Multi-Objective Optimisation of Sustainable Closed-Loop Supply Chain Networks in the Tire Industry

Abstract

As environmental concerns and social legislation continue to gain importance, supply chain decision-makers are increasingly required to consider economic and ecological objectives. A potential strategy for mitigating sustainability issues entails the utilisation of discarded tyres through the process of recycling. Nevertheless, the establishment of a closed-loop supply chain that is both sustainable and profitable presents a noteworthy challenge. This study proposes a novel multi-objective mixed-integer linear programming model to design a sustainable closed-loop supply chain network in the tire industry. The objective of the model is to optimise the overall cost of the network, taking into account the environmental consequences related to the establishment of facilities, tire processing, and transportation. While metaheuristic algorithms have been extensively employed to solve network design problems, they are not very effective in handling large-scale networks. To overcome this limitation, our study introduces six new multi-objective evolutionary algorithms based on decomposition (MOEA/D) variants. The present study introduces a prospective methodology for devising supply chain networks that are sustainable in nature, while simultaneously ensuring a harmonious equilibrium between economic and environmental considerations. The efficacy of the proposed multi-objective mixed-integer linear programming model and its MOEA/D variants in addressing large-scale networks has been demonstrated through the obtained results. As such, this study contributes to sustainable supply chain management, which is becoming increasingly important in the current environment.

Keywords: Sustainability; Closed-loop supply chain; Network design; Metaheuristics.

1. Introduction

The current markets are witnessing rapid economic and industrial changes at an unprecedented pace. The globalization of commercial activities, breakthrough technological advancements, and limited resources have intensified competition among businesses. Companies must prioritise maintaining or increasing profitability to survive in such a dynamic environment. A supply chain refers to a complex system of interrelated entities that work together to enable the transportation of materials, information, and financial transactions(Aazami and Saidi-Mehrabad, 2021). This can include businesses involved in manufacturing components, finished goods, transportation, warehousing, and retail services. The significance of customers in this network cannot be overstated, as they serve as the ultimate link in the chain (Ghahremani Nahr et al., 2020).

A sustainable closed-loop supply chain network design (CLSC) that balances economic and environmental considerations is a highly intricate and demanding task that necessitates a multidisciplinary approach (Soon et al., 2022). The ultimate objective of such a network is to minimize environmental impacts while concurrently ensuring economic viability (Dehshiri et al., 2022). As stated, the structure of a CLSC network encompasses two essential domains of business operations, namely economic and environmental. The implementation of CLSC networks has been acknowledged as a proficient, potent, and economical approach for manufacturing enterprises to adopt ecologically sustainable practises (Olugu et al., 2010;

Razavi et al., 2022). A network of suppliers, manufacturers, and distributors known as a traditional or forwards (progressive) supply chain was created to produce and deliver an item or service (Eskandarpour et al., 2015). Reverse logistics include collecting, monitoring, and disposing of discarded items and recycling, reprocessing, refurbishment, and eventual disposal. The designed network is known as a CLSC if both forwards and reverse supply chains are assessed simultaneously (Govindan et al., 2015). In other words, at its core, a CLSC network is a system that combines reverse logistics processes with conventional forward logistics to facilitate the recovery, reuse, and recycling of materials and products (Easwaran and Uster, 2010). This network entails the coordination of multiple stakeholders, including suppliers, manufacturers, distributors, retailers, and customers, who work together to optimize the flow of goods and materials (Ramezani et al., 2013). The aforementioned principles aid organisations in making informed determinations regarding the future of their products, whether they have reached the end of their useful life or have been utilised, with respect to recycling or disassembling them (Tavana et al., 2022).

The implementation of sustainable supply chain management is a crucial facilitator that motivates companies to reduce their adverse environmental effects and yields increased economic benefits (Zailani et al., 2012). The sustainable design of a CLSC network entails an economic dimension that prioritises the minimisation of costs and maximisation of revenue, while ensuring the preservation of high standards of quality and client fulfilment (Sahebjamnia et al., 2018). The green dimension of a sustainable CLSC network design focuses on minimizing environmental impacts by reducing waste, transportation pollution, and resource depletion (Kazancoglu et al., 2022). The implementation of environmentally conscious manufacturing methods, utilisation of sustainable energy sources, mitigation of carbon emissions, and integration of sustainability standards in supplier assessment and product development are integral components of this approach (Garg et al., 2015; Kazancoglu et al., 2022). The green dimension also encompasses the development of end-of-life product recovery and recycling systems that foster circularity and minimize waste. Besides, the CO2 emission index is frequently included to quantify environmental consequences and could serve the purpose of supply chain simulation (Huang et al., 2020). Apart from energy consumption, solid waste, water consumption, and water waste, various other factors are taken into account when assessing environmental consequences. The aforementioned indicators have been subjected to a detailed examination in a scholarly article authored by Ahi and Searcy (2015) and another study conducted by Zimon et al. (2020).

Various factors, such as the nature of the products and materials involved, the characteristics of the market and demand, the availability of resources and infrastructure, and the regulatory environment, play a role in realizing a sustainable CLSC network design that encompasses both economic and green dimensions (MahmoumGonbadi et al., 2021). A holistic and integrated approach is imperative, necessitating collaboration and cooperation among all stakeholders in the supply chain network (Raza, 2020).

