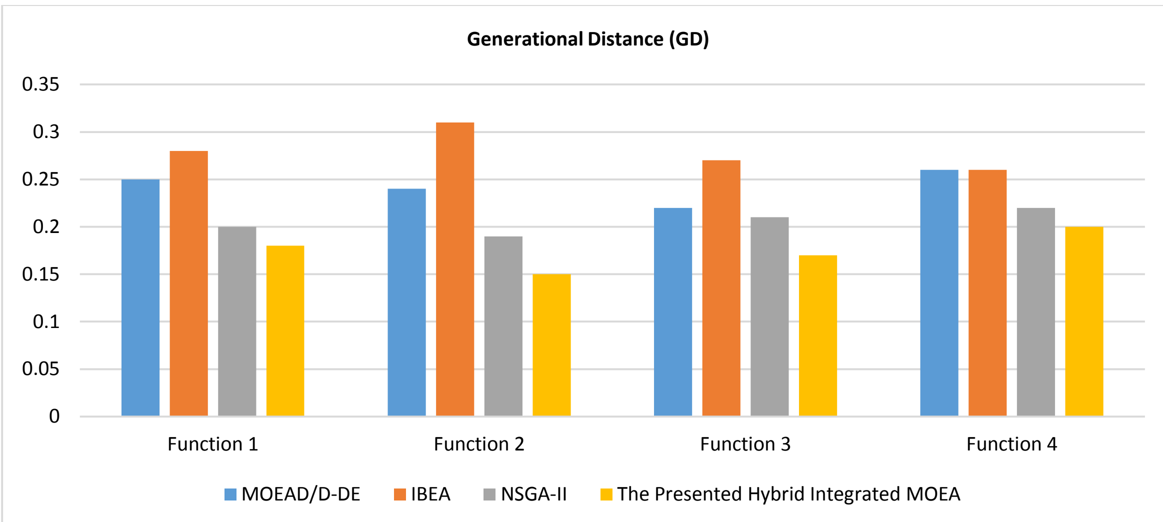

FIGURE 3
COMPARATIVE ANALYSIS OF GENERATIONAL DISTANCE

According to Figure 3, the proposed algorithm demonstrates distinct superiority in Generational Distance (GD) when compared to NSGA-II, IBEA and MOEA/D-DE. GD quantifies the average distance between the solutions generated by the algorithm and the true Pareto front. The values attained by the proposed algorithm are closer to zero, indicating a more accurate approximation to the true solution. This closer alignment signifies the algorithm's effectiveness in minimizing the deviation of its solutions from the optimal front, highlighting its superior ability to converge to Pareto-optimal solutions.

- ***Hypervolume (HV)***

The hypervolume (HV) serves as a widely used performance metric in multi-objective optimization for evaluating the quality of a Pareto front approximation. It quantifies the volume of the objective space dominated by a set of solutions (Pareto front) concerning a reference point. Mathematically, the hypervolume (HV) calculation is typically expressed as the volume of the dominated portion of the objective space under a given Pareto front P with respect to a reference point Z [55]. The hypervolume equation is as follows:

$$HV(P, Z) = \int_{-\infty}^{z_1} \int_{-\infty}^{z_2} \dots \int_{-\infty}^{z_m} dy \quad (19)$$

Here:
P is the Pareto front,
Z is the reference point,
m is the number of objectives,
y= $(y_1, y_2, \dots, y_m)$ represents a point in the objective space.
The integration is performed across the dominated region of the objective space, delineated by the reference point Z along each objective axis. In practical applications, this integral is frequently numerically approximated, and there

exist specialized algorithms designed to efficiently compute the hypervolume of a given Pareto front concerning a reference point.

