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Synergizing Efficiency, Flexibility, and Sustainability of Value Chain to Optimization of Energy Consumption

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Abstract

In response to the dynamic requirements of contemporary businesses, this research delves into the imperative for organizations to optimize the efficiency, flexibility, and sustainability of their value chains, especially concerning energy consumption. The study introduces a multi-objective model meticulously designed to align efficiency, flexibility, and sustainability, aiming for a well-balanced and optimal energy consumption profile throughout the entire value chain. The optimization process employs multi-objective programming, aiming to maximize minimum levels of flexibility, stability, and efficiency while minimizing the maximum energy consumption. Addressing the intricacies of large-scale multi-objective models, the research proposes a two-phase Multi-Objective Evolutionary Algorithm (MOEA), leveraging the strengths of NSGA-II and MOACO. The effectiveness of the proposed model is substantiated through a series of numerical experiments and sensitivity analyses, providing conclusive evidence of its capability to navigate the complexities of optimizing energy consumption in value chains. Furthermore, the performance of the proposed algorithm is affirmed through the examination of indicators such as generation gap (GD), high volume (HV), error ratio (ER), and non-dominant vector generation (ONVG). Hence, the presented model and solution algorithm are suitable for real-world problems.

Keywords: Value Chain, Optimization, Energy Consumption, Two-phase Multi-Objective Evolutionary Algorithm, Evaluation Metrics

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1. Introduction

In the dynamic contemporary business environment, organizations are confronted with a compelling need to elevate the efficiency, flexibility, and sustainability of their value chains. This imperative arises as industries grapple with the challenges posed by resource constraints and environmental concerns. A holistic and comprehensive approach to optimizing energy consumption becomes paramount in this context (Nguyen et al., 2022). Traditional optimization approaches have tended to concentrate on individual aspects of the value chain, such as cost reduction or process efficiency (Pan et al., 2023). While the value chain, comprising a series of interconnected activities designed to add value to a product or service, assumes a pivotal role in determining the overall performance of an organization (Asgharizadeh et al. 2022; Tanveer et al., 2023). Therefore, acknowledging the interdependence of efficiency, flexibility, and sustainability necessitates a more integrated and interconnected strategy (Nguyen and Kanbach, 2023).

Efficiency in the value chain involves streamlining processes, minimizing waste, and optimizing resource utilization. This involves a systematic approach to ensure that each step in the value chain contributes effectively to the overall production or service delivery, without unnecessary delays, redundancies, or resource wastage. The goal is to enhance productivity and output while using resources in a strategic and optimized manner (Zaninovic et al., 2024).

Flexibility, on the other hand, empowers organizations to respond rapidly to shifts in market conditions, evolving customer preferences, and unforeseen disruptions. It entails the capacity to adjust strategies, processes, and operations promptly in order to accommodate changes in the business environment. This adaptive capability enables organizations to stay resilient and agile, ensuring they can effectively navigate uncertainties and capitalize on emerging opportunities (Lee et al., 2024).

Sustainability involves a comprehensive dedication to environmental and social responsibility, with a focus on reducing carbon footprints and conserving valuable resources (Amirian et al. 2022; Sudipta Ghosh, 2024). This commitment extends beyond immediate business considerations and emphasizes practices that minimize adverse impacts on the environment. Efforts to reduce carbon footprints aim to decrease greenhouse gas emissions, contributing to the broader goal of mitigating climate change. Simultaneously, the conservation of resources involves responsible management and preservation of natural resources, aligning with a sustainable and environmentally conscious approach to business operations (Ghalandari et al. 2023; Ali et al., 2024).

Indeed, the academic concepts underpinning the synergistic efficiency, flexibility, and sustainability within the context of optimizing energy consumption in the value chain involve a multidisciplinary approach drawing from industrial engineering, supply/value chain management, and sustainable business practices (Babaeinesami et al. 2022; Alkaraan et al., 2023). In industrial engineering, foundational concepts such as lean management, Six Sigma, and operations research contribute to the understanding and enhancement of efficiency (Walter et al., 2023). Lean principles emphasize the elimination of waste, while Six Sigma focuses on minimizing variations for improved processes (Widiwati et al., 2024). Supply chain management literature provides insights into flexibility, with concepts like agile and responsive supply chains offering theoretical frameworks for swift adaptation to dynamic conditions (Chobar et al. 2022; Munir et al., 2023). Sustainability, encompassing environmental and social dimensions, leverages theories from sustainable supply chain management and corporate environmental and social responsibility (Daneshvar et al. 2023; Husnah and Fahlevi, 2023). The integration of these academic concepts aims to establish a comprehensive framework for optimizing energy consumption by harmonizing efficiency, flexibility, and sustainability across the value chain.

The research scope of this study encompasses a comprehensive exploration of the interplay between efficiency, flexibility, and sustainability within the value chain, with a primary focus on optimizing energy consumption in industrial processes. The study aims to investigate the theoretical foundations and practical implications of integrating these three critical factors, drawing from industrial engineering, supply chain management, and sustainable business practices. This research seeks to investigate the synchronization of efficiency, flexibility, and sustainability within organizations to attain a well-balanced and optimized energy consumption profile across the entire value chain. While traditional approaches may improve specific elements, a more holistic strategy is imperative to address the interconnected nature of efficiency, flexibility, and sustainability. Through the adoption of a comprehensive approach, organizations can not only diminish their environmental impact but also bolster their competitiveness in a dynamic market environment. The overarching aim of this research is to contribute valuable insights to both academia and industry, fostering a deeper comprehension of the interconnected dynamics among efficiency, flexibility, and sustainability in the context of optimizing energy consumption within the value chain (Amini Khouzani et al. 2023; Almusaed et al., 2023). It is anticipated that this understanding will equip organizations to navigate the intricacies of modern business, simultaneously achieving economic success and environmental responsibility.

In the quest to optimize energy consumption throughout the value chain, a precise tool in the form of a mathematical objective function is employed to synergize efficiency, flexibility, and sustainability. This research details the development of such a function and explains its application in achieving comprehensive optimization goals. Within this research paper, the methodology utilizes multi-objective programming, serving a dual purpose by maximizing certain objectives while concurrently minimizing others. The specific objectives earmarked for maximization and minimization are intricately woven into the study's framework to address the complexities associated with optimizing energy in the value chain. The multi-objective programming approach facilitates a nuanced and balanced optimization strategy. The model presented aims to maximize profit, flexibility, sustainability, and efficiency, while concurrently minimizing energy consumption. Essentially, the multi-objective programming in this research paper navigates the intricate landscape of the value chain with the overarching goal of simultaneously maximizing positive outcomes and minimizing adverse impacts across a spectrum of interconnected objectives.

Furthermore, a solution approach has been proposed for a multi-objective model based on heuristic algorithms. This method employs a Two-Phase Multi-Objective Evolutionary Algorithm (MOEA) that integrates the population variety and searching capability of NSGA-II into the feedback operation of MOACO. The advantages of this approach are manifold. Firstly, incorporating the diverse population of NSGA-II enhances exploration, preventing premature convergence and facilitating the discovery of varied high-quality solutions. Secondly, the algorithm benefits from the superior searching capabilities of NSGA-II (bi, et al., 2024), ensuring effective exploration and exploitation in multi-objective optimization problems. Striking a balance between exploration and exploitation, the Two-Phase MOEA is essential for achieving optimal or near-optimal solutions, making it well-suited for complex problem landscapes. Lastly, the integration of population variety and searching capabilities enhances the algorithm's efficiency in handling intricate and diverse decision-making scenarios (El-kenawy, et al., 2023), rendering it a robust and versatile tool for real-world applications. In summary, proposing this Two-Phase MOEA is imperative to create a comprehensive optimization algorithm capable of addressing the challenges inherent in diverse, complex, and multi-objective decision-making scenarios.

The chief contributions of the presented paper are summarized as follows:

- Development of a Multi-Objective Model: The paper proposes a comprehensive Multi-Objective Model (Multi-Objective Mixed-Integer Non-Linear Programming: MOMINLP) designed to address complex optimization challenges.
- Integration of Two-Phase MOEA: To tackle the complexity of large-scale multi-objective models, the paper proposes a Two-Phase Multi-Objective Evolutionary Algorithm (MOEA). This algorithm strategically combines the strengths of NSGA-II for efficient initial convergence and MOACO for parallelism and suitable feedback.

In essence, this paper introduces an innovative multi-objective optimization model, underpinned by a Two-Phase MOEA (Multi-Objective Evolutionary Algorithm). It meticulously outlines the formulations for objective functions, constraints, and budget components, offering a comprehensive framework for tackling complex decision-making scenarios. The primary contributions of this research are directed towards pushing the boundaries of knowledge and application in optimization techniques within intricate decision-making contexts. By presenting a novel model and algorithm, the paper strives to enhance the understanding and practical utilization of optimization methodologies in addressing complex decision-making challenges.

In the next section, a summary of previous research is presented. In the third part, the mathematical problem is defined. In section four, solution methods are presented. In the fifth section, the numerical results and sensitivity analysis of the presented model and the efficiency of the proposed algorithm are shown. The sixth part deals with the managerial advantages of research. Finally, a summary of the paper's process and results and suggestions for future research are mentioned.

2. Literature Review

This study is structured into three key sections to present a comprehensive view of the outlined problem framework. Section 2.1 introduces the subjects explored in value chain optimization. Section 2.2 delves into the development of solution algorithms. The concluding section outlines the identified research gaps and underscores the particular contributions of this study in pushing forward advancements in this domain.

2.1. Value Chain Optimization Frameworks

The evolution of research topics in value chain management reflects the dynamic nature of the field, progressing through sequential developments where certain themes gain prominence at different stages. The modeling process of a value or supply chain involves a systematic examination of various components and their interactions, with the goal of maintaining and enhancing the market share of each operation. Initially, there was a notable emphasis on sustainability in the supply chain, with researchers and practitioners recognizing the importance of integrating environmentally and socially responsible practices. This emphasis is exemplified by studies such as those conducted by Ibrahim et al. (2018), Tseng et al. (2019), Andalib and Soltanmohammadi (2019), and Ehtesham and Sohanian (2021). Subsequently, the focus shifted to Green Supply Chain Management (GSCM), involving a deeper exploration of strategies to reduce environmental impacts, enhance resource efficiency, and optimize the use of sustainable materials. Companies embraced practices such as eco-design, green logistics, and reverse logistics to align with environmental goals. This phase is illustrated by the work of researchers such as Amjad et al. (2022), Roh et al. (2022), Gawusu et al. (2022), Delshad et al. (2024), and

Dzikriansyah et al. (2023). The evolution continued with an increased interest in the closed-loop supply chain concept, emphasizing recycling, remanufacturing, and reusing products and materials within the supply chain. The closed-loop approach aims to minimize waste, reduce the consumption of new resources, and create a more circular and sustainable economy. This phase is exemplified by the studies conducted by Abbasi and Erdebilli (2023), Gorji (2023), and Ullah (2023). Facing increasing uncertainties and disruptions, attention in the supply chain landscape turned towards risk management. Researchers explored ways to identify, assess, and mitigate risks, with a crucial focus on disruption resilience to enable supply chains to adapt and recover swiftly from unforeseen events. Notable contributions in this area include the works of Browning et al. (2023) and Gruchmann et al. (2024). More recently, the discourse expanded to highlight the significance of collaborative practices within the supply chain. Articles discuss how collaboration among supply chain partners can lead to improved efficiency, innovation, and overall performance. This collaborative focus includes technological collaboration, strategic partnerships, joint decision-making, and information sharing among stakeholders. Research in this area is exemplified by the works of Ramjaun et al. (2024) and Yang and Gan (2024). Details of the articles have been written in the Table 1, providing a comprehensive overview of the evolution of research topics in value chain management.