Because of the urgent need to cut down on the use of raw materials, bring environmental degradation under control, and improve recycling practises, many academics are focusing on CLSC networks (Zohal and Soleimani, 2016). The strategic decision-making process concerning the supply chain network design aims to ascertain the requisite number of facilities for the network. Furthermore, the optimisation of the supply chain network is crucial in determining the optimal positioning of stated facilities within the network and the most effective connections between them to efficiently satisfy consumer demand while minimising costs. The strategic location and arrangement of facilities within the network have an immense effect on investment costs, customer service levels, and other crucial indicators in contemporary remanufacturing enterprises (Cui et al., 2017; Razavi et al., 2022).

Handling the difficulty of building and organizing a CLSC as an NP-hard problem necessitates a method that provides a dependable solution in a reasonable time, particularly for situations of practical dimensions. This is supported by previous research that sought to offer novel solutions to the issue (Mardan et al., 2019; Naderi et al., 2020; Soleimani et al., 2013). Hence, several exact and imprecise techniques have been reviewed. Using exact procedures is impractical or prohibitively time-consuming for greater dimensions and more intricate situations. Innovative ways might be used to identify a suitable solution in a comparatively short time to solve these sorts of difficulties (Oliveira and Machado, 2021; Soleimani et al., 2017).

The primary objective of our study is to aid firms operating within the supply chain in making informed decisions regarding the selection of suppliers, manufacturers, distribution centres, retailers, and recycling centres for collaboration or establishment. It is imperative to ascertain the movement of goods and services across every tier of the network. This study considers multiple factors in a holistic approach to address the challenge of balancing two conflicting objectives. The stated objectives encompass two primary goals: reducing overall costs and mitigating environmental impacts. The research model developed for this study employs a distinctive methodology that involves the simultaneous examination of both products and raw materials. This approach is necessary due to the fact that the goods in question are composed of numerous detachable and recyclable components. The present article examines a comprehensive model that encompasses various levels and products, spanning from suppliers to recycling facilities and client zones.

The subsequent organisation of the study is outlined as follows. The subsequent segment pertains to the literature that is dependent on certain conditions or circumstances. Section 3 of the document encompasses a comprehensive discussion of the modelling framework, which includes the problem statements, notations, and mathematical modelling. Section 4 outlines the methodology employed for risk modelling and scenario generation. Section 5 presents the computational findings and sensitivity analyses conducted to evaluate the suitability and reliability of the proposed model. The final section of the study presents the outcomes and suggestions for future investigations.

There have been an array of limitations in solving multi-objective mixed integer linear programming (MILP); however, they can be categorised into scalability, computation complexity, integer solutions and constraints, restrictions in dealing with non-convexity, and difficulty handling multiple Objectives. Most MINLP models are NP-hard; therefore, as the scale of the problem increases (becomes large-scale), the time taken to solve the problem grows significantly (Chauhan et al., 2023; Iannino et al., 2021; Tavana et al., 2022). Integer constraints and solutions also add to the complexity of the model and, to some extent, make the model NP-hard and further the combinational process. In the literature, there have been some methods for handling that; however, some of them do not have guarantees that reduce the complexity and scalability significantly, such as branch-and-bound, cutting plane, and relaxation methods (Adelgren and Gupte, 2022; Bökler et al., 2021; Khorshidvand et al., 2021). In the realm of solutions for mixed-integer problems, the feasible area inherently lacks convexity due to the integer variables and constraints involved. This is because these integer solutions introduce discontinuities in the solution space, which are essentially the crux of the issue. To put it differently, when visualized in three dimensions, the solution surface - the function representing the space - is not uniform and contains discontinuities. This uneven terrain created by non-convexity complicates the pursuit of the global optimal solution (Ghasemy Yaghin and Sarlak, 2020). Capturing all points on the pareto front and choosing the best solution from the pareto optimal set according to the trade-off is another issue that can be seen as a limitation (Chen et al., 2023). A critical drawback of the multi-objective evolutionary algorithm (MOEA) is its tendency to converge on local optima rather than discovering the global optimum. This pitfall often arises in such algorithms due to a decrease in population diversity, which in turn diminishes the capability to explore broader areas of the solution space (Iannino et al., 2021). Dependency on weight vectors is of the essence due to the fact that it limits the applicability of the solution. Enervating and tuning the weight vectors becomes increasingly complex and computationally expensive. As a result, it should be handed over completely (Sajadiyan et al., 2022). Another limitation is rooted again in combinational optimisation. The algorithms were first designed for continuous optimisation. Therefore, handling multi-objective MILP often requires modifications. In this research by adding these properties, mentioned limitations are handled, including parallel processing capabilities, integer handling mechanisms, robust heuristic search strategy, pareto-based approach, diversity preservation techniques, adaptive weight vector adjustment, and hybridization capability.