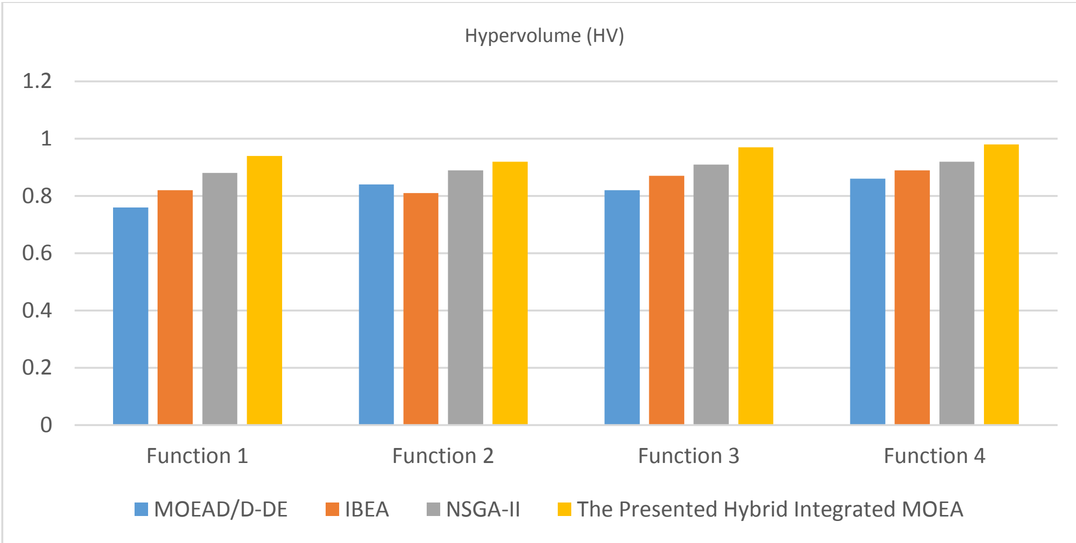

FIGURE 4
COMPARATIVE ANALYSIS OF HYPERVOLUME

The results illustrated in Figure 4 highlight the superior performance of the proposed algorithm in terms of Hypervolume (HV) compared to NSGA-II, IBEA, and MOEA/D-DE. HV serves as a metric for evaluating the volume of space covered by an algorithm's solutions in the objective space. In this context, the proposed algorithm excels by achieving a significantly larger hypervolume, indicating superior coverage of the Pareto front. This suggests that the proposed algorithm not only discovers diverse solutions but also explores a more extensive section of the Pareto front. The larger hypervolume obtained by the proposed algorithm signifies its capacity to provide decision-makers with a more comprehensive set of trade-off solutions, establishing it as a promising choice for multi-objective optimization tasks.

- ***Error Ratio (ER)***

The Error Ratio (ER) serves as an evaluation metric employed to gauge the accuracy of an approximation set, typically obtained from a multi-objective optimization algorithm, with respect to a true Pareto front [56]. The mathematical formulation of the Error Ratio is as follows:

$$\mathrm{ER} = \frac{\text{Area between the true Pareto front and the approximation set}}{\text{Total area of the true Pareto front}} \tag{20}$$

In this equation, the term "area between the true Pareto front and the approximation set" denotes the region where the approximation set deviates from the true Pareto front. The "total area of the true Pareto front" represents the entirety of the space covered by the true Pareto front.

A lower Error Ratio signifies a superior approximation, indicating a smaller deviation from the true Pareto front. It offers a quantitative measure of the effectiveness of the generated solutions in approximating the optimal trade-offs along the objectives compared to the actual Pareto front.