Table 1. Literature Review of Value/Supply Chain Optimization

Sustainable Value/Supply Chain	Ibrahim et al. (2018)	• Introduction model of HSSCM • Determinants identification (halal policy, moral responsibility, global ethics, environmental purchasing, sustainable packaging, and related activities) • Purpose of ensuring halal integrity
	Tseng et al. (2019)	• Enhancement of sustainable supply chain capabilities in the textile industry. • Introduction the integration of social media as a crucial reference for decision-making. • Utilization of fuzzy synthetic evaluation and decision-making trial evaluation laboratory methods. • Determination key impacting criteria (outbound logistics flexibility, supply chain reconceptualization, information quality, coevolution, market-oriented perception, partner development, and knowledge acquisition and absorptive capacity)
	Andalib & Soltanmohammadi (2019)	• Investigation the factors of sustainable supply chain management. • Analysis through partial least squares path modeling • Positive impact of green product development on social issues through environmental performance • The direct effect of green supply chain management on environmental performance • Important implications on the importance of sustainable supply chain management and related management practices

	Ehtesham & Sohanian (2021)	• Developing and strengthening economic and environmental aspects in a sustainable supply chain network (SSC) • Development of a mixed integer linear programming (MILP) model for multi-objective optimization of SSC network • The primary goal of using high quality raw materials while minimizing pollution emissions and maximizing profits • Using two algorithms, multi-objective genetic and multi-objective particle swarm, to address sustainable supplier selection • optimization sustainability performance indicators in supply chain network design, considering cost minimization, time efficiency and maximizing sustainability indicators.
Green Supply Chain Management (GSCM)	Amjad et al., (2022)	• Investigating the impact of green supply chain management practices of a payment company. • Examining the intermediation of competition and investment improvement • Using Partial Least Square Structural Equation Modeling (PLS-SEM) to evaluate the proposed model • Investigating, relying on the resource dependence theory, how external resources affect organizational behavior • Results of a positive relationship between green supply chain management activities and firm performance
	Roh et al., (2022)	• A study including 452 South Korean companies. • Focus on internal green activities (green management innovation, green supply chain management and green innovation) • Investigating the impact of intellectual property rights on green innovation in the studied companies • Investigating the mediating role of green supply chain management in the relationship between intellectual property rights and green innovation • Examining how green marketing innovation relates between green innovation and environmental performance • Emphasis of the findings on the importance of green marketing innovation in the field of clean production and environmental performance
	Gawusu et al., (2022)	• A comprehensive review of green supply chain management (GSCM) in the field of renewable energy sources • Creating a standard framework for green management in companies. • Exploring the environmental, economic and social dimensions • Emphasizing the transformative impact of renewable energy and sustainable manufacturing practices on traditional supply chain management (SCM) and business models. • Providing insights to increase performance and overcome barriers in renewable energy GSCM (REGSCM). • Proposing economical and efficient control chain management techniques. • Introducing a new conceptual model that is rooted in distributed energy systems network. • Empowering renewable energy producers to participate in peer-to-peer (P2P) networks or sell directly on the public market and create value for companies.
	Dzikriansyah et al., (2023)	• Focusing on SMEs, small and medium enterprises in Indonesia • Using Partial Least Squares - Structural Equation Modeling (PLS-SEM) • Absence of internal factors such as strategic orientation and internal environmental management are primary drivers for SMEs in adopting green supply chain management practices • The key influencing role of external factors, especially government regulations, plays a fundamental role in the adoption of green supply chain management

		• The positive effect of green supply chain management on environmental performance • positive effects of green practices government regulations on improving environmental performance of SMEs
Closed-loop Supply Chain	Abbasi and Erdebilli's (2023)	• Focusing on optimizing logistics management during the COVID-19 pandemic. • Aimed to design a green closed-loop supply chain based on carbon regulatory rules. • Exploring three common CO2 restriction types to optimize costs and emissions in supply chain activities. • Considerations of factors such as location selection, shipment alternatives, fees, and releases, to balance • Affirming the impact of various policies on costs and their effectiveness in reducing emissions. • Presentation the valuable insights for managers to predict how regulatory changes may influence overall emissions in supply chain operations.
	Gorji (2023)	• A study with a specific emphasis on analyzing the green hydrogen supply chain. • Comprehensive analysis of covering production, storage, transportation, and consumption aspects of green hydrogen. • Metaheuristic optimization methods to address challenges at each stage of the supply chain. • Challenges (included optimizing water electrolysis for green hydrogen production, exploring storage methods, evaluating transportation options, and assessing hydrogen consumption methods) • Affirmation of potential of metaheuristic optimization in enhancing efficiency and sustainability within the dynamic field of green hydrogen supply chain.
	Ullah (2023)	• Objective and Focus on optimizing logistics management and developing a Green Closed-Loop Supply Chain (GCLSCD) during the COVID-19 pandemic. • Carbon regulatory framework, addressing three common CO2 restrictions to align with environmental goals. • Optimization strategies into optimizing costs and emissions within proposed models, emphasizing a delicate balance in factors like location selection, shipment alternatives, fees, and releases. • Utilizing numerical experiments for showing the impact of various policies on costs and their efficiency in reducing emissions.
Supply Chain Disruption Risk	Browning et al. (2023)	• Aiming to increase supply chain resilience during system-wide disruptions, focusing on lessons from the Covid-19 pandemic. • Three main areas for flexibility (forecasting, supply chain risk management practices, and product design). • Strategic changes in human-augmented forecasting, transition to supply chain risk management, and reorientation of product design for adaptability. • The findings emphasize the importance of human-augmented forecasting with visual analytics for effective supply chain flexibility • Organizational focus on transitioning from enterprise to supply chain risk management to better address evolving disruptions • The need to change the direction of product design principles towards adaptation in response to changing perspectives on supply chain risk • Confirming the interconnected nature of these strategies, reflecting their evolution in response to the changing supply chain risk landscape catalyzed by the pandemic.

	Gruchmann et al. (2024)	• Evolution in Response to supply chain strategies in response to the altered perspective on risk catalyzed by the pandemic. • Critical Address of the imperative of enhancing Supply Chain Resilience (SCRES) amid system-wide disruptions like pandemics and geopolitical conflicts. • Definition of SCRES as the network's capacity to recover and endure unforeseen events, emphasizing a comprehensive understanding of SCRES as a system-wide quality. • Introduction a theoretical framework extending the traditional proactive/reactive taxonomy, incorporating multiple system states involving supply system properties, behaviors, and responses to disruptions. • Practical guidelines for resilience-building in diverse industrial contexts, supporting the shift towards more robust supply chains. • Contribution to middle-range theory building for an overarching theory in supply chain resilience, identifying potential future research avenues in the field.
Co-operative Supply Chain	Ramjaun et al., (2024)	• Focusing on horizontal collaboration among small businesses, particularly breweries, within umbrella organizations. • Supply Chain Support (how this collaboration supported supply chain activities, emphasizing its role in enhancing the overall network.) • Illustration of conceptual framework development the linkages between group formation, collaborative activities, and outcomes in the supply chain. • Comparison of networks, involving five networks, revealing insights into how social mechanisms as a crucial role in fostering network development.
	Yang and Gan (2024)	• Focusing on the complex dynamics of supply chain external integration and bilateral innovation in Chinese firms. • Empirical findings, based on firm-level data (important insights into the relationship) • Positive effects in companies with higher cooperative goal interdependence with suppliers and customers. • Emphasizing common goal setting, the importance of cooperation to maximize the benefits of external integration • Anonymity of external knowledge acquisition as a partial mediator • Explaining the acquisition of external knowledge as a mechanism through which supplier-customer integration affects bilateral innovation.

2.2. Solution Approaches

In the domain of solution algorithms, the evolutionary trajectory has witnessed substantial advancements, particularly within industrial engineering, supply chain management, and artificial intelligence. A significant milestone in this journey was the introduction of genetic algorithms as a pioneering approach. Subsequently, researchers embarked on a mission to explore and enhance other single-objective algorithms, aiming to diversify and optimize problem-solving methodologies. Noteworthy articles contributing to the strengthening of the genetic algorithm include those by Song et al. (2019), Albadr et al. (2020), and Yeh et al. (2021). As the field progressed, a crucial development emerged with the introduction of multi-objective algorithms, acknowledging the intrinsic complexity of real-world problems characterized by multiple conflicting objectives. These algorithms sought to find solutions that represent a balance among various objectives, a critical consideration in domains such as supply chain management where diverse and conflicting goals coexist. Notable contributions in this direction include works by Fromer et al. (2023), Jangir et al. (2023), and Xu et al. (2023). A significant evolution in algorithmic design was the realization that combining diverse algorithms could result in superior outcomes. This approach, termed algorithmic hybridization, involves integrating the strengths of different algorithms to enhance overall performance. Researchers discovered that synergistic combinations could leverage the strengths of individual algorithms, leading to improved problem-solving capabilities. Examples of such hybridization efforts include works by Behera and Sobhanayak (2024), Parhi and Panigrahi (2024), and also Rajyalakshmi and Lakshmanna (2024). Details of the articles are documented in Table 2, offering a comprehensive overview of the evolution of research topics in value chain management.

Table 2. Literature Review of Solution Algorithm

Single Objective Algorithm	Song et al., (2019)	• Proposing an improved real-coded genetic algorithm (RCGA-rdn) to tackle poor search ability and population diversity loss. • Integrating three specialized operators - ranking group selection (RGS), direction-based crossover (DBX), and normal mutation (NM) - to enhance search capabilities. • Introducing a replacement operation to conduct periodic local initialization, increasing population diversity. • Comparing RCGA-rdn with several advanced algorithms on 21 constrained and 10 unconstrained optimization problems. • Confirmation of the effectiveness of RCGA-rdn in terms of search ability, convergence speed, and population diversity. • Exhibition of better search ability, faster convergence speed, and maintains population diversity, showcasing its superiority in optimization tasks.
	Albadr et al., (2020)	• Introducing a new genetic algorithm based on natural selection theory (GABONST) that focuses on improving the balance between exploitation and exploration in optimization problems. • GABONST is further applied to language recognition (LID) by integrating it with extreme learning machine (ELM), formation (GABONST-ELM). • This study evaluates the performance of the algorithm using statistical measures and shows the superiority of GABONST in producing high-quality solutions compared to conventional algorithms. • Effective control: GABONST exhibits better control over exploitation and exploration, which is an important aspect in optimization processes and separates it from traditional genetic algorithm and other benchmarked algorithms. • Performance of (GABONST-ELM)-LID: Integration with ELM is successful in language recognition
	Yehet al., (2021)	• Introducing a new algorithm based on simplified crowd optimization. • Focus on optimization of hyperparameters for LeNet CNN model. • Higher accuracy on MNIST, Fashion MNIST and Cifar10 datasets compared to original LeNet and PSO-LeNet models • The potential of the proposed algorithm to extend to more complex models, including AlexNet
Multi-Objective Algorithm	Fromer et al., (2023)	• Investigating pool-based and novel generative approaches in multi-objective molecular discoveries, focusing on Pareto optimization algorithms • Pool-based molecular discovery as a direct extension of multi-objective Bayesian optimization • Using different generative models, which are critical for single-objective and multi-objective optimization, from non-dominated sorting to different methods • Reinforcement learning uses non-dominant sorting on the reward function while distribution learning uses it to select molecules for retraining. • Highlighting the potential integration of Bayesian optimization techniques in de novo multi-objective design

	Jangir et al., (2023)	• Introducing the Marine-Predator Multi-Objective Algorithm (MOMPA), a new multi-objective algorithm based on elitist non-dominated sorting and crowding distance mechanism. • MOMPA is inspired by the biological interaction between predators and prey, specifically based on the Marine-Predator algorithm. • A proposal for effectively handling optimization problems with multiple and conflicting objectives by combining elitist non-dominated classification and crowding distance mechanism. • An overview of formulations including the integration of elitist crowding distance and sorting mechanisms with a robust approach to diverse optimization challenges • Demonstrate MOMPA competence, both qualitatively and quantitatively
	Xu et al., (2023)	• Introducing improved computational efficiency in Multi-Objective Evolutionary Algorithms (MOEA) by introducing a pioneering concept - the Pareto Front Network - to guide the search process. • Propose a rare point estimation strategy with the most efficient possible to reduce the computation time • Network-based knee point selection in next-generation environment selection process • Introduction of PFG-MOEA is a network-based decomposition multi-objective evolutionary algorithm with Pareto front network with the aim of balancing computational efficiency and algorithmic effectiveness. • Validating the effectiveness of PFG-MOEA by comparing its performance against multi-objective evolutionary algorithms
Hybrid Algorithm	Behera & Sobhanayak (2024)	• Introducing a hybrid algorithm that combines Gray Wolf Optimization (GWO) with Genetic Algorithm (GA). • Timing improvements using genetic algorithm mutation and crossover operators • The hybrid algorithm has the advantage of faster convergence of GA-based GWO, especially when dealing with large-scale scheduling problems. • The use of both synthetic and real-world datasets are used in the evaluation process and ensure the capabilities of the algorithm • Verifying the results obtained using statistical analysis, especially the analysis of variance (ANOVA) tool. • Validating the effectiveness of the hybrid GWO-GA algorithm as a competitive solution to address multi-objective task scheduling challenges in cloud computing environments.
	Parhi & Panigrahi (2024)	• Investigating the applicability of a simulated-cuckoo annealing search optimization approach for fine-tuning machine learning algorithms • The hybrid approach effectively navigates the meta-parameter space, identifying optimal configurations that minimize prediction errors and increase the predictive ability of the models. • A significant improvement in the prediction accuracy of ASR expansion is achieved through the simulated annealing-cuckoo search optimization method. • Understanding the FAST global sensitivity analysis of the key factors affecting the spread of ASR with time, the percentage of reactive grains and the alkali content that show the highest sensitivity indicators. • The importance of this approach for practical engineering scenarios and accurate predictions of ASR expansion in decision-making processes related to material selection, design choices and long-term durability of concrete structures.