2. Literature review

The research agendas of various businesses and academic fields have focused on supply chains for numerous years, given their significant role in the contemporary economy. This section presents a thorough literature review on the evolution of environmentally sustainable supply chains, carbon emissions, and CLSC models. The predominant focus of research in this domain pertaining to multi-product CLSC networks has been on the network structure, the strategic perspectives of the supply chain, or the interplay among various individual manufacturers, retailers, and other stakeholders.

Paksoy et al. (2011) evaluated various operational and environmental performance parameters, particularly those linked to transport systems inside a CLSC. They developed a linear model that incorporates the trade-offs between different expenses, such as emissions and transferring goods along the supply chain. Khatami et al. (2015) sought to develop a reverse supply chain network, incorporate it into an existing multi-product forward supply chain network, and simultaneously revamp the current forward supply chain. The Benders decomposition method was employed to tackle the issue at hand, while Cholesky's factoring technique was utilised to generate scenarios based on the demand distribution function, taking into account the interdependence among the demands for different items. Tao et al. (2015) evaluated the equilibrium of the CLSC network across a multi-period planning horizon, taking into account producers, retailers, markets, and recyclers. They used variational inequality and complement theory to construct the optimum behaviours and equilibrium conditions of the many actors in the network. Then they used these results to build a model of network equilibrium. Garg et al. (2015) suggested a CLSC network that would solve environmental concerns by having four forward and five backward tiers, respectively. This study presents a bi-objective integer nonlinear programming problem aimed at maximising the flow of goods and components within a network, while also optimising the number of trucks utilised by facilities in the forwards chain. The present study proposes a solution utilising an interactive multi-objective programming Approach Algorithm. Furthermore, some case studies are conducted to validate the proposed model. The research illustrates the trade-offs between the two goals. It demonstrates how integrating the extended supply chain may generate a green image for a product while lowering transportation consumption and boosting demand. Keyvanshokooh et al. (2016) presented a paradigm for building CLSC networks that maximises profits. The mathematical model employed is a MILP formulation that allows for adaptability in ascertaining the fractions of demand fulfilled and returns obtained in accordance with organisational guidelines. The problem was resolved through the utilisation of an accelerated stochastic Benders decomposition technique, which incorporated valid inequalities and Pareto-optimal cut generation strategies to enhance the convergence rate. Radhi and Zhang (2016) addressed the configuration issue of a remanufacturing production network in a mixed integer nonlinear programming (MINLP) model, including decisions for return quality thresholds and demand allocation across various remanufacturing facilities, as well as a CLSC with numerous facilities. In order to optimise the system's profit, they decided which facilities would run, what quality would be considered acceptable, how many returns would be accepted, and how demand would be distributed.

Soleimani et al. (2017) concentrated on the design of a CLSC, including suppliers, producers, distribution centres, clients, warehousing centres, return centres, and recycling facilities. The design challenge took into account environmental issues, overall profit optimisation, the reduction of missed working days, and the responsiveness to consumer demand. They used a genetic algorithm to solve the model and analyse numerous possibilities. Zheng et al. (2017) investigated the effect of forwards channel rivalry and power structure on a two-channel CLSC that included a maker, a retailer, and a collection centre. Each channel participant was found to have the incentive to assume the position of channel leader. They realized that in a situation with comparative channel symmetry, the most efficient CLSC might be either manufacturer-led or retailer-led, depending on the rate of channel replacement. Xu et al. (2017) analysed the effect of carbon emissions legislation and market considerations on developing hybrid and specialized CLSCs using MILP. Customer demand was a more significant factor in overall cost and emissions than the scale effect or the product return rate. They also showed that under a carbon tax scheme, specialized CLSCs are more cost-effective than mixed CLSCs because of the lower emissions they produce while dealing with varying amounts of returned items. Jalil et al. (2019) introduced a multi-objective programming framework for networks with two decision-making tiers. They considered three goal functions dispersed throughout the tiers, with each decision-maker pursuing a single target. In addition, they developed a technique for solving the model is proposed. Sahebjamnia et al. (2018) developed a multi-objective MILP model for the construction of a sustainable tyre CLSC network that optimises overall cost as well as environmental, social, and processing effects. They employed extended computational tests and sensitivity analysis to assess the performance of four hybrid metaheuristics designed to solve the massive network effectively. Fard and Hajaghaei-Keshteli (2018) developed a three-level location allocation issue that concurrently examines the forward and reverse networks. The issue is expressed as a static Stackelberg game, including distribution centres, client zones, and recovery centres. They also examined the performance of five distinct algorithms, including three older techniques and two more modern algorithms derived from nature. The findings demonstrated that the suggested tri-level metaheuristics are efficient methods for resolving large-scale network challenges. Hajiaghaei-Keshteli and Fard (2019) developed a MINLP framework to optimise the design of a CLSC network that is environmentally sustainable. The model incorporates discounted transportation expenses as a key factor in the decision-making process. The integration of conventional and contemporary metaheuristics is employed to tackle the intricacy of the issue at hand. The study employs four assessment metrics to evaluate the efficacy and efficiency of the proposed algorithms. The findings indicate that the performance of the new hybridization algorithms is superior. Mosallanezhad et al. (2021) created a model for the shrimp supply chain (SSC) to minimise the overall cost. The model considered distribution hubs, wholesalers, processing plants, marketplaces, and shrimp waste centres. Yet, the model is NP-hard and unable to address large-scale issues, therefore the research evaluates three metaheuristic algorithms and two hybrid techniques. The research comprises a practical application with many cases to validate the efficacy of the SSC model and solution approaches in attaining cost reductions.