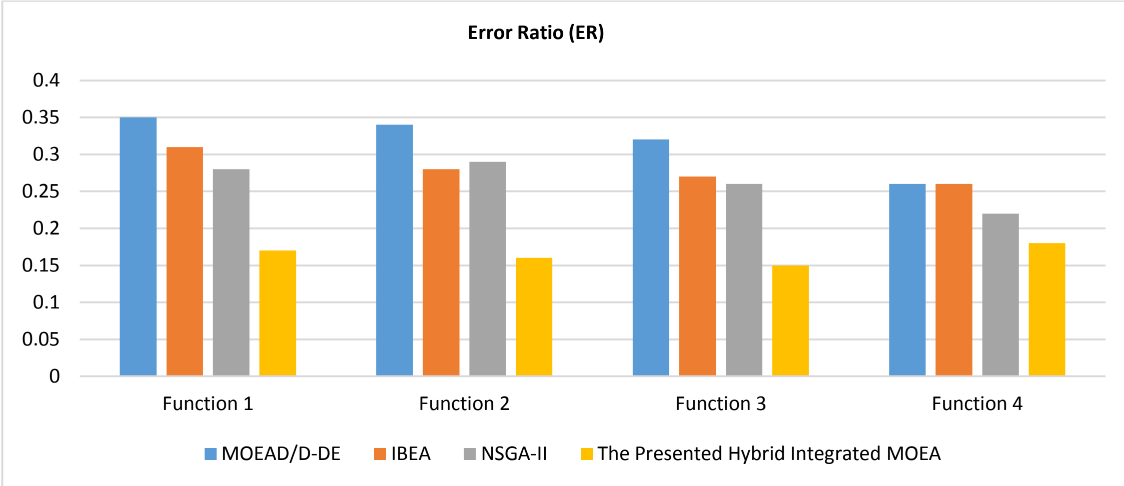

FIGURE 5
COMPARATIVE ANALYSIS OF ERROR RATIO

As depicted in Figure 5, it becomes evident that the Error Ratio (ER) further emphasizes the superiority of the proposed algorithm. ER evaluates the accuracy of the generated solutions by comparing them to the true Pareto front. The proposed algorithm consistently exhibits lower error rates compared to NSGA-II, IBEA, and MOEA/D-DE, showcasing its capacity to generate solutions that closely align with the actual Pareto front. This heightened accuracy is of paramount importance for decision-makers relying on the algorithm's results, positioning the proposed algorithm as a more reliable choice.

- ***Overall Non-Dominated Vector Generation (ONVG)***

Overall Non-Dominated Vector Generation (ONVG) serves as a metric utilized to evaluate the effectiveness of a multi-objective optimization algorithm in generating non-dominated solutions across multiple objectives. This metric is commonly applied to assess the diversity and spread of solutions obtained from the optimization process [57]. The ONVG is determined through the following steps:

1. Generate the Pareto Front: Acquire the Pareto front, representing the set of non-dominated solutions in the objective space.
2. Divide the Objective Space: Segment the objective space into a grid or a set of bins to enable the analysis of solution distribution.
3. Count Non-Dominated Vectors in Each Bin: For each bin, tally the number of non-dominated vectors (solutions) falling within it.
4. Calculate Overall Non-Dominated Vector Generation: Compute the ONVG by considering the count of non-dominated vectors in each bin relative to the total number of solutions.
5. $$\mathrm{ONVG} = \frac{\text{Sum of non}-\text{dominated vectors in each bin}}{\text{Total number of solutions}} \qquad (21)$$

A higher ONVG value indicates a more uniform distribution of non-dominated solutions throughout the objective space. This metric assists in evaluating the algorithm's capability to thoroughly explore and encompass the entire Pareto front, offering insights into the diversity and quality of the generated solutions.