	Rajyalakshmi and Lakshmanna (2024)	• Introducing the Hybrid Deep DenseNet Optimization (HDDNO) algorithm, a combination of machine learning (ML) and deep learning techniques, to predict parking space availability. • The HDDNO-based ML model uses secondary data obtained from the National Research Council Park (CNRPark) located in Pisa, Italy. • Using different regression algorithms in the forecasting process with a focus on increasing accuracy • Application of DenseNet technique and its promising results • The superior accuracy of the HDDNO model • Using optimizers (five optimizers, i.e., adaptive moment estimation (Adam), root mean square propagation (RMSprop), adaptive gradient (AdaGrad), AdaDelta, and stochastic gradient (SGD)) to further increase performance

2.3. Research gap

Upon thorough examination of existing studies in this domain, a discernible gap in the background research becomes evident—specifically, the lack of an integrated approach that synergizes efficiency, flexibility, and sustainability within processes as part of a comprehensive strategy to optimize energy consumption. This research endeavors to fill this gap by introducing an extensive multi-objective modeling framework. The primary objective is to optimize the energy consumption of value chains by incorporating a holistic approach that integrates and harmonizes the elements of efficiency, flexibility, and sustainability. In contrast to previous studies that may have focused on individual aspects in isolation, this research seeks to bridge these dimensions, recognizing their interdependence, and create a unified solution to enhance the overall energy efficiency of value chains. Through this innovative approach, the study aims to contribute to a more comprehensive understanding and effective optimization of energy consumption within the broader context of value chain operations.

Also, in tackling the formidable challenges presented by extensive problems and the intricate nature of large-scale multi-objective models, this research introduces a cutting-edge solving algorithm. Acknowledging the demand for innovation, a dedicated Multi-Objective Evolutionary Algorithm (MOEA) takes center stage. This algorithm strategically combines the efficiency of NSGA-II, known for its adept initial convergence, with the strengths of MOACO (Multi-Objective Ant Colony Optimization). MOACO brings to the table advantages like parallelism and well-suited feedback mechanisms, making it particularly adept at solving complex problems. The resulting Two-phase MOEA is crafted to offer a comprehensive solution to the MOMINLP model, accommodating its unique constraints and characteristics. This hybrid approach is meticulously designed to synergize the individual strengths of NSGA-II and MOACO, creating a powerful effect that enhances the overall optimization process for the given problem. By integrating efficient initial convergence from NSGA-II and the parallelism and feedback mechanisms from MOACO, the Two-phase MOEA stands out as a robust and adaptive algorithm, capable of addressing the complexities inherent in large-scale multi-objective models. The overarching objective is to develop a sophisticated algorithm that not only navigates the challenges posed by extensive real-world problems but also elevates the optimization process to unprecedented levels of effectiveness and efficiency. The Two-phase MOEA represents a significant advancement in addressing real-world complexities through a carefully curated integration of diverse algorithmic strengths.

3. Model Description

In general, however, the choice between mathematical modeling and simulation in the field of value chain management depends on the specific goals, characteristics of the system under consideration, and the available data, there are several scenarios where mathematical modeling is favored over simulation in the context of value chain analysis (Chen and Hammad, 2023). Here are some reasons:

- Deterministic Nature of Mathematical Models: Mathematical models are often deterministic, providing precise and exact solutions to well-defined problems. In the field of value chain management, where certain processes and relationships are well understood and have clear mathematical representations, deterministic models can offer accurate predictions and insights.
- Analytical Rigor and Optimization: Mathematical models are particularly powerful when the goal is to optimize a system. Value chain management often involves optimizing various components such as production, distribution, and inventory. Mathematical models allow for the application of optimization techniques to find the most efficient and cost-effective solutions.
- Efficiency in Certain Types of Analysis: Mathematical models can be more computationally efficient for certain types of analyses, especially when dealing with large datasets or complex relationships. Simulation, on the other hand, may require extensive computational resources and time, particularly when simulating a dynamic system over a long time period.

Accordingly, this research provides a multi-objective programming to maximize the minimum economic viability, efficiency, flexibility and sustainability; Also to minimize the maximum of energy consumption. This investigation is introduced for value chains process, relying on strategic and step-by-step flow.

Indeed, the Max(Min(x)) and Min(Max(x)) Function are used instead of Max(x) and Min(x). Obviously, these used functions have several preferences than sample functions. This approach is useful when there are constraints that involve both maximizing and minimizing conditions within a nested structure. Then, it's beneficial when optimized value subject should be to constraints. For example, finding the maximum value while ensuring it is greater than or equal to a certain minimum value; And also when objective functions are involved both maximizing and minimizing components, using max(min(x)) allows to handle a more complex objective in a structured manner (Mahmoudinazlou and Kwon, 2024).
Also, the factors of objective function of economic viability, efficiency, flexibility and sustainability are expressed in following:

3.1. Economic Viability Factors

Economic viability factors play a crucial role in assessing the financial health and sustainability of a value chain. These factors provide a quantitative evaluation of how well a system contributes to economic development and whether it is capable of sustaining itself over the long term. Here's a more detailed explanation of some key economic viability factors in the context of a value chain (Kitole and Sesabo, 2024):

1. Profitability: it is a fundamental economic viability factor that measures the ability of the value chain to generate positive financial returns. Its calculation involves assessing the balance between total revenue and total costs associated with the value chain activities. A profitable value chain generates more revenue than it incurs in costs.

2. Job Creation: it is a social and economic viability factor that evaluates the value chain's contribution to employment opportunities. Its calculation involves quantifying the number and quality of jobs created within the value chain. Job creation is significant for both local and regional economies, as it can enhance the livelihoods of individuals and contribute to community development.
3. Contributions to Economic Development: This factor assesses how the value chain contributes to broader economic development goals, including the growth of the regional or national economy. Its calculation: It considers the value chain's impact on factors such as GDP (Gross Domestic Product) growth, infrastructure development, and overall economic diversification. Positive contributions to economic development often involve increased economic activities, investments, and improved living standards.

By systematically evaluating these economic viability factors, stakeholders can gain a comprehensive understanding of the financial health and sustainability of the value chain. This assessment helps guide strategic decisions, identify areas for improvement, and ensure the long-term economic success of the value chain.

3.2. Sustainability Factors

Sustainability factors in a value chain are represented by a quantitative assessment of the system's performance across environmental, social, and economic dimensions. A comprehensive evaluation of how well a value chain is operated in a manner that is environmentally responsible, socially equitable, and economically viable is provided by these factors. A detailed explanation of key sustainability factors within a value chain is presented below (Abulibdeh et al., 2024):

Environmental Sustainability Factors (Becker, 2023):

1. Resource Efficiency: The efficiency with which natural resources, including raw materials, water, and energy, are utilized by the value chain is measured to minimize waste and environmental impact.
2. Carbon Footprint: The greenhouse gas emissions associated with the value chain's activities, production processes, and transportation are quantified with the aim of reducing the overall carbon footprint.
3. Waste Management: The effectiveness of waste reduction and recycling initiatives within the value chain is evaluated to minimize environmental pollution and promote circular economy principles.
4. Biodiversity Impact: The impact of value chain activities on local ecosystems and biodiversity is assessed with the goal of mitigating negative effects and promoting conservation.

Social Sustainability Factors (Mogale et al., 2023):

1. Labor Practices: The fairness of labor practices within the value chain, including aspects such as fair wages, safe working conditions, and adherence to labor rights and regulations, is evaluated.
2. Diversity and Inclusion: The commitment of the value chain to diversity and inclusion is assessed, considering factors such as gender equality, cultural diversity, and equal opportunities for all employees.
3. Community Engagement: The extent to which the value chain engages with and benefits local communities, including initiatives for community development, education, and healthcare, is measured.

4. Supply Chain Ethics: The ethical considerations throughout the supply chain are evaluated, ensuring that suppliers and partners adhere to ethical business practices and human rights standards.

Economic Sustainability Factors (Sadiq et al., 2023):

1. Local Economic Impact: The contribution of the value chain to local economies through job creation, support for local businesses, and investments in infrastructure and community development is assessed.
2. Fair Trade Practices: Fair and equitable trade practices throughout the value chain are ensured, promoting fair compensation for producers and suppliers in the global marketplace.
3. Financial Stability: The overall financial stability of the value chain is evaluated, considering factors such as profitability, return on investment, and resilience to economic shocks.
4. Innovation and Adaptability: The capacity of the value chain for innovation and adaptation to changing economic conditions, technological advancements, and market demands is measured.

By systematically evaluating these sustainability factors, operational practices within the value chain can be aligned to minimize negative impacts on the environment, promote social equity, and contribute to long-term economic viability. The integration of sustainability into the core of the value chain's strategy enhances its resilience and relevance in a rapidly changing global landscape.

3.3. Flexibility Factors (Singh, and Kumar, 2020)

Flexibility factors in the context of a system, such as a production or operational system, are attributes that contribute to the system's ability to adapt to changes, variations, or unexpected events. These factors are critical for organizations to respond efficiently to dynamic and evolving conditions. To delve deeper into the explanation of flexibility factors:

1. Changeover Time: This factor refers to the time required to switch a production system from producing one type of product to another. A shorter changeover time allows the system to be more responsive to changes in product demand or specifications. It enhances the system's ability to produce a variety of products in a timely manner.
2. Production Scalability: It is the system's capacity to adjust its output level quickly and efficiently in response to changes in demand. A scalable production system can easily accommodate fluctuations in demand, preventing underutilization or overloading of resources. It enables the system to match production levels with market demands.
3. Resource Adaptability: It involves the ability of the system to adjust the utilization of resources, including machinery, labor, and materials, to meet changing requirements. An adaptable system can reallocate resources based on shifting demands, preventing bottlenecks or resource shortages. It enhances overall operational efficiency.

In summary, flexibility factors provide a systematic and quantifiable approach to assess and enhance the adaptability of a system. By assigning numerical values and weights to key parameters, organizations can prioritize and measure the impact of flexibility-related improvements, contributing to more agile and responsive operations.

3.4. Efficiency Factors (Ma et al., 2022)

Efficiency factors in the context of a value chain represent the elements that contribute to the system's effectiveness in optimizing processes. These factors are critical for ensuring that the value chain operates smoothly, minimizing waste, reducing costs, and delivering high-quality products or services in proper time. To explore these efficiency factors in more detail:

1. Production Processes: These refer to the methods and procedures used to transform raw materials into finished products or services within the value chain. Efficient production processes streamline operations, reduce cycle times, and ensure optimal resource utilization. Optimization in these processes leads to increased output with fewer resources.
2. Time Management: It involves the effective allocation of time resources to various tasks and processes within the value chain. Efficient time management minimizes idle time, reduces lead times, and enhances overall productivity. It ensures that tasks are completed within specified timeframes, contributing to the timely delivery of products or services.
3. Quality Control: This factor encompasses measures and processes implemented to monitor and maintain the quality of products or services throughout the value chain. Efficient quality control mechanisms help prevent defects, reduce rework, and ensure that products or services meet or exceed customer expectations. This contributes to customer satisfaction and brand reputation.

In summary, efficiency factors in a value chain are central to achieving operational excellence. By quantitatively evaluating and optimizing production processes, time management, and quality control, organizations can enhance their overall efficiency, reduce costs, and deliver value to customers in a timely and effective manner. Continuous monitoring and improvement of these efficiency factors are essential for staying competitive and responsive in dynamic business environments (Adams et al., 2024).

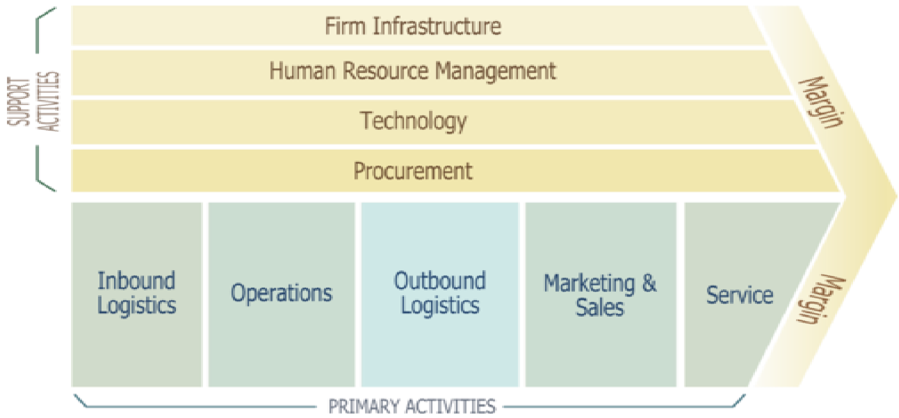

Fig 1. Structure of Value Chain

The value chain is a concept used in business management to describe the series of activities that a company engages in to create and deliver a product or service to its customers. These activities can be categorized into two main types: primary activities and support as Figure 1(Grimm and Walz, 2024).

Primary Activities:

- Inbound Logistics: Involves receiving, storing, and distributing the raw materials or inputs needed for production.
- Operations: The processes through which the raw materials are transformed into the final product or service.
- Outbound Logistics: The distribution and delivery of the finished product to customers.
- Marketing and Sales: Activities related to promoting and selling the product or service.
- Service: Providing support and assistance to customers after the sale.

Support Activities:

- Procurement: The acquisition of goods, services, or resources needed for the value chain.
- Technology Development: Involves research, development, and innovation to enhance the production process.
- Human Resource Management: Encompasses the recruitment, training, and management of the workforce.
- Firm Infrastructure: The overarching support systems, including planning, finance, and organizational structure.

Accordingly, it is clear that the value chain has many parts that to establish a suitable model, the initial step involves defining identifiers, variables, and parameters based on the information presented in Table 3.