The CLSC network was devised by Salehi-Amiri et al. (2021) with a focus on the walnut industry. The evaluation of both forwards and reverse flow by the network was conducted to meet market demands and facilitate the reutilization of returned items. The MILP model was devised with the aim of minimising overall costs. To solve this model, a variety of exact and metaheuristic techniques are employed. The quality of the solutions provided was evaluated through the utilisation of the Taguchi methodology. Tirkolaee et al. (2022) proposed a mathematical model for the development of a sustainable CLSC) Network for masks amidst the COVID-19 pandemic.

Pareto-optimal solutions may be found with the help of multi-objective grey wolf optimization (MOGWO) and non-dominated sorting genetic algorithm (NSGA) NSGA-II. They determined that the MOGWO algorithm is more dependable. Tavana et al. (2022) developed a multi-objective MILP model to establish environmentally sustainable CLSC networks. The model incorporates several variables, including cross-docking, location-inventory routeing, supplier selection, order allocation, and transportation systems. The authors devised a simulation methodology for generating data on CLSC networks, incorporating probabilistic distributions and technically feasible solution spaces.

Turning to MOAEs, Cheng et al. (2023) pioneered a fresh technique known as the reference-points-centered nondominated sorting approach, or MOMaTO-RP. This strategy is designed to optimize multiple objectives concurrently and relies on a unique sorting process centered around reference points, making it a revolutionary approach in the multi-objective optimization domain. The application of MOMaTO-RP efficiently tackles issues related to the transfer of knowledge among similar tasks and the maintenance of diversity within populations. Consequently, there's a notable increase in the rate at which the population converges. Galeano-Brajones et al. (2023) used a multi-objective optimisation strategy to address high energy usage in 5G network densification. The goal of this research is to find a balance between conserving energy and maintaining service quality. Hybrid MOEAs use problem-specific operators to improve algorithm outcomes.

Liu et al. (2023) focused on the complex issue of flow sensor configuration, treating it as a problem requiring multi-objective optimization. As a solution, they introduced a novel MOEA, named D&A-AGE-MOEA. This innovative method incorporates a unique environmental selection operator designed to reduce duplication, and a comprehensive strategy that merges various dichotomies with the allocation of search volume into an adaptive geometry estimation-based MOEA (AGE-MOEA). This approach results in an improved search process. Liu's team asserted that their algorithm exhibits superior performance, demonstrating both improved convergence and increased diversity within a more favorable feasible space.

Wang, X. et al. (2023) turned their attention to the task of efficiently scheduling virtual machines (VMs) and associated tasks within the landscape of cloud computing. They introduced an enhanced version of the MOEA/D-M2M framework, termed MOEA/D-PD. To determine the best solutions, they used a tool called a support vector machine (SVM). They adopted a flexible strategy for resource allocation, coupled with a two-phase guided search approach, to ensure a balance between utilizing what's available and seeking out new opportunities. When put head-to-head with other algorithms in benchmark tests, their MOEA/D-PD algorithm showcased superior performance.

Rivera et al. (2023) introduced the idea of hyper ant colony optimisation (ACO) to specifically improve MaOPs. The achievement involved identifying the optimal blend of interval outranking models for integration into MOEAs. The algorithms they used were MOEA/D and MOEA/D/O. These algorithms combine seven main heuristics to customise MOEAs and make it easier to adapt them to specific problems. The model's performance was confirmed to be superior through extensive evaluations and statistical analyses. The suggestion was to potentially make future improvements by adapting control parameters and including a broader range of preference models.

(Zheng et al., 2023) presented a new MOEA, termed MOEA/D-ND, which operates on the principles of preference orientation. This strategy employed a weight vector developed through normal distribution. The goal of this method is to overcome the drawbacks observed in previous preference-based research by integrating the preferences of the decision-maker. This integration assisted in directing solutions towards a more tailored area of interest.

The MOEA/D-ND algorithm utilises a niche selection strategy based on angles, which is specifically designed to maintain diversity. It avoids the potential pitfall of being confined to local optima during exploration. Evidence from the results, where the objectives spanned between 2 to 15 across an array of benchmark issues, showed promising results. Nevertheless, there is still room for refinement in this method. Specifically, the algorithm's generation of reference points isn't entirely uniform. Furthermore, its performance when dealing with intricate shapes of Pareto sets leaves room for improvement.

Zapotecas-Martínez et al. (2023) introduced a novel algorithm which considered both continuous and box-constrained paradigms, providing Pareto fronts that are distinctively different from those commonly observed in scalable multi-objective problems. The innovative suite that they proposed brings in unique attributes that make the exploration of Pareto-optimal solutions more challenging. Nevertheless, these characteristics can be readily enabled or disabled by the user, allowing for a more tailored examination of MOEAs.