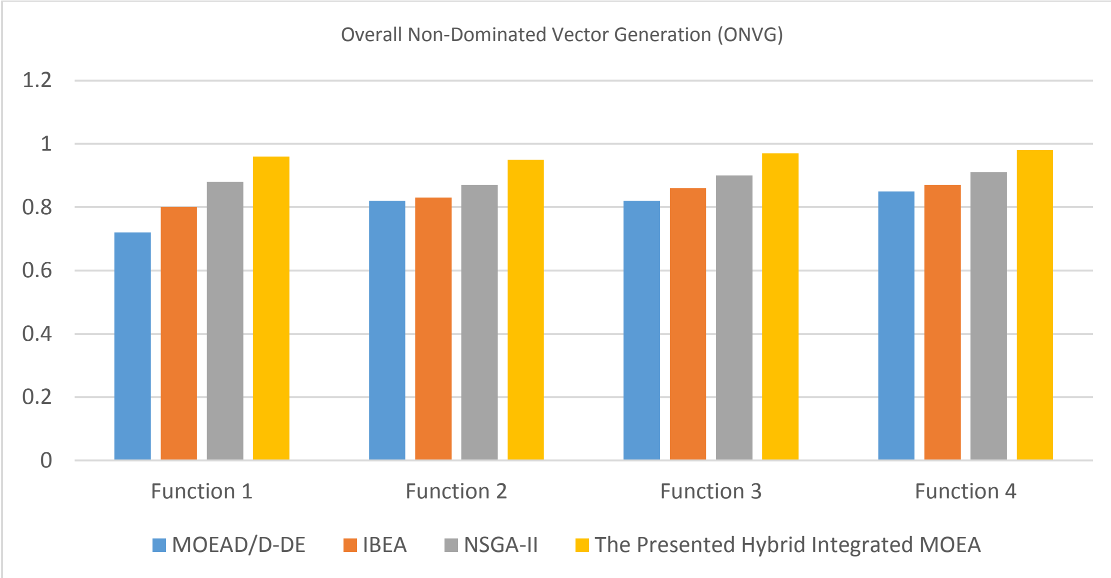

FIGURE 6
OVERALL NON-DOMINATED VECTOR GENERATION

As illustrated in Figure 6, the Overall Non-Dominated Vector Generation (ONVG) metric underscores the superior capability of the proposed algorithm in generating non-dominated solutions. It reflects the diversity and optimality of the solution set, consistently yielding a higher number of non-dominated solutions compared to NSGA-II, IBEA, and MOEA/D-DE. This showcases the proposed algorithm's effectiveness in exploring a broader range of trade-off solutions. The superior performance in non-dominated vector generation signifies the algorithm's ability to furnish decision-makers with a more comprehensive and diverse set of Pareto-optimal solutions.

In summary, the proposed algorithm consistently outperforms NSGA-II, IBEA, and MOEA/D-DE across various evaluation metrics. It provides more precise approximations, indicating closer proximity to the true solution. The algorithm achieves broader coverage of the Pareto front, implying a more thorough exploration of the solution space. Additionally, it demonstrates increased accuracy, reflected in lower error rates compared to the individual algorithms. Moreover, the proposed algorithm generates a richer set of non-dominated solutions, highlighting its capacity to offer diverse and optimal solutions. These collective strengths position the algorithm as well-suited for real-world applications, offering enhanced performance and versatility in addressing multi-objective optimization challenges.

- ***Sensitivity Analysis***

The research fundamentally establishes a crucial iterative process involving result scrutiny, sensitivity analysis, and model refinement [19]. This iterative approach aids in a deeper understanding of the supply chain network optimization model, refining its accuracy, and enhancing its applicability to real-world scenarios [58]. The model's adaptability is strengthened, ensuring robustness in accommodating diverse scenarios within the supply chain network. Subsequent stages include a meticulous analysis of obtained results, examining how changes in parameter values impact outcomes of interest in the value chain network optimization model [59]. This analysis provides valuable insights into the model's performance, highlighting areas that may require further attention or refinement. Sensitivity analysis plays a pivotal role in identifying parameters with a significant impact on the model's outputs [60]. Understanding the sensitivity of the model to different input variations allows prioritization of key factors, directing efforts towards refining the model's representation of these critical elements. In the refinement stage, insights gained from simulations and sensitivity analyses are incorporated [61]

This study undertakes sensitivity analysis on two critical parameters within the omni-channel network. The first analysis focuses on the disruption parameter, aiming to demonstrate the model's reliability by assessing its response to variations in this parameter. By subjecting the model to different levels of disruption, we gain insights into its robustness and ability to handle unforeseen challenges within the omni-channel environment. Simultaneously, sensitivity analysis is conducted on the service level parameter, providing a comprehensive evaluation of the model's efficiency. This analysis explores how changes in the service level parameter impact the overall performance of the model, shedding light on its capacity to maintain and enhance operational efficiency within the omni-channel network. Through these sensitivity analyses, the study aims to validate the model's reliability under disruptive conditions and underscore its efficiency in achieving desired service levels.