Table 3. Parameters and Variables

Parameters	
B	Total budget
α	Coefficient interdependence (It is unique for each factor, which is specified by the index)
W	Weighting factor (It is unique for each factor, which is specified by the index)
UP	A maximum allowed value (It is unique for each factor, which is specified by the index)
DOWN	A minimum allowed (It is unique for each factor, which is specified by the index)
Variables	
β	Percentage coefficients indicating the proportion of objective functions (It is unique for each factor, which is specified by the index)
BE	Budget component of energy consumption
BF	Budget component of flexibility
BEF	Budget component of efficiency
BEV	Budget component of economic viability
BS	Budget component of sustainability

E	Total energy consumption
$E_{efficiency}$	Energy consumption component of efficiently
$E_{flexibility}$	Energy consumption component of flexibility
$E_{sustainability}$	Energy consumption component of sustainability
$E_{sustainability- efficiency}$	Interdependence between sustainability and efficiency
$E_{sustainability- flexibility}$	Interdependence between sustainability and flexibility
$E_{flexibility - efficiency}$	Interdependence between flexibility and efficiency
EF	Total efficiency
$\boldsymbol{EF_{production\ processes}}$	Coefficient of production processes of total efficiency
$\boldsymbol{EF_{time\ management}}$	Coefficient of time management of total efficiency
$\boldsymbol{EF_{quality\ control}}$	Coefficient of quality control of total efficiency
$\boldsymbol{EF_{production\ processes-time\ management}}$	Interdependence between $production\ processes\ and\ time\ management$
$\boldsymbol{EF_{production\ processes-quality\ control}}$	Interdependence between $production\ processes\ and\ quality\ contro$l
$\boldsymbol{EF_{quality\ control-time\ management}}$	Interdependence between $time\ management$ and $quality\ contro$l
F	Total flexibility
$\boldsymbol{F_{changeover\ time}}$	Coefficient of c$hangeover\ time$of total flexibility
$\boldsymbol{F_{production\ scalability}}$	Coefficient of $production\ scalability$ of total flexibility
$\boldsymbol{F_{resource\ adaptability}}$	Coefficient of $resource\ adaptability$ of total flexibility
$\boldsymbol{F_{changeover\ time-production\ scalability}}$	Interdependence between $time\ management$ and $quality\ contro$l
$\boldsymbol{F_{resource\ adaptability-changeover\ time}}$	Interdependence between $time\ management$ and $quality\ contro$l
$\boldsymbol{F_{resource\ adaptability-production\ scalability}}$	Interdependence between $time\ management$ and $quality\ contro$l
S	Total sustainability
$\boldsymbol{S_{environmental}}$	Coefficient of environmental of total sustainability
$\boldsymbol{S_{social}}$	Coefficient of social of total sustainability
$\boldsymbol{S_{economic}}$	Coefficient of economic of total sustainability
$\boldsymbol{S_{environmental-social}}$	Interdependence between $environmental\ and\ social$
$\boldsymbol{S_{environmental-economicl}}$	Interdependence between $environmental\ and\ economic$
$\boldsymbol{S_{economic-social}}$	Interdependence between $social\ and\ economic$
EV	Total economic viability

$\boldsymbol{EV}_{profitability}$	Coefficient of profitability of total economic viability
$\boldsymbol{EV}_{job\ creation}$	Coefficient of job creation of total economic viability
$\boldsymbol{EV}_{contribution\ economic}$	Coefficient of economic development of total economic viability
$\boldsymbol{EV}_{profitability-job\ creation}$	Interdependence between $profitability\ and\ job\ creation$
$\boldsymbol{EV}_{profitability-contribution\ economic}$	Interdependence between $profitability\ and\ contribution\ economic$
$\boldsymbol{EV}_{job\ creation-contribution\ economic}$	Interdependence between $contribution\ economic\ and\ job\ creation$

In general, the model operates based on the following assumptions:

- Parameter values are specified as deterministic data.
- The AHP-TOPSIS method is utilized to determine weight parameters in the objective functions.
- The interdependence coefficients are defined as a linear function.

It should be noted that, in general the correlation coefficient, often denoted by ɾ, is a statistical measure that quantifies the strength and direction of the linear relationship between two variables (Tanni et al., 2020). Indeed, when the rise or fall of one factor leads to a corresponding increase or decrease in another factor, it signifies a positive relationship between the two. Conversely, if an increase in one factor results in a decrease in the other, or vice versa, it indicates a negative relationship between the two factors (Ramezanpour et al., 2023). If the relationship between variables is nonlinear, the correlation coefficient might not fully capture the association. Additionally, correlation does not imply causation (Oliver et al., 2023). The correlation coefficient ranges from -1 to 1, where:

$$\begin{cases} 0 < ɾ \leq 1 & indicates\ a\ positive\ linear\ relationship \\ ɾ = 0 & indicates\ no\ linear\ relationship \\ -1 \leq ɾ < 0 & indicates\ a\ negative\ (inverse)\ linear\ relationship \end{cases} \tag{1}$$

$$ɾ = \frac{\sum(x_i - \overline{X})(y_i - \overline{Y})}{\sqrt{\sum(x_i - X)^2}\ .\sqrt{(y_i - Y)^2}} \tag{2}$$

Where:

x_i and y_i are individual data points for variables X and Y.

$\overline{X}\ and\ \overline{Y}$ are the means of variables X and Y.

The distribution function used for the correlation coefficient is based on the assumption of a bivariate normal distribution for the paired data (X, Y). This means that the variables X and Y follow a joint normal distribution. In practice, the correlation coefficient is often calculated using statistical software packages. in this research, the np.corrcoef function from NumPy is used to calculate the correlation coefficient between arrays X and Y.. These tool have built-in functions to compute the correlation coefficient, making the process efficient and accurate (Manenti et al., 2024).

The implemented model is systematically applied throughout the entirety of the value chain, encompassing both primary and support activities. This application spans all stages of the value chain, including Inbound Logistics, Operations, Outbound Logistics, Marketing and Sales, Service, along with supporting activities such as Firm Infrastructure, Human Resources, Technological Development, and Procurement. In an effort to maintain clarity and prevent the modeling text from becoming overly detailed, this section furnishes a broad overview of the modeling approach. The primary objective is to articulate the overall methodology and structure employed for modeling without delving into the specific intricacies of each stage of the value chain. This approach ensures a succinct presentation while effectively communicating the comprehensive application of the model across all pertinent aspects of the value chain.

$$\boldsymbol{Min(\ Max(\ E)) = W_{efficiency}\ E_{efficiency} + W_{flexibility}\ E_{flexibility} + W_{sustainability}\ \ E_{sustainability} + E_{efficiency-flexibility} + \ E_{efficiency-sustainability} + E_{sustainability-flexibility}} \tag{3}$$

$$\boldsymbol{Max(\ Min(EF)) = W_{production\ processes}\ EF_{production\ processes} + W_{time\ management}\ EF_{time\ management} + W_{quality\ control}\ EF_{quality\ control} + EF_{production\ processes-time\ management} + \ EF_{production\ processes-quality\ control} + EF_{time\ management-quality\ control}} \tag{4}$$

$$\boldsymbol{Max(\ Min(F)) = W_{changeover\ time}\ F_{changeover\ time} + W_{production\ scalability}\ F_{production\ scalability} + W_{resource\ adaptability}\ F_{resource\ adaptability} + F_{changeover\ time-production\ scalability} + F_{changeover\ time-resource\ adaptability} + F_{resource\ adaptability-production\ scalability}} \tag{5}$$

$$\boldsymbol{Max\ (Min\ (S)) = W_{environmental}\ S_{environmental} + W_{social}\ S_{social} + W_{economic}\ S_{economic} + S_{environmental-social} + S_{environmental-economic} + S_{sicial-economic}} \tag{6}$$

$$\boldsymbol{Max(Min(EV)) = W_{profitabilityly}\ EV_{profitability} + \ W_{job\ creation} EV_{job\ creation} + W_{contribution\ economic}\ EV_{contribution\ economic} + EV_{profitabilityly-job\ creation} + EV_{profitabilityly-\ contribution\ economic} + EV_{job\ creation-\ contribution\ economic}} \tag{7}$$

The first objective, which is related to energy consumption (E), $E_{efficiency}$ the energy consumption component related to efficiency. It could be a measure of how effectively energy is utilized within the system. $E_{flexibility}$ represents the energy consumption related to flexibility. It might capture aspects of energy use that are associated with adaptability or flexibility in the system. $E_{sustainability}$ shows the energy consumption related to sustainability. It could measure the environmental impact or eco-friendliness of the energy consumption. $W_{efficiency}$,$W_{flexibility}$ and $W_{sustainability}$ are weighting factors assigned to the respective components. They determine the relative importance of each energy consumption aspect in the overall objective. Adjusting these weights allows decision-makers to emphasize certain aspects over others based on their priorities. Also, the terms

$E_{efficiency-flexibility}$, $E_{efficiency-sustainability}$ and $E_{sustainability-flexibility}$ represent the interdependencies between the different components of energy consumption. They account for how the energy-related objectives are interconnected and influence each other. The objective of this expression is to minimize the maximum value of E. This implies finding a solution where, even in the worst-case scenario (maximum among multiple objectives), the overall energy consumption is minimized. The inclusion of weighting factors allows decision-makers to prioritize specific aspects (efficiency, flexibility, sustainability) based on their preferences. The interdependence terms account for relationships between different components of energy consumption, considering how they interact and impact each other.

The aim of the expression (4) is to maximize the minimum value of total efficiency (EF). This involves seeking a solution where, even under the most favorable conditions (minimum among multiple objectives), the overall efficiency is optimized. The incorporation of weighting factors enables decision-makers to prioritize specific efficiency aspects such as production processes, time management, and quality control based on their preferences. The interdependence terms take into account the relationships between different efficiency components, considering how they interact and influence one another.

The goal of the function (5) is to maximize the minimum value of total flexibility (F). This entails finding a solution where, even in the most challenging scenarios (minimum among multiple objectives), the overall flexibility is optimized. The incorporation of weighting factors enables decision-makers to prioritize specific flexibility aspects, such as changeover time, production scalability, and resource adaptability, based on their preferences. The interdependence terms consider the relationships between different flexibility components, examining how they interact and mutually influence each other.

The objective of the expression (6) is to maximize the minimum value of total sustainability (S). This mathematical formulation encapsulates a comprehensive strategy for sustainability optimization, seeking a solution that excels in sustainability even under the most challenging conditions. The inclusion of weighting factors allows decision-makers to prioritize specific sustainability aspects, such as environmental, social, and economic sustainability, aligning with their preferences. The interdependence terms acknowledge the intricate relationships between these sustainability components, considering how they interact and impact each other.

The objective of this expression (7) is to maximize the minimum value of the total economic viability (EV). This implies finding a solution where, even under the most challenging conditions (minimum among multiple objectives), the overall economic viability is optimized. The inclusion of weighting factors allows decision-makers to prioritize specific economic viability aspects, such as profitability, job creation, and contribution to economic development, based on their preferences. The interdependence terms account for relationships between different economic viability components, considering how they interact and impact each other.

Generally, the functions capture a comprehensive approach to optimization, considering various factors and their interconnections in the field of industrial systems and value chain management.