Zhou et al. (2023) devised multi-objective co-evolutionary algorithm (MOCA-PD) for use in MOEAs. The central aim of this creation was to focus on the preferred outcomes of those making decisions. This was done by creating a hub for searches, choosing leaders in line with these specific preferences, and implementing a unique diversity preservation strategy. The constructed algorithm was successful in effectively steering the population towards the outcomes deemed most desirable.

Wang, F. et al. (2023) designed a novel dynamic constrained multi-objective evolutionary algorithm (NDCMOEA) tailored for dynamic constrained multi-objective optimization problems. The NDCMOEA employs an penalty function to guide the selection of near-optimal solutions, driving efficient problem-solving. In the face of environmental changes, a dynamic strategy incorporating random initialization and predictive modelling swiftly responds.

Jiang et al. (2022) suggested a two-phase MOEA explicitly intended for large-scale sparse multi-objective problems (LSMOPs), which they named TS-SparseEA. The algorithm encompasses a binary weight optimization procedure that converts complex, high-dimensional issues into simpler, low-dimensional ones, effectively managing large-scale sparse variables. Following this transformation, an adapted evolutionary algorithm is implemented that combines hybrid encoding with a bespoke matching strategy.

Junqueira et al. (2022) created a unique algorithm named MOEA/D-LNA. The primary intent of this algorithm was to improve the capacity of multi-objective evolutionary algorithms to manage multi-objective issues, particularly those presenting with irregular Pareto fronts. The team used weight vectors to assess the algorithm's performance on a benchmark that operates based on the generalized Position-Distance (GPD) generator. The algorithm displayed exceptional performance, particularly with disconnected and inverted Pareto fronts. However, it encountered difficulties with some degenerate fronts. The researchers proposed that this issue could stem from a fixed angle in the weight vector generator, suggesting that future research might focus on addressing this potential limitation.

Junqueira et al. (2022) understood using adaptive weight vectors can better tackle complex problems. Therefore, a new version of MOEA/D-LNA was introduced by them that improved the handling of irregular pareto fronts. In order to achieve their aim. they progressively adjusted vectors of irregular pareto front. In their research, the proposed method was evaluated against different benchmarks and performed perfectly, especially with challenging pareto fronts. However, it struggled with degenerated fronts, suggesting further improvements could be made by modifying vector angles.

Hong et al. (2022) delved into combining different selection methods in multi-objective evolutionary algorithms for achieving optimal outcomes. They designed an approach that integrates the strengths and compensates for the weaknesses of different methods to solve MOPs.

Lin et al. (2021) conducted an examination of an adaptive operator selection (B-AOS) strategy for evolutionary algorithms. They used two criteria for decision-making: convergence (Pareto) and diversity (crowding). Two operator pools, intended for exploitation and exploration respectively, were utilized. The Pareto criterion played a role in indicating the preferred pool, while the crowding criterion assisted in the selection of a specific operator. The results from the experiments showed that B-AOS surpassed existing adaptive operator selection methods in terms of performance. The researchers recommended that future work should look at integrating other evolutionary operators to more effectively handle complex multi-objective benchmark problems.

Falcón-Cardona et al. (2021) developed a new method, known as the Island-based Multi-Indicator Algorithm (IMIA), has been developed, which cleverly harnesses multiple indicator-driven algorithms to tackle intricate optimization problems. Notably, IMIA outshines traditional methods, showcasing remarkable robustness, particularly when handling problems with irregular outcomes. The research also noted a distinct link between the performance and the running time of the algorithm, which depends on the size of specific sub-groups and the cost associated with the so-called hypervolume island. For future research they suggested that potential enhancements might involve exploring parameters related to migration, refining the linkages between islands, and developing an innovative migration mechanism to reduce unproductive idle times.

Su et al. (2021) delved into multi-objective testing resource allocation problem (MOTRAP), with the aim of enhancing system reliability. At the same time, They tried to reduce both the cost and time. They identified the minimum amount of time to be spent on different modules in order to meet the set reliability target. Furthermore, they employed advanced constraint-managing methods (ECHTs), designed specifically for individual initialization, simulated binary crossover, and polynomial mutation. A series of comprehensive tests were performed on 195 instances, randomly generated, across three different software systems of increasing size and complexity. The outcomes of these tests showed that the developed ECHTs surpassed previous solutions to MOTRAP. The research opened up multiple avenues for further exploration, such as a more in-depth analysis of the ECHTs' capabilities and limitations, exact lower bounds, upper bounds based on predefined cost constraints, and the integration of both reliability and cost constraints.

Song et al. (2020) introduced a novel path evolution (PE) reproduction operator for MOEAs. The introduced MOEAs can eliminate the need for mating selection and simplify evolution path calculation. They were of the opinion that it could be incorporated into different MOEAs and enhance their performance. The structure of PE revolves around being adaptively adjusted during the evolutionary process and improving solution generation. However, they mentioned that future work should assess its effectiveness on many-objective and large-scale optimisation problems.