- ***Sensitivity Analysis on Disruption Parameter***

The Figure 7 presents a compelling illustration of the robustness of the reliable model under various scenarios. Regardless of changes in the average and spread of disruptions, the functions (Function 1, Function 2, Function 3, and Function 4) exhibit consistent values, indicating a high level of stability. The minimal fluctuations in function values across different disturbance scenarios suggest that the model is resilient to such variations, emphasizing its reliability.

This resilience is crucial, as it highlights the model's ability to maintain consistent performance even when faced with disruptions of varying magnitudes. The fact that alterations in disruption characteristics do not significantly impact the computed function values underscores the effectiveness of the model in handling disturbances. This is particularly important in real-world applications, where disruptions are inevitable, and a reliable model ensures consistent and trustworthy results. The demonstrated stability and robustness of the model across diverse disturbance scenarios contribute to its credibility and suitability for addressing complex challenges in supply chain management and optimization [62].

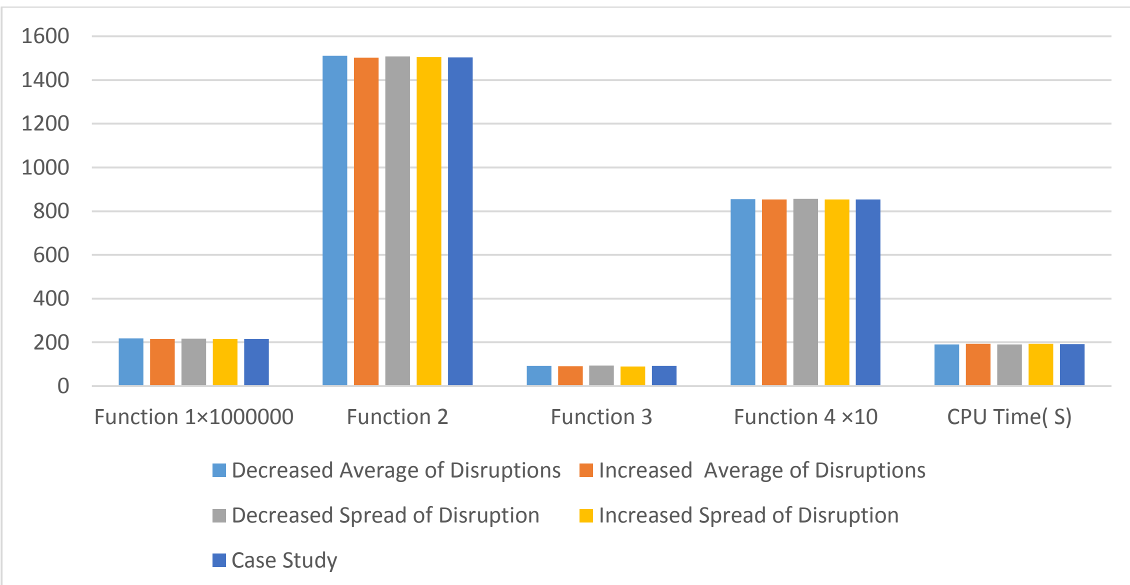

FIGURE 7
RESULTS OF SENSITIVITY ANALYSIS (ON DISRUPTION)

- ***Sensitivity Analysis on Service Level Parameter***

Considering Figure 8 the significance of service levels in the optimization process is highlighted by the observable impact on the system's performance metrics. When the service level is elevated, there is a discernible positive influence on the optimization process. This elevation correlates with notable improvements in the values of various functions that are integral to the overall performance and efficiency of the system. These functions encompass crucial aspects such as cost minimization, lead time reduction, and enhanced service level and residual capacity, all contributing to the optimization goals of the system. Conversely, a reduction in the service level yields a contrary effect, introducing a deleterious impact on the optimization process. This reduction is associated with a noticeable decline in the values of the essential functions that play a pivotal role in shaping the operational effectiveness of the system.