Subject to:

$$\boldsymbol{E_{efficiency-flexibility} = \alpha_{efficiency-flexibility} E_{efficiency} \; E_{flexibility}} \tag{8}$$

$$E_{efficiency-sustainability} = \ \alpha_{efficiency-sustainability}\, E_{efficiency}\ \ E_{sustainability} \tag{9}$$

$$E_{sustainability-flexibility} = \ \alpha_{sustainability-flexibility}\, E_{lexibility}\ \ E_{sustainability} \tag{10}$$

$$EF_{time\ management-quality\ control} = \alpha_{time\ management-quality\ control}\ EF_{time\ management}\, EF_{quality\ control} \tag{11}$$

$$EF_{production\ processes-time\ management} = \alpha_{production\ processes-time\ management}\, EF_{production\ processes}\, EF_{time\ management} \tag{12}$$

$$EF_{production\ processes-quality\ control} = \ \alpha_{production\ processes-quality\ control}\ \ EF_{production\ processes}\ EF_{quality\ control} \tag{13}$$

$$F_{changeover\ time-production\ scalability} = \alpha_{changeover\ time-production\ scalability}\ \ F_{changeover\ time}\ F_{production\ scalability} \tag{14}$$

$$F_{changeover\ time-resource\ adaptability} = \alpha_{changeover\ time-resource\ adaptability}\, F_{changeover\ time}\ F_{resource\ adaptability} \tag{15}$$

$$F_{resource\ adaptability-production\ scalability} = \alpha_{resource\ adaptability-production\ scalability}\ \ F_{resource\ adaptability}\, F_{production\ scalability} \tag{16}$$

$$S_{environmental-social} = \ \alpha_{environmental-social}\ \ S_{environmental}\, S_{social} \tag{17}$$

$$S_{environmental-economic} = \ \alpha_{environmental-economic}\ \ S_{environmental}\, S_{economic} \tag{18}$$

$$S_{economic-social} = \ \alpha_{economic-social}\ \ S_{economic}\, S_{social} \tag{19}$$

$$EV_{profitabilityly-job\ creation} = \alpha_{profitabilityly-job\ creation}\ \ EV_{profitability}\, EV_{job\ creation} \tag{20}$$

$$EV_{profitabilityly-\ contribution\ economic} = \alpha_{profitabilityly-\ contribution\ economic}\ \ \ EV_{profitability}\ EV_{contribution\ economic} \tag{21}$$

$$EV_{job\ creation-\ contribution\ economic} = \ \alpha_{job\ creation-\ contribution\ economic}\, EV_{job\ creation}\ EV_{contribution\ economic} \tag{22}$$

$$0 < E \le UP_{E} \tag{23}$$

$$F \ge Down_{F} \tag{24}$$

$$EF \ge Down_{EF} \tag{25}$$

$$EV \ge Down_{EV} \tag{26}$$

$$S \ge Down_{S} \tag{27}$$

$$0 < \beta_{efficiency}\, E_{efficiency}\ \ \le E \tag{28}$$

$$0 < \beta_{sustainability}\ \ E_{sustainability} \le E \tag{29}$$

$$0 < \beta_{flexibility}\, E_{flexibility} \le E \tag{30}$$

$$E = \ \beta_{efficiency}\, E_{efficiency}\ + \ \beta_{sustainability}\ \ E_{sustainability} + \ \beta_{flexibility}\, E_{flexibility} \tag{31}$$

$$0< \boldsymbol{\beta}_{quality\ control}\ \boldsymbol{EF}_{quality\ control} \leq \boldsymbol{EF} \tag{32}$$

$$0< \boldsymbol{\beta}_{production\ processes}\ \boldsymbol{EF}_{production\ processes} \leq \boldsymbol{EF} \tag{33}$$

$$0< \boldsymbol{\beta}_{time\ management}\ \boldsymbol{EF}_{time\ management} \leq \boldsymbol{EF} \tag{34}$$

$$\mathrm{EF}= \boldsymbol{\beta}_{quality\ control}\ \boldsymbol{EF}_{quality\ control} + \boldsymbol{\beta}_{production\ processes}\ \boldsymbol{EF}_{production\ processes} + \boldsymbol{\beta}_{time\ management}\ \boldsymbol{EF}_{time\ management} \tag{35}$$

$$0< \boldsymbol{\beta}_{changeover\ time}\ \boldsymbol{F}_{changeover\ time} \leq \boldsymbol{F} \tag{36}$$

$$0< \boldsymbol{\beta}_{production\ scalability}\ \boldsymbol{F}_{production\ scalability} \leq \boldsymbol{F} \tag{37}$$

$$0< \boldsymbol{\beta}_{resource\ adaptability}\ \boldsymbol{F}_{resource\ adaptability} \leq \boldsymbol{F} \tag{38}$$

$$\mathrm{F} = \boldsymbol{\beta}_{changeover\ time}\ \boldsymbol{F}_{changeover\ time} + \boldsymbol{\beta}_{production\ scalability}\ \boldsymbol{F}_{production\ scalability} + \boldsymbol{\beta}_{resource\ adaptability}\ \boldsymbol{F}_{resource\ adaptability} \tag{39}$$

$$\mathbf{0} < \boldsymbol{\beta}_{environmental}\ \boldsymbol{S}_{environmental} \leq \boldsymbol{S} \tag{40}$$

$$0< \boldsymbol{\beta}_{social}\ \boldsymbol{S}_{social} \leq \boldsymbol{S} \tag{41}$$

$$0< \boldsymbol{\beta}_{economic}\ \boldsymbol{S}_{economic} \leq \boldsymbol{S} \tag{42}$$

$$\mathrm{S}= \boldsymbol{\beta}_{environmental}\ \boldsymbol{S}_{environmental} + \boldsymbol{\beta}_{social}\ \boldsymbol{S}_{social} + \boldsymbol{\beta}_{economic}\ \boldsymbol{S}_{economic} \tag{43}$$

$$0< \boldsymbol{\beta}_{profitabilityly}\ \boldsymbol{EV}_{profitability} \leq \boldsymbol{EV} \tag{44}$$

$$0< \boldsymbol{\beta}_{job\ creation}\boldsymbol{EV}_{job\ creation} \leq \boldsymbol{EV} \tag{45}$$

$$0< \boldsymbol{\beta}_{contribution\ economic}\ \boldsymbol{EV}_{contribution\ economic} \leq \boldsymbol{EV} \tag{46}$$

$$\mathrm{EV}=\boldsymbol{\beta}_{profitabilityly}\ \boldsymbol{EV}_{profitability} + \boldsymbol{\beta}_{job\ creation}\boldsymbol{EV}_{job\ creation} + \boldsymbol{\beta}_{contribution\ economic}\ \boldsymbol{EV}_{contribution\ economic} \tag{47}$$

$$\mathrm{B= BF + BE+ BEF+ BEV+BS} \tag{48}$$

$$\boldsymbol{BE} = \boldsymbol{\beta}_{efficiency}\ \boldsymbol{BE}_{efficiency} + \boldsymbol{\beta}_{sustainability}\ \boldsymbol{BE}_{sustainability} + \boldsymbol{\beta}_{flexibility}\ \boldsymbol{BE}_{flexibility} \tag{49}$$

$$\boldsymbol{\beta}_{efficiency} + \boldsymbol{\beta}_{sustainability} + \boldsymbol{\beta}_{flexibility} = \mathbf{1} \tag{50}$$

$$\mathrm{BEF}= \boldsymbol{\beta}_{quality\ control}\ \boldsymbol{BEF}_{quality\ control} + \boldsymbol{\beta}_{production\ processes}\ \boldsymbol{BEF}_{production\ processes} + \boldsymbol{\beta}_{time\ management}\ \boldsymbol{\beta EF}_{time\ management} \tag{51}$$

$$\boldsymbol{\beta}_{changeover\ time} + \boldsymbol{\beta}_{production\ scalability} + \boldsymbol{\beta}_{resource\ adaptability} = \mathbf{1} \tag{52}$$

$$\mathrm{BF} = \boldsymbol{\beta}_{changeover\ time}\ \boldsymbol{BF}_{changeover\ time} + \boldsymbol{\beta}_{production\ scalability}\ \boldsymbol{BF}_{production\ scalability} + \boldsymbol{\beta}_{resource\ adaptability}\ \boldsymbol{BF}_{resource\ adaptability} \tag{53}$$

$$\boldsymbol{\beta}_{changeover\ time} + \boldsymbol{\beta}_{production\ scalability} + \boldsymbol{\beta}_{resource\ adaptability} = \mathbf{1} \tag{54}$$

$$\mathrm{BS}= \boldsymbol{\beta}_{environmental}\ \boldsymbol{BS}_{environmental} + \boldsymbol{\beta}_{social}\ \boldsymbol{BS}_{social} + \boldsymbol{\beta}_{economic}\ \boldsymbol{BS}_{economic} \tag{55}$$

$$\boldsymbol{\beta}_{environmental} + \boldsymbol{\beta}_{social} + \boldsymbol{\beta}_{economic} =1 \tag{56}$$

BEV= $\boldsymbol{\beta_{profitabilityly}}\ \boldsymbol{BEV_{profitability}} + \ \boldsymbol{\beta_{job\ creation}}\boldsymbol{BEV_{job\ creation}} + \boldsymbol{\beta_{contribution\ economic}}\ \boldsymbol{BEV_{contribution\ economic}}$ (57)

$$\boldsymbol{\beta_{profitabilityly}} + \ \boldsymbol{\beta_{job\ creation}} + \ \boldsymbol{\beta_{contribution\ economic}} = \mathbf{1} \quad (58)$$

All of variables $\geq \mathbf{0}$ (59)

All $\boldsymbol{\beta} \leq \mathbf{1}$ (60)

These constraints capture the intricate interdependencies between different components, such as energy consumption, efficiency, flexibility, sustainability, and economic viability. For instance, Constraints (8), (9), and (10) illustrate how the energy consumption components are interrelated, reflecting the complex dynamics within the system. Similarly, Constraints (11) to (22) detail the interdependence of efficiency, flexibility, sustainability, and economic viability components, emphasizing the holistic approach of the optimization process. Constraints (23) to (58) encompass budget considerations and set bounds for the various components, ensuring a balanced allocation of resources. Constraint (59) enforces the non-negativity of variables, while Constraint (60) places a limit on the β values. In essence, this set of constraints forms the basis for a sophisticated optimization model that takes into account the multifaceted relationships between different factors, allowing decision-makers to tailor solutions to their priorities within the specified constraints.

Overall, the equations include coefficients (α, β) representing the impact and proportion of each factor, and weighting factors (W) determining their relative importance. Constraints are imposed on the values of various components, such as energy consumption (E), flexibility (F), sustainability (S), and economic viability (EV), ensuring that they fall within specified bounds. Additionally, budget components are defined, and relationships between them are established to maintain a coherent allocation of resources. The optimization problem aims to find values for the variables that satisfy the given equations, meeting the objectives and constraints of the system.

4. Solution approach

In this section, a Two-phase MOEA is introduced to solve the proposed multi-objective model and find near-optimal solutions. In Section 4.1. the strengths and weaknesses of NSGA-II and MOACO algorithms are disclosed .In Section 4.2. the proposed Two-phase MOEA algorithm to solve the problem is expressed. Section 4.3. is related to parameter selection of the proposed solution approach

4.1. NSGA-II and MOACO

Indeed, considering the notion of Darwin's evolution theory and Mondel's heredity theory, Genetic Algorithm (GA) and following it, the Non-Dominated Sorting Genetic Algorithm (NSGA-II) have been presented as the bionic optimization algorithm (Deb et al., 2002). This is an imitation of the evolution of live populations in the nature, which tries to find the optimal case for some complicated problems by evolving determined chromosomes from generation to generation. The NSGA-II algorithm is an elitist algorithm that uses an initial population to reach near-optimal solutions. The elitism operator provides this chance for the elites of a population that can be directly transmitted to the next generation. The philosophy of the existence of elitism is that an answer will not be lost unless a better answer is made. NSGA-II uses fast non-dominated sorting to categorize individuals and decreases time complexity. The crowded-comparison operator without defining the sharing parameter replaces the fitness sharing mechanism (Gargari et al.,2021).

In NSGA-II, the problem be coded based on binary codes, and then searching processes to find optimal solution are accomplished by operators of selection, crossover and mutation. NSGA-II has known as a global optimization method and has benefits of proper global search capability, self-adaption and self-organization (Shuai et al., 2019). Nevertheless, most of the comparisons between solutions in non-dominated sorting are redundant or inessential. Hence, its feedback mechanism is not appropriate, so that it causes to create excessive number of redundant iterations, resulting in a scant efficiency (Zhang and Ma, 2015).

On the other side, regarding to foraging behavior of ants in the real world, the Ant Colony Optimization and Multi-Objective Ant Colony Optimization algorithms have been appeared (Dorigo and Gambardella, 1997). Obviously, in the whole foraging flow, should never is there a food encountered before in the road, the ant randomly opts one path. And therefore, several pheromones are release by prior ants for other ants to be guide for them in decision-making. With time passaging, when the more pheromones accumulate in a path, the possibility is more to select that path by other ants. Hence, pheromone path on such a trail can cumulate swifter and can attain positive feedback from other ants. So, the MOACO algorithm explore the solution space parallel and utility based on initial pheromones (Liu and Liu, 2019). According to the nature process, bereft any prior knowledge, ant colonies discover the optimal solution via information exchange among individuals. MOACO algorithm has qualifications of parallel calculation, self-learning, and appropriate information feedback as a group intelligence optimal algorithm. However, the convergence speed of this algorithm is slow at the initial searching step when there is less or no available information (Huang et al., 2019).

4.2. 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. Hence, based on the described pros and cons of NSGA-II and MOACO in Section 4.1., it can be concluded that to solve the redundant repetitions and lacking impressive feedback for NSGA-II, another algorithm with more feedback capability and speed is required. As well, to settle the initial searching process for MOACO, another algorithm with high speed and proper initial convergence is needed. Hence, in this section, we propose a Two-phase MOEA that integrates the population variety and appropriate searching capability of NSGA-II into the feedback operation of MOACO. The Two-phase MOEA utilizes the high speed and proper quality of initial convergence of NSGA-II and parallelism and efficient feedback of MOACO to find the Pareto optimal solutions.

As can be seen from the speed-time curve of NSGA-II and MOACO (Figure 2), t_a is the most appropriate fusion time. Indeed, fusion time is when should NSGA-II be terminated and the MOACO be initiated. In this paper, the main concept of altering from NSGA-II to MOACO is relied on the lack of response improvement in the NSGA-II algorithm. So that if the rate of improvement of the answer is less than the rate expected by the decision makers, the algorithm changes. In other word, to find a good fusion time t_a in the interval $[t_b, t_c]$, we need to introduce the proper numbers of iterations. Therefore, we introduce evolutionary rate as the alteration rate of optimal fitness values between two adjacent repetitions. In fact, when the evolutionary rate does not improve from an expected level, which is even no a strict one, it means that the NSGA-II cannot find a better response among the population at the right time. Accordingly, it loses proper performance after a few iterations and it is time to change the algorithm. Thus, the two-phase algorithm turns into MOACO phase.