3. Problem statement and mathematical modelling

The objective of the current investigation is to tackle a crucial matter within the tire supply chain network. The initial phase of this study involves elucidating the problem at hand, followed by the formulation of a mathematical model that can effectively address the intricacies and fluctuations inherent in the problem. The model integrates innovative characteristics that facilitate the capture of intricate dynamics and interrelationships within the system being studied. The aim of this undertaking is to make a meaningful contribution towards the progression of the tire supply chain network and to provide pragmatic perspectives for participants and professionals.

3.1. Problem statement

Waste tires represent a non-biodegradable material that is presently amassing in stockpiles. The auto industry, that is in a state of constant growth, is responsible for generating a growing amount of waste in the form of used tyres. These tyres constitute a significant portion, up to 80%, of the total rubber waste generated globally (Wiśniewska et al., 2022). The present recycling rate of end-of-life tyres is relatively low, and the predominant utilisation of discarded tyres for energy generation raises apprehensions regarding environmental and health impacts (Meng et al., 2023). The escalation in solid waste generation resulting from demolition operations also constitutes an additional source of waste that heads towards garbage dumps

(Arulrajah et al., 2019). The global annual production of tires for vehicles is estimated to be 1.5 billion, while the current number of discarded tyres in landfills and stockpiles is approximately 4 billion (Yaqoob et al., 2021). Besides, the quantity of tyre wear that is released into the environment on a global scale varies between 0.2 and 5.5 kg per capita per year (Baensch-Baltruschat et al., 2020). It is imperative to underscore that the aforementioned rationales highlight the importance of implementing a closed-loop tire supply chain as a means of mitigating the ecological repercussions.

The tire industry is a major contributor to environmental pollution due to generating a high volume of waste tires yearly. The traditional linear supply chain model of the tire industry, where raw materials are converted into finished products and disposed of after use, is no longer sustainable. In recent years, there has been a growing interest in adopting CLSC models in the tire industry, which aim to minimize waste and environmental impact by promoting reuse, remanufacturing, and recycling. However, implementing a sustainable CLSC network in the tire industry is challenging. One of the main challenges is the lack of a well-established infrastructure for collecting, sorting, and processing waste tires. This can make it difficult for companies to source sufficient used tires to support their green supply chain operations. Another challenge is the high costs associated with implementing green CLSC practices, such as adopting new technologies for remanufacturing and recycling and developing sustainable transportation and logistics systems. These costs can be a significant barrier for small and medium-sized companies adopting green practices. Furthermore, there is a need for coordination and collaboration among different stakeholders in the supply chain, including tire manufacturers, retailers, and recyclers companies, to ensure the efficient and effective implementation of green CLSC practices. This requires a significant investment in communication and information-sharing technologies to facilitate stakeholder collaboration and cooperation.

CLSC network for the tire industry also involves a complex set of decisions related to the collection, processing, and distribution of produced and used tires. The CLSC network aims to create a sustainable and economic system that minimizes waste, reduces environmental impact, and promotes the reuse, remanufacturing, and recycling of used tires. The selection of recycling centres for used tyres is one of the most crucial design considerations for the CLSC network. This entails finding areas ideal for tyre retailers and recycling facilities. The collecting procedure must be efficient and cost-effective and promote involvement from all supply chain partners. The manufacturer adopts a quality control (QC) strategy based on a screening procedure that involves a hundred per cent inspections. Following the screening procedure, the QC identifies the goods as either perfect or defective with probabilities of (1-δ_p) and (δ_p), respectively. Hence, defective items are separated into two groups: scrap and reworkable products, with probabilities of ($\delta_p * \gamma_p$) and (δ_p (1-γ_p)). The manufacturer is responsible for ensuring that the discarded items are transferred to recycling facilities from the manufacturer's inventory system. The producer reworks the goods that can be repaired and then adds them to the stockpile. To better comprehend the proposed CLSCN components, Figure 1 provides a schematic representation.