The adverse consequences of decreased service levels are reflected in compromised cost management, prolonged lead times, and a reduction in service level and residual capacity, collectively diminishing the system's ability to achieve optimal performance. Intriguingly, amid the dynamic fluctuations in service levels, a noteworthy observation emerges – the CPU time maintains a consistent stability. This observed stability in CPU time signifies a uniform running time, indicative of sustained computational efficiency even amidst diverse scenarios of service level adjustments. This steadfast uniformity in CPU time highlights the reliability and consistency of computational efficiency across the spectrum of service level conditions. This finding is particularly significant as it suggests that the system's optimization process remains robust and efficient, irrespective of changes in service levels. The stability in CPU time implies that the algorithm's execution time is not significantly affected by variations in service levels, attesting to its resilience and ability to maintain consistent computational performance. In essence, while the optimization of service levels showcases a positive correlation with enhanced performance metrics, underscoring its pivotal role in improving system functionality, the concurrent stability in CPU time reinforces the system's reliability and efficiency in adapting to diverse service level conditions. This dual aspect emphasizes the intricate balance between performance enhancement and computational consistency, crucial for the overall effectiveness of the system.

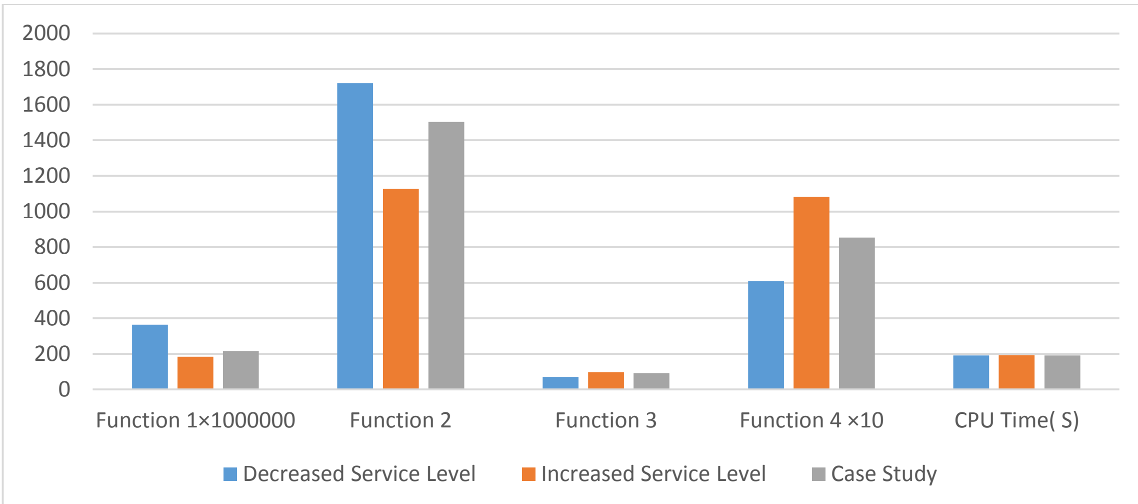

FIGURE 8
RESULTS OF SENSITIVITY ANALYSIS (ON SERVICE LEVEL)

MANAGERIAL AND SIGNIFICANCE IMPLICATIONS

In the realm of supply chain management, the implementation of a reliable omnichannel approach presents significant managerial implications. This approach integrates a robust model capable of effectively managing disruptions and fluctuations in demand, providing managers with a dependable tool for optimizing supply chain networks. The following are key managerial implications and significance:

1. Resilient Decision-Making: The model's reliability empowers managers to make resilient decisions in the face of disruptions. Leveraging the robustness of the omnichannel approach enables managers to confidently navigate uncertainties and implement strategies to ensure the continuity of supply chain operations.
2. Cost Optimization: The optimization capabilities of the model play a vital role in reducing costs within the supply chain. Through efficient resource allocation, minimized lead times, and maximized service levels, the model facilitates the creation of a streamlined and cost-effective supply chain network.
3. Adaptability to Dynamic Environments: The model's capacity to maintain stability across various disturbance scenarios makes it particularly well-suited for dynamic business environments. Managers can utilize this approach to effectively adapt and respond to changing market conditions, thereby ensuring the resilience and adaptability of their supply chain networks.
4. Enhanced Service Levels: Prioritizing service level optimization ensures the efficient fulfillment of customer demands. This not only leads to heightened customer satisfaction but also establishes a competitive edge in the market by delivering reliable and timely services.
5. Strategic Collaboration: The collaborative nature of the algorithm, which integrates the strengths of multiple optimization algorithms, promotes strategic collaboration within the supply chain. By fostering synergies and enhancing cooperation among different entities in the network, managers can achieve improved overall performance.

6. Future-Proofing Supply Chains: The reliability and robustness of the omnichannel approach contribute significantly to future-proofing supply chains. Given the inherent disruptions and uncertainties in global markets, having a dependable model becomes essential for managers aiming to build resilient and sustainable supply chain networks.

In summary, adopting the presented reliable omnichannel approach has far-reaching managerial implications. From enabling informed and resilient decision-making to optimizing costs and enhancing service levels, this approach equips managers with a powerful tool to navigate the complexities of modern supply chain management.

CONCLUSION

In this study, a comprehensive model aimed at optimizing supply chain networks, with a specific focus on leagile demand-driven systems, is presented. Critical aspects such as cost minimization, lead time reduction, service level maximization, and efficient resource utilization are addressed through precise mathematical formulations within the integrated multi-objective optimization objectives of the model. An effective omni-channel approach is proposed to reliably manage disruptions and uncertainties in the supply chain. The hybrid meta-heuristic algorithm proposed in this research combines the strengths of MOEA/D-DE, IBEA, and NSGA-II, resulting in a versatile and robust optimization tool. Collaborative integration of these algorithms at various stages of the optimization process ensures adaptability, efficiency, and the generation of high-quality solutions across a broad spectrum of complex problems. To validate the model and algorithm, a case study focusing on the supply of sanitary masks in Tabriz, Iran, during 2021 was conducted, providing insights into the applicability and reliability of the proposed approach. Consistent performance across different disturbance scenarios was demonstrated by the model, highlighting its resilience and stability in the face of disruptions.

The significant managerial implications of adopting this reliable omnichannel approach include enabling resilient decision-making, cost optimization, adaptability to dynamic environments, enhanced service levels, strategic collaboration, and future-proofing of supply chains. The collaborative and integrated nature of the algorithm empowers managers to effectively navigate uncertainties and challenges. In conclusion, this research contributes to the field of supply chain management by presenting a reliable omnichannel approach that combines mathematical modeling and hybrid meta-heuristic optimization. The demonstrated robustness of the model, as evidenced through the case study, positions it as a valuable tool for managers seeking to optimize their supply chain networks in the face of dynamic and uncertain market conditions. The presented approach offers a promising avenue for building resilient and efficient supply chain systems as the business landscape continues to evolve.

Limitation and Further Research Directions

While the presented model and hybrid algorithm offer a robust framework for optimizing supply chain networks, certain limitations should be acknowledged. Firstly, the collaborative nature of the hybrid algorithm relies on effective information exchange between the participating algorithms. Fine-tuning the collaboration points and parameters is essential, and suboptimal configurations may hinder performance. Furthermore, the application of the model and algorithm to diverse industries and supply chain structures requires careful consideration, as the specific characteristics of different sectors may influence the generalizability of the proposed approach.

Future research endeavors could explore enhancements to the presented model and algorithm. Incorporating machine learning techniques for dynamic parameter estimation, considering real-time data, could improve the accuracy of disruption and lead time predictions. Additionally, investigating the scalability and adaptability of the hybrid algorithm to larger and more complex supply chain networks would be valuable. Exploring the integration of emerging technologies, such as blockchain or Internet of Things (IoT), could enhance the model's ability to address real-world challenges. Moreover, extending the research to encompass a broader range of industries and geographical locations would contribute to assessing the generalizability and applicability of the proposed approach in diverse contexts.

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