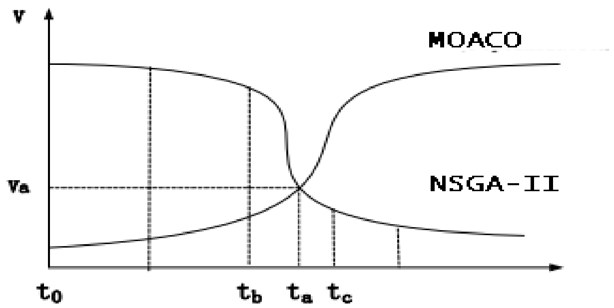

Fig 2. Difference of speed curve of searching (convergence) NSGA-II and MOACO

According to the operation of GA and ACO algorithms that Luan et al. (2019) have clarified, as well as the similarity of these two algorithms to the NSGA-II and MOACO algorithms (Huang et al., 2019), Figure 4 Shows the steps and phases of the proposed solution algorithm.

Phase I: NSGA-II. Firstly, the non-dominated population (P_t) is randomly generated based on the initial parameters of NSGA-II algorithm. After objective functions calculation, the offspring population (P_{t+1}) is created by mutation and crossover. After the combination of parents and offspring set, the non-dominated fronts are selected by elitism capability of fast sorting of NSGA-II. Then, crowded distance is calculated, and the presented process is repeated until reaching an optimal rate of evolutionary (Zheng and Doerr, 2023) (as Figure 3).

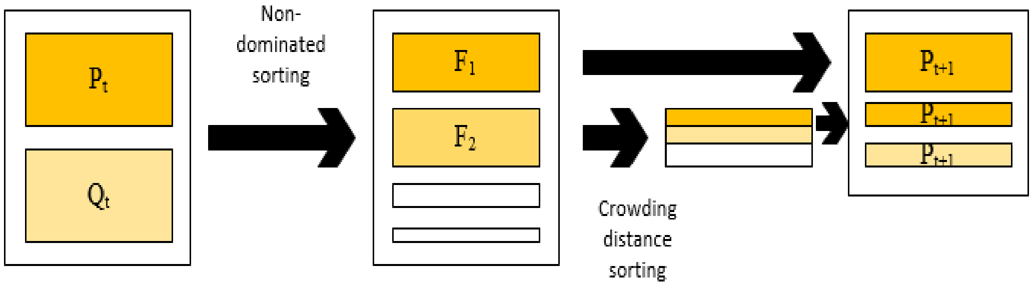

Fig 3. Elitist Non-Dominated Sorting Genetic Algorithm (NSGA-II)

Phase II: MOACO. The achieved final population of NSGA-II is used as initial pheromone of MOACO algorithm. Then, considering other initial parameters of MOACO algorithm, the feasible solution set is made. Each ant moves to the next node considering a transition probability. After the accomplishment of this process for all determined number of ants, the fitness value should be calculated. These steps are repeated without ceasing to reach maximum searching time. Finally, best solutions are obtained (Comert and Yazgan,2023).

4.3. Generic operations

The used parameters of NSGA-II and MOACO for the proposed Two-phase MOEA are defined in Section 4.3.1 and Section 4.3.2, respectively.

4.3.1. Parameters of NSGA-II

For the population-based metaheuristic algorithms, the initial solutions and operators play an essential role in the productivity of the algorithm. In this paper, the initial solutions of the NSGA-II algorithm are randomly generated. Also, the search progress in the NSGA-II algorithm is accomplished by three fundamental breeding operations (selection, crossover, and mutation) (Wu et al., 2022).

- Selection: In this paper, a binary tournament is utilized. For this operator, two individuals are randomly selected from the population and then are compared with others. The best dominant individual is nominated as the first parent. A similar process is accomplished to find all parents.
- Crossover: The crossover operator in this paper is a uniform crossover. At first, two parents are selected. If the value of the parents' chromosome is more than the probability of combination, the first offspring get the gene at index i from parent 1, and the second offspring get the identical index from parent 2. But if it is not, this process is reversed. This type of crossover operator is demonstrated in Table 4.
- Mutation: For mutation operator, after selecting for a chromosome for each genome of the chromosome, a random number is created. Should this number be less than the mutation rate, the genome will be altered randomly; otherwise, the genome will not mutate. The mutation operator is shown in Table 5.

Table 4. Crossover operation

Chromosome 1 (Parent 1)	1	0	0	1	0
Chromosome 2 (Parent 2)	0	0	1	1	1
Random Numbers String	0.52	0.68	0.89	0.13	0.94
Possibility of Combination (0.72)	<0.72	<0.72	>0.72	<0.72	>0.72
Offspring 1	0	0	0	1	0
Offspring 2	1	0	1	1	1

Table 5. Mutation operation

Chromosome (Parent)	1	0	0	1	0
Random Numbers String	0.69	0.22	0.51	0.11	0.09
Possibility of Mutation (0.28)	>0.28	<0.28	>0.28	<0.28	<0.28
Offspring	1	1	1	0	1

4.3.2. Parameters of MOACO

There are two basic processes for this algorithm, pheromone updating, and transition probability that have a fundamental impact on results (Muthana and Ku-Mahamud, 2023).

- Pheromone updating: In this paper, regarding Max-Min MOACO, only pheromones of the optimal solution are updated after each iteration (Luan et al., 2019).
- Transition probability: It is determined to assign which node will be chosen by ants. As MOACO is inclined to get bogged down in the local optima, it is preferred to use Niu's work (Niu et al., 2012) that presents randomness in the transition possibility.

Then, 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 (Srikantha Dath, 2023). 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. 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 (Allmendinger et al., 2023).

4.4. The preferences of the proposed hybrid algorithm

The presented Two-phase Multi-Objective Evolutionary Algorithm (MOEA) emerges as a distinctive solution approach for multi-objective models, offering notable advantages. Its standout feature lies in the swift convergence rate during the initial stages, leveraging the efficiency inherent in the NSGA-II algorithm. Furthermore, the algorithm sets itself apart by incorporating parallelism and providing impressive feedback in later stages through the MOACO component. Specifically tailored for NP-hard problems, this algorithm adeptly tackles large-sized instances of intricate optimization challenges, presenting Pareto-optimal solutions that signify optimal trade-offs among conflicting objectives. The holistic framework of the Two-phase MOEA, integrating interdependence coefficients and budgetary constraints, ensures a realistic representation of intricate relationships within complex systems. This quality renders it a versatile and robust tool for decision-making in scenarios involving energy consumption, efficiency, flexibility, sustainability, and economic viability. The algorithm's capabilities make it well-suited for addressing complex decision landscapes and contribute significantly to advancing optimization methodologies.

In summary, the proposed algorithm goes beyond conventional approaches by presenting a hybrid solution that strategically combines the strengths of two distinct algorithms. The clear and detailed explanation provided showcases the algorithm's unique contributions, addressing the reviewer's concerns and emphasizing the significance of the proposed Two-phase MOEA in advancing multi-objective optimization methodologies.

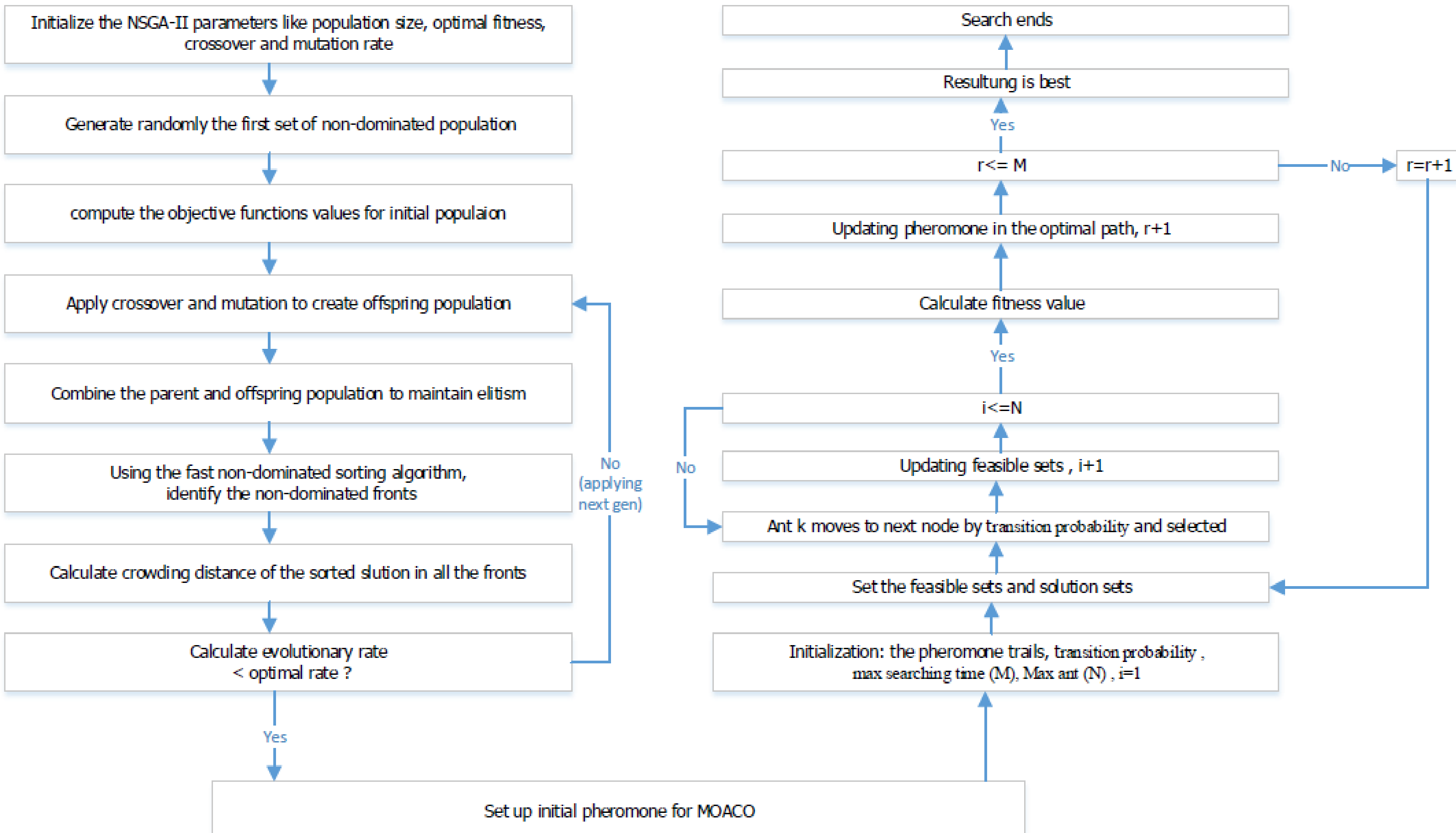

Fig 4. Two-phase algorithm of NSGA-II and MOACO

5. Computational Evaluation and Statistical Experimentations

In this section, several numerical experiments for introduced model are generated and solved by the proposed Two-phase MOEA. The model's parameter values and the algorithm parameters are chosen randomly using a uniform distribution that aligns with real-world conditions. The parameter values are randomly selected in uniform fashion (Table 6). Also, AHP-TOPSIS approach was used to quantify each of the qualitative factor (depending on the nature of optimization problem.) To tune the parameters of the proposed Two-phase MOEA, a Trial and Error process was completed by the suggested values in Table 7. The highlighted numbers in this table show the best values for parameters. For instance, (0.75, 0.03) for (Probability of combination, probability of mutation) in NSGA-II and 0.70 for Transition probability in MOACO.

Table 6. Parameters Value

Parameter	Value	Parameter	value
$\boldsymbol{B}$	~ uniform (10000,100000)	$\boldsymbol{UP}$	~ uniform (10000,100000)
$\boldsymbol{\alpha}$	~ uniform (-1,1)	$\boldsymbol{DOWN}$	~ uniform (100,1000)
$\boldsymbol{W}$	~ uniform (0,1)		

Table 7. Levels of parameters of the NSGA-II and MOACO

	Parameters	**Levels**			
		1	2	3	4
NSGA-II	Number of generations	300	**400**	500	600
	Population	150	200	**250**	300
	(Probability of combination, probability of mutation)	(0.65,0.05)	(0.70,0.0.04	**(0.75,0.03**)	(0.80,0.02)
MOACO	evolutionary rate	0.010	0.015	0.020	**0.025**
	Transition probability	**0.70**	0.75	0.80	0.85
	Maximum ant	150	**200**	250	300
	Maximum search	15	**20**	25	30

Table 8 and 9 illustrate the values of objective functions for the experiments by the proposed Two-phase MOEA, NSGA-II, MOACO.