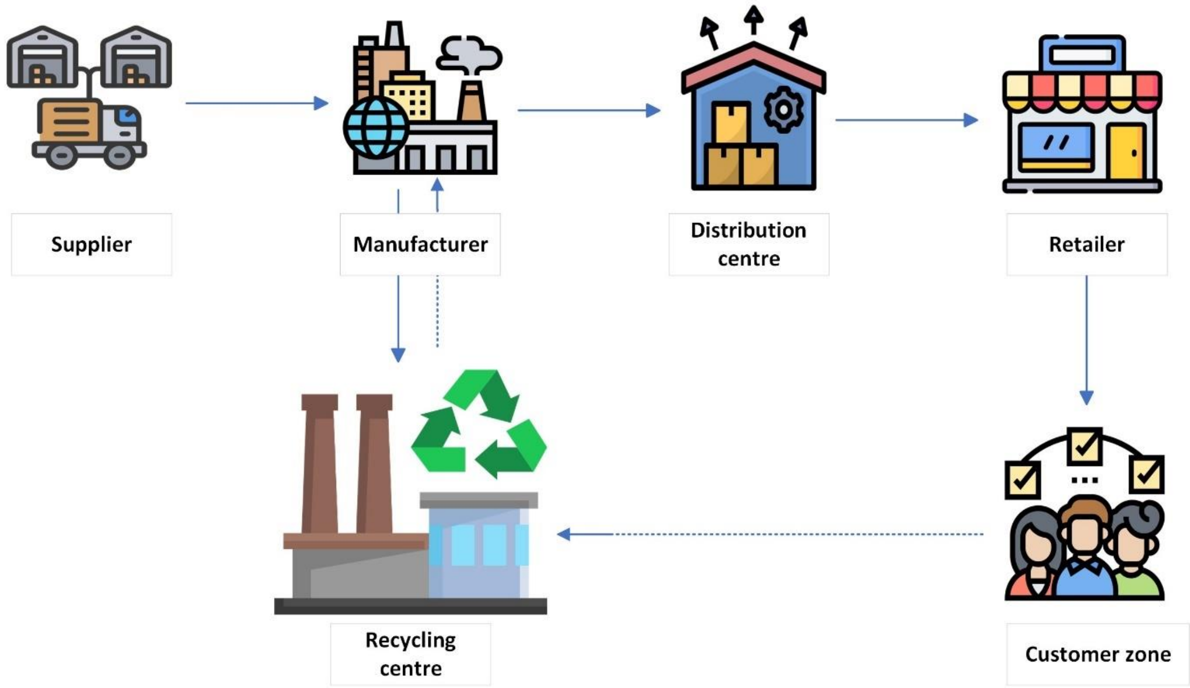


Figure 1: Configuration of the proposed tire CLSCN.

The following outlines the underlying assumptions of the model.

- Several tiers of suppliers, manufacturers, distribution centres, retailers, consumer zones, and recycling facilities are accounted for in the suggested CLSC configuration.
- The suppliers, manufacturers, distribution centres, retailers, and recycling facilities make judgements on location.
- One of the sources of pollutant emission is operations and transportation between various levels and operational activities at separate sites.
- All Parameters are deterministic.
- The capacity of facilities is constrained.
- Some raw materials and certain finished goods must be provided.
- There are no flows between the same facilities on different echelons. For example, there is no exchange between retailers.
- The raw materials collected from recycling centres are cheaper than those purchased from suppliers.
- A key assumption in the tire closed-loop system is that the rate at which used tyres are returned to recycling facilities is negligible compared to the demand in customer zones.

3.2. Designed model

To design tire supply chain network, a multi-objective MILP model is presented.

3.2.1. Notation

This part of the publication describes the primary notations used over this research before moving on to provide a more in-depth analysis of the topic and the mathematical formulation.

Indices	
S	Set of suppliers indexed by $i = 1, 2, \ldots, \|I\|$
M	Set of potential manufacturers indexed by $m = 1, 2, \ldots, \|M\|$
F	Set of potential distribution centres indexed by $f = 1, 2, \ldots, \|F\|$
R	Set of potential retailers indexed by $r = 1, 2, \ldots, \|R\|$
B	Set of potential recycler centre indexed by $b = 1, 2, \ldots, \|B\|$
P	Set of products indexed by $p = 1, 2, \ldots, \|P\|$
N	Set of the demand zone indexed by $n = 1, 2, \ldots, \|N\|$
H	Set of transportation mode indexed by $h = 1, 2, \ldots, \|H\|$
T	Set of technology indexed by $t = 1, 2, \ldots, \|T\|$
I	Set of raw materials indexed by $i = 1, 2, \ldots, \|I\|$
Parameters	
Fs_s	Fixed opening cost of supplier s.
Fm_m	Fixed establishment cost of manufacturer m
Fd_f	Fixed opening cost of distribution centre f.
Fr_r	Fixed opening cost of retailer r.
Re_{bt}	Fixed opening cost of recycle centre b with technology t
tsm_{ismh}	Unit transportation cost per Km of raw materials i from supplier s to manufacture m by mode h.
tmd_{mfph}	Unit transportation cost per Km of product p from manufacturer m to distribution centre f by mode h.
tmd_{frph}	Unit transportation cost per Km of product p from distribution centre f to retailer r by mode h.
tmb_{mbph}	Unit transportation cost per Km of product p from manufacturer m to recycle centre b by mode h.
trb_{rbph}	Unit transportation cost per Km of product p from retailer r to recycle centre b by mode h.
$trbm_{ibmh}$	Unit transportation cost per Km of raw material i from recycle centre b to manufacturer m by mode h.
Dsm_{sm}	Distance (Km) between supplier s and manufacturer m.
Dmf_{mf}	Distance (Km) between manufacturer m and distribution centre f.
Ddr_{fr}	Distance (Km) between distribution centre f and retailer r.
Dmb_{mb}	Distance (Km) between manufacturer m and recycle centre b.
Drb_{rb}	Distance (Km) between retailer r and recycle centre b.
man_{pm}	Unit manufacturing cost of product p at manufacturing centre m
Pac_{pf}	Packing cost of product p in distribution centre f.
Sc_{pm}	Unit screening cost of product p at manufacturer m.
rc_{pm}	Unit reworking cost of product p at manufacturer m.
δ_p	Percentage of the defective product in product p.
γ_p	Percentage of scrap products of the defective ones in product p.
cg_{pb}	Collection and recycling cost of product p in recycling centre b.
Dem_n	Demand of customer zone n.
Ret_{pr}	Fraction of used product p returned from customer zone to retailer r to recycling centre b.
cas_{si}	Capacity of supplier s for raw material i.
cam_{mp}	Capacity of manufacturer m of product p.
cad_{fp}	Capacity of distribution centre f of product p.
car_{rp}	Capacity of retailer r of product p.