Table 8. The calculated objective function values for experiments by presented two-phase MOEA

No	Two-phase MOEA					
	F_1	F_2	F_3	F_4	F_5	CPU Time(S)
1	71301	1732	259	1220	2778	122
2	29658	287	199	906	3501	195
3	59369	2421	403	351	1472	256
4	42697	3095	670	389	2166	601
5	32008	1872	798	1667	987	753
6	69639	1596	1031	629	2561	709
7	52396	2697	479	664	1246	352
8	12596	5632	2109	1909	532	148
9	52555	1239	3105	3872	1986	916
10	42698	1088	1156	1203	2467	652
Mean	44506	2156	864	1281	3140	4704

Table 9. The calculated objective function values for experiments by each single MOEA

No	NSGA-II						MOACO					
	F_1	F_2	F_3	F_4	F_5	CPU Time(S)	F_1	F_2	F_3	F_4	F_5	CPU Time(S)
1	91256	1564	241	1185	2142	189	97134	1601	239	1198	2023	122
2	49408	152	184	883	3087	428	45610	204	179	897	3004	204
3	71063	2168	358	309	1396	549	69254	2365	349	311	1330	378
4	45113	29562	661	352	2091	762	49872	2906	627	359	2087	651
5	36952	1458	701	1253	884	970	37124	1625	703	1296	873	768
6	70985	1324	972	601	2322	998	71548	1433	979	609	2387	774
7	60008	2012	423	622	1102	403	63626	2422	407	637	1054	394
8	18509	5507	2017	1799	501	609	19526	5111	1999	1762	475	180

9	58011	1196	3196	3531	1752	922	54982	1092	3223	3504	1784	986
10	46032	985	1114	1085	2256	526	46797	994	1110	1097	2187	835
Mean	54734	4593	987	1162	1753	636	55547	1975	981	117	1720	529

In the presented findings, the Two-phase Multi-Objective Evolutionary Algorithm (MOEA) emerges as a standout performer when compared to two other prominent meta-heuristic algorithms, NSGA-II and MOACO. The analysis, as illustrated in Table 7, emphasizes the remarkable efficiency of the Two-phase MOEA in terms of run time. Across all solved experiments, it consistently exhibits shorter run times than both NSGA-II and MOACO, indicating superior computational speed. This noteworthy advantage positions the proposed Two-phase MOEA as a faster and more agile solution, crucial in scenarios where timely optimization is paramount. Additionally, the algorithm's prowess extends beyond speed, as it consistently provides better solutions in comparison to its counterparts, as evidenced by the mean values of objective functions.

An in-depth examination of the objective functions further reinforces the Two-phase MOEA's dominance. The mean values of the first objective function highlight its superiority, with a value of 44506 compared to 54734 and 55547 for single NSGA-II and single MOACO, respectively. Moreover, in the critical aspect of maximizing the minimum efficiency, the Two-phase MOEA outperforms both NSGA-II and MOACO with significantly lower mean values (2156 compared to 4593 and 1975). This superiority extends across all four objective functions and run time metrics. Consequently, the overall conclusion drawn from this comprehensive analysis is that the proposed Two-phase MOEA stands out as an impressive and highly effective optimization method. Its attributes include not only high computational speed but also a demonstrated ability to yield solutions of superior quality. Furthermore, the algorithm showcases proper initial convergence quality and provides appropriate feedback, solidifying its position as a robust and promising solution for a diverse range of optimization challenges.

The following sub-sections will be dedicated to examining the performance and evaluating the functionality of the suggested algorithm, as well as assessing the sensitivity of the proposed model.

5.1. Multi-objective Evaluation Metrics

The analysis of multi-objective evaluation metrics is essential for comparing the performance of optimization algorithms, aiding in algorithm selection, fine-tuning parameters, and benchmarking. These metrics offer a standardized approach for assessing an algorithm's ability to approximate the true Pareto front. The insights gained from this analysis contribute to the advancement of research, providing researchers and practitioners with a basis for making informed decisions, understanding algorithm behaviour, and ultimately improving the effectiveness of optimization solutions in real-world applications. Indeed, to evaluate the performance of the proposed algorithm and compare its efficiency with single-objective algorithms, it is necessary to assess the optimization using multi-objective evaluation metrics. These metrics provide insights into how well the algorithm is able to achieve a balance between conflicting objectives (Mishra et al., 2024). In the paper, the Generational Distance (GD), Hypervolume (HV), Error Ratio (ER) and Overall Non-Dominated Vector Generation (ONVG) are analyse.

- Generational Distance (GD)

The Generational Distance (GD) is a metric used to measure the average distance between each solution in the obtained Pareto front and the true Pareto front (Kalita et al., 2024). It is often defined mathematically as follows:

Let $PF_{obtained}$ be the set of solutions in the obtained Pareto front, and PF_{true} be the set of solutions in the true Pareto front. The Generational Distance (GD) is then calculated as:

$$GD = \sqrt{\frac{1}{|PF_{true}|}\sum_{i=1}^{|PF_{true}|} d_i^2} \qquad (61)$$

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

In this equation:

$|PF_{true}|$ represents the number of solutions in the true Pareto front.

The Euclidean distance d_i is calculated between each solution in the true Pareto front and its nearest neighbour in the obtained Pareto front.

The square root and normalization ensure that GD provides a meaningful measure of the average distance, and a lower GD value indicates a better convergence of the obtained Pareto front to the true Pareto front.

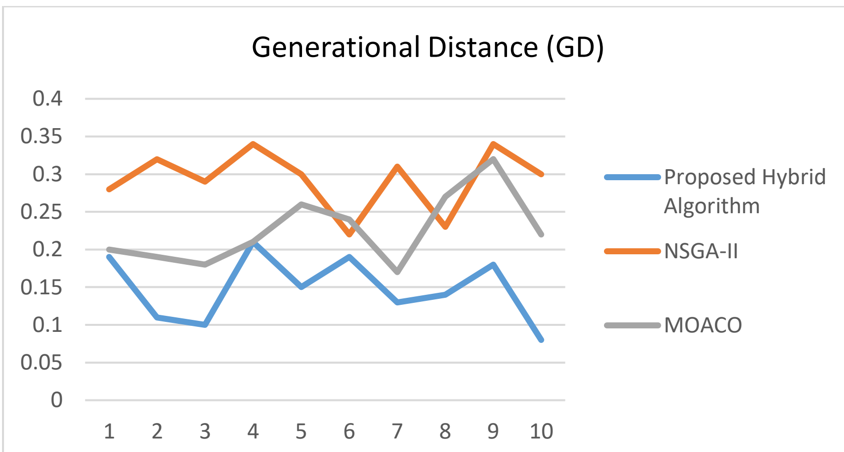

Fig 5. Comparative Analysis of Generational Distance

According Figure 5, the proposed algorithm exhibits a clear superiority in Generational Distance (GD) compared to NSGA-II and MOACO. GD measures the average distance of the algorithm's solutions from the true Pareto front. The values achieved by the proposed algorithm are closer to zero, indicating a more precise approximation to the true solution. This closer alignment signifies the algorithm's effectiveness in minimizing the deviation of its solutions from the optimal front, showcasing a superior ability to converge to Pareto-optimal solutions.

- Hypervolume (HV)

The hypervolume (HV) is a performance metric commonly used in multi-objective optimization to assess the quality of a Pareto front approximation. It measures the volume of the objective space that is dominated by a set of solutions (Pareto front) concerning a reference point. The hypervolume (HV) calculation is typically expressed mathematically as the volume of the dominated portion of the objective space under a given Pareto front P with respect to a reference point Z (Cai et al., 2024). The hypervolume equation is as follows:

$$HV(P, Z) = \int_{-\infty}^{Z_1} \int_{-\infty}^{Z_2} \dots \int_{-\infty}^{Z_m} dy \qquad (62)$$

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 integral is taken over the dominated portion of the objective space, bounded by the reference point Z along each objective axis.

In practice, this integral is often approximated numerically, and there are algorithms designed to efficiently compute the hypervolume of a given Pareto front with respect to a reference point.

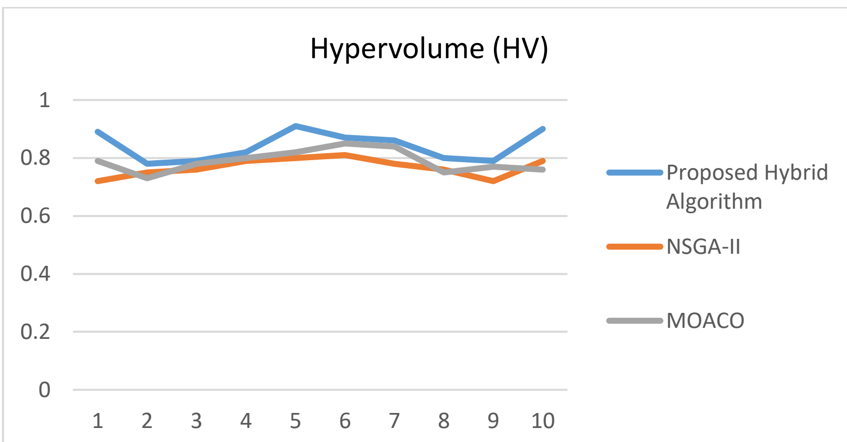

Fig 6. Comparative Analysis of Hypervolume

The results depicted in the Figure 6 indicate the superiority of the proposed algorithm in terms of Hypervolume (HV) when compared to NSGA-II and MOACO. HV serves as a metric for assessing the volume of space covered by an algorithm's solutions in the objective space. In this context, the proposed algorithm excels by achieving a notably larger hypervolume, showcasing superior coverage of the Pareto front. This implies that the proposed algorithm not only discovers diverse solutions but also explores a more extensive portion of the Pareto front. The larger hypervolume attained by the proposed algorithm signifies its ability to provide decision-makers with a richer set of trade-off solutions, making it a promising choice for multi-objective optimization tasks.

- Error Ratio (ER)

The Error Ratio (ER) is an evaluation metric used to assess the accuracy of an approximation set (typically obtained from a multi-objective optimization algorithm) concerning a true Pareto front (Usman and Lu, 2024). The mathematical formulation of the Error Ratio is as follows:

$$\mathrm{ER} = \frac{\textbf{Area between the true Pareto front and the approximation set}}{\textbf{Total area of the true Pareto front}} \tag{63}$$

In this equation:

The "area between the true Pareto front and the approximation set" represents the region where the approximation set deviates from the true Pareto front.

The "total area of the true Pareto front" is the entire space covered by the true Pareto front.

A lower Error Ratio indicates a better approximation, as it signifies a smaller deviation from the true Pareto front. It provides a quantitative measure of how well the generated solutions approximate the optimal trade-offs along the objectives compared to the actual Pareto front.

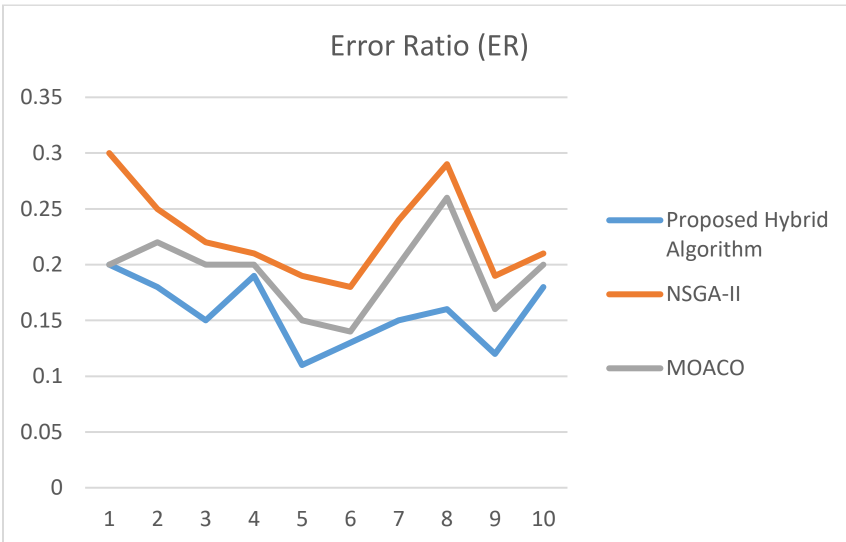

Fig 7. Comparative Analysis of Error Ratio

According to Figure 7. it is obvious the Error Ratio (ER) further accentuates the superiority of the proposed algorithm. ER measures the accuracy of the generated solutions by comparing them to the true Pareto front. The proposed algorithm consistently demonstrates lower error rates compared to NSGA-II and MOACO, showcasing its ability to generate solutions that more closely align with the actual Pareto front. This heightened accuracy is crucial for decision-makers relying on the algorithm's results, establishing the proposed algorithm as a more reliable choice.

- Overall Non-Dominated Vector Generation (ONVG)

Overall Non-Dominated Vector Generation (ONVG) is a metric used to assess the effectiveness of a multi-objective optimization algorithm in generating non-dominated solutions across multiple objectives. It is often employed to evaluate the diversity and spread of the solutions obtained from the optimization process (Jiang et al., 2024). The ONVG is calculated using the following steps:

1. Generate the Pareto Front: Obtain the Pareto front, which represents the set of non-dominated solutions in the objective space.

2. Divide the Objective Space: Divide the objective space into a grid or set of bins. This discretization allows for the analysis of solution distribution.
3. Count Non-Dominated Vectors in Each Bin: For each bin, count the number of non-dominated vectors (solutions) that fall within it.
4. Calculate Overall Non-Dominated Vector Generation: The ONVG is then computed by considering the count of non-dominated vectors in each bin and the total number of solutions.

$$\mathrm{ONVG} = \frac{\textbf{Sum of non-dominated vectors in each bin}}{\textbf{Total number of solutions}} \tag{64}$$

A higher ONVG value indicates a more even distribution of non-dominated solutions across the objective space. This metric helps assess the algorithm's ability to explore and cover the entire Pareto front, providing insights into the diversity and quality of the generated solutions.

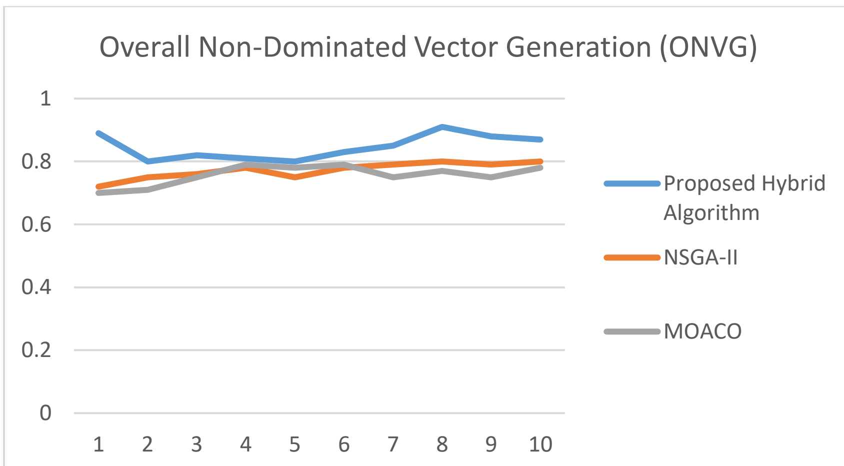

Fig 8. Overall Non-Dominated Vector Generation

As shown in Figure 8, the Overall Non-Dominated Vector Generation (ONVG) metric highlights the proposed algorithm's superiority in generating non-dominated solutions. It indicates the diversity and optimality of the solution set. The proposed algorithm consistently produces a higher number of non-dominated solutions compared to NSGA-II and MOACO, showcasing its ability to explore a broader range of trade-off solutions. This superiority in non-dominated vector generation signifies the proposed algorithm's effectiveness in providing decision-makers with a more comprehensive and diverse set of Pareto-optimal solutions.

In summary, the proposed algorithm exhibits consistent superiority across various evaluation metrics compared to NSGA-II and MOACO. It demonstrates more precise approximations, indicating a closer proximity to the true solution. The algorithm achieves broader coverage of the Pareto front, implying a more comprehensive exploration of the solution space. Additionally, it showcases increased accuracy, as reflected in lower error rates compared to the individual algorithms. Moreover, the proposed algorithm generates a richer set of non-dominated solutions, highlighting its ability to provide diverse and optimal solutions. These collective strengths make the algorithm well-suited for real-world applications, offering enhanced performance and versatility in addressing multi-objective optimization challenges.

5.2. Sensitivity Analysis

In essence, a vital iterative process is established by scrutinizing results, conducting sensitivity analysis, and refining the model (Gao et al., 2024). This iterative approach enables a deeper comprehension of the supply chain network optimization model, refining its accuracy, and enhancing its applicability to real-world scenarios (Mohamadi et al., 2024). The model's adaptability is bolstered, ensuring robustness in accommodating diverse scenarios within the supply chain network. Subsequent stages involve a meticulous analysis of obtained results, examining how changes in parameter values impact the outcomes of interest in the value chain network optimization model (Richey et al., 2023) . 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 (Yusriza et al., 2023). Understanding the sensitivity of the model to different input variations allows prioritization of key factors, focusing efforts on refining the model's representation of these critical elements. In the refinement stage, insights gained from simulations and sensitivity analyses (Barbhuiya et al., 2023) are incorporated. In the research. the sensitivity analysis of the model has been conducted by examining two key parameters: The Coefficient of Interdependence and the overall budget parameter.

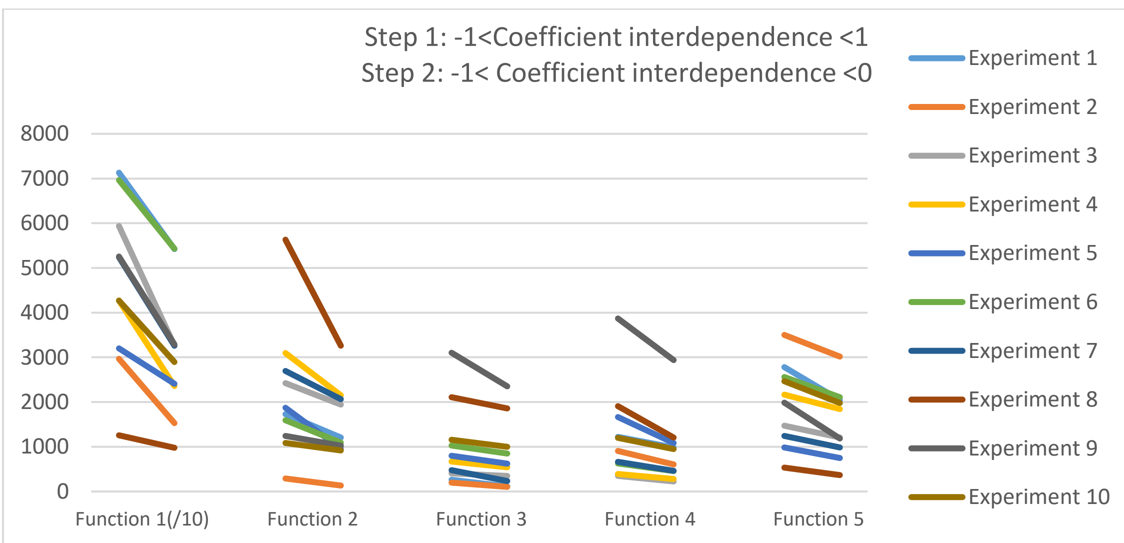

Fig 9. Results of Sensitivity Analysis (based on changing coefficient interdependence)

Upon examination, the results of the presented model are consistent with the logical predictions. Therefore, the model behaves in accordance with expectations when the α parameter is altered.

Moreover, by examining the obtained results from the objective functions (Figure 9), it is evident that the parameter range of α in the initial model is appropriate. Imposing constraints on it adversely affects the optimization process of the model. When the Coefficient of Interdependence is constrained to exclusively negative values, the outcome is a reduction in the overall values of the objective functions. This decrease signifies a deviation from the genuine optimization process. It is important to note that not all relationships can be exclusively negative or positive; they must have logical orientations.

In practical terms, this implies that when the Coefficient of Interdependence is limited to negative values, it introduces a disruptive element into the relationships between various factors. As a result, the values of the objective functions, representing key aspects such as energy consumption, efficiency, flexibility, sustainability, and economic viability, tend to decrease. This reduction in the values of objective functions indicates a suboptimal state in the optimization process. The model, when constrained in this manner, faces challenges in aligning factors harmoniously within the value chain. The negative orientation of interdependencies can hinder the model's ability to achieve real and effective optimization.

In summary, constraining the Coefficient of Interdependence to negative values disrupts the optimization process, leading to aد unrealistic decrease in the values of objective functions. This deviation from the expected optimization path emphasizes the importance of considering logical orientations in relationships between factors, ensuring a more realistic and achievable optimization in the context of the value chain.

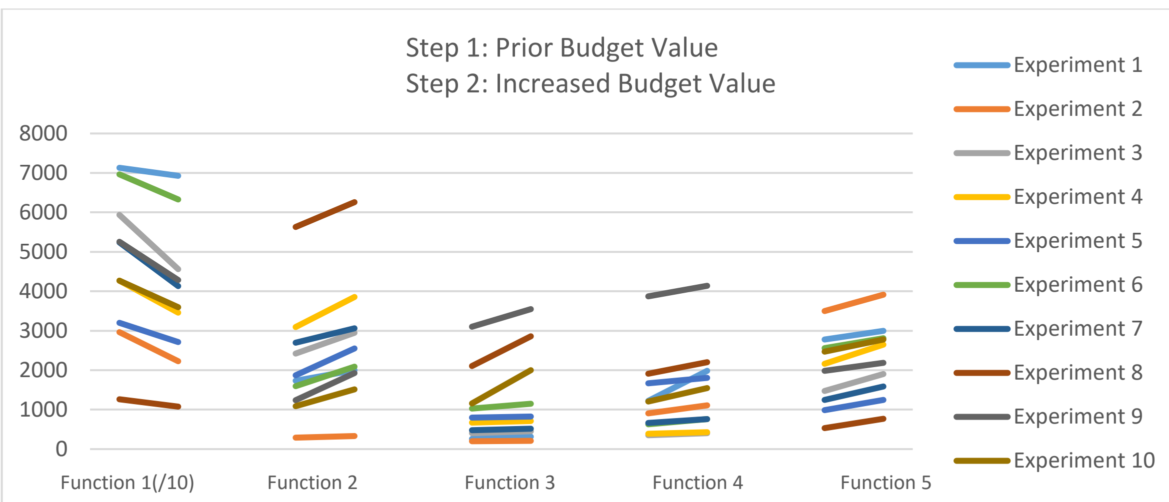

Fig 10. Results of Sensitivity Analysis (based on changing budget)

Upon closer examination of the model (Figure 10), it becomes evident that increasing the parameter representing the overall budget (budget parameter) has a profound impact on the optimization process and subsequent outcomes.

When the budget parameter is augmented, the model gains access to a larger pool of resources. This increase in available resources opens up avenues for a more refined and nuanced optimization path. The optimization algorithm can now explore a broader spectrum of possibilities, leading to superior solutions for the objective functions. In essence, a higher budget empowers the model to make more optimal decisions at each stage of the value chain. It allows for increased investment in critical factors such as energy efficiency, flexibility, sustainability, and economic viability. As a result, the model can navigate the intricate relationships between these factors more adeptly, ultimately contributing to a more effective and realistic optimization process.

The improved optimization path, facilitated by the augmented budget parameter, is reflected in the enhanced values of the objective functions. In summary, elevating the budget parameter in the model positively influences the optimization process by providing additional resources. This, in turn, leads to a superior optimization path and yields more favorable outcomes for the objective functions, contributing to a more effective and realistic representation of the value chain's dynamics.

6. Managerial and Significance Implications

This research makes a substantial contribution to the discussion on sustainable industrial practices by presenting a comprehensive approach to energy optimization. The proposed framework, shaped by both theoretical insights and practical applications, carries the potential to redefine industry standards. In the face of the challenges posed by energy consumption in manufacturing networks, this research emerges as a guiding force, laying the groundwork for a future characterized by sustainability, efficiency, and adaptability.

Generally, the paper emphasizes the crucial necessity for a holistic perspective on energy optimization within manufacturing networks. By harmonizing efficiency, sustainability, and flexibility, this research advocates for a transformative paradigm. This paradigm not only tackles the intricacies of contemporary industrial challenges but also charts a trajectory towards a more robust and sustainable industrial ecosystem.

7. Conclusion

The presented multi-objective optimization model serves as a comprehensive framework for decision-making in complex systems involving intricate considerations such as energy consumption, efficiency, flexibility, sustainability, and economic viability. By incorporating interdependence coefficients and budgetary constraints, the model offers a realistic representation of the complex relationships within the system. The use of PyGMO as an optimization tool underscores the feasibility of addressing such intricate multi-objective problems. Notably, the model's capability to concurrently optimize multiple conflicting objectives provides decision-makers with a valuable tool for achieving a well-balanced and sustainable system. The incorporation of interdependence factors adds a layer of sophistication, capturing nuanced relationships between different components of the system to enhances the model's utility in real-world decision-making scenarios.

Given that large-sized instances of this problem fall under the category of NP-hard problems, a Two-phase Multi-Objective Evolutionary Algorithm (MOEA) was specifically developed to address and discover Pareto-optimal solutions. The proposed algorithm adopts a strategic approach wherein the initial pheromones for the Multi-Objective Ant Colony Optimization (MOACO) are determined by the NSGA-II algorithm, leveraging its high speed in the initial steps. Subsequently, the MOACO component identifies the best solution for the problem, harnessing the benefits of parallelism and impressive feedback. This innovative approach combines the advantage of the faster converging rate of the NSGA-II algorithm in the initial stages of the searching process with the advantages of parallelism and effective feedback offered by MOACO in later stages. The integration of these components contributes to the algorithm's efficiency in tackling large-sized instances of NP-hard problems, making it a robust and effective tool for complex optimization challenges.

7.1. Limitation and Further Research Directions

One of the primary limitations of this paper is the utilization of the proposed model for numerical examples, while it is highly recommended that this model be applied to actual industrial cases in future studies. Another limitation of this study is considering deterministic values in programming. Accordingly, it is proper to extend the model to incorporate dynamic and stochastic elements to better capture real-world uncertainties and variations. This could involve considering time-dependent parameters or introducing probabilistic elements into the constraints and objectives.

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