$cacr_{bit}$	Capacity of recycling centre b with technology t of raw material i.
ors_{ism}	Fixed ordering cost of raw material i from supplier s by manufacturer m.
orb_{ibm}	Fixed ordering cost of raw material i from recycle centre b with technology t by manufacturer m.
Pum_{mfp}	Unit cost of purchasing product p from manufacturer m by distribution centre f.
Pud_{frp}	Unit cost of purchasing product p from distribution centre f by retailer r.
$Purb_{rbp}$	Unit cost of purchasing product p from retailer r by recycling centre b.
$Pumb_{mbp}$	Unit cost of purchasing product p from manufacturer m by recycle centre b.
IM_{im}	Logical matrix with entities equal 1 if raw material i can be used to produce product m, otherwise 0.
Pwp_t	The percentage of waste products for recycling technology t.
W	The minimum percentage of the demand of the customer zone n that should be satisfied.
MM	A very large number.
Es_s	Environmental impact of opening supplier s.
Ea_m	Environmental impact of establishing manufacturer m.
Ed_f	Environmental impact of opening distribution centre f.
Er_r	Environmental impact of opening retailer r.
Erc_{bt}	Environmental impact of opening recycling centre b with technology t.
Pe_{mp}	Per unit environmental impact of production for manufacturer m for product p.
Pd_{fp}	Per unit environmental impact of distribution for distribution centre f for product p.
Pr_{rp}	Per unit environmental impact of selling for retailer r for product p.
Pb_{btp}	Per unit environmental impact of recycling for recycling centre b with technology t for product p.
$Etsm_{smih}$	Per unit environmental impact of transportation from supplier s for raw material i by mode h.
$Etmd_{mfph}$	Per unit environmental impact of transportation from manufacturer m to distribution centre f for product p by mode h.
$Etdr_{frph}$	Per unit environmental impact of transportation from distribution centre f to retailer r for product p by mode h.
$Etrb_{rbph}$	Per unit environmental impact of transportation from retailer r to recycle centre b for product p by mode h.
$Etbm_{bmith}$	Per unit environmental impact of transportation from recycle centre b with technology t to manufacturer m for raw material i by mode h.
$Etmb_{mbtph}$	Per unit environmental impact of transportation from manufacturer m to recycle b with technology t for product p by mode h.
dis_{bt}	Per unit environmental impact of disposing of in recycling centre b with technology t.
Es_p	Environmental impact of sold product p on the environment.
Decision variables	
X_s	1 if supplier s is opened, 0 otherwise.
FA_m	1 if manufacturer m is opened, 0 otherwise.
DC_f	1 if distribution centre f is opened, 0 otherwise.
RT_r	1 if retailer r is opened, 0 otherwise.
RC_{bt}	1 if recycle centre b with technology t is opened, 0 otherwise.
asm_{ismh}	The amount of raw material i transported from supplier s to manufacturer m by mode h.
abm_{ibmth}	The amount of raw material i transported from recycle centre b with technology t to manufacturer m by mode h.

amf_{pmfh}	The amount of product p transported from manufacturer m to distribution centre f by mode h.
afr_{pfrh}	The amount of product m transported from distribution centre f to retailer r by mode h.
aap_{pmbht}	The amount of product p transported from manufacturer m to recycle centre b with technology t by mode h.
arb_{prbth}	The amount of product m are transported from retailer r to recycle centre b with technology t by mode h.

3.2.2. Objective functions

we have provided formulas that demonstrate all components of our proposed MILP mathematical model.

$$Min\ Z1: \sum_{s} Fs_s * X_s + \sum_{m} FA_m * Fm_m + \sum_{f} DC_f * Fd_f + \sum_{r} RT_r * Fr_r \tag{1}$$
$$+ \sum_{s}\sum_{t} Re_{bt} * RC_{bt}$$
$$+ \sum_{i}\sum_{s}\sum_{m}\sum_{h} tsm_{ismh} * Dsm_{sm} * asm_{ismh}$$
$$+ \sum_{p}\sum_{m}\sum_{f}\sum_{h} tmd_{mfph} * Dmf_{mf} * amf_{pmfh}$$
$$+ \sum_{p}\sum_{f}\sum_{r}\sum_{h} tmd_{frph} * Ddr_{fr} * afr_{pfrh}$$
$$+ \sum_{p}\sum_{m}\sum_{b}\sum_{h} tmb_{mbph} * Dmb_{mb} * aap_{pmbh}$$
$$+ \sum_{p}\sum_{r}\sum_{b}\sum_{h}\sum_{t} trb_{rbtph} * Drb_{rb} * arb_{prbh}$$
$$+ \sum_{i}\sum_{m}\sum_{b}\sum_{h}\sum_{t} trbm_{ibmh} * Dmb_{mb} * abm_{ibmth}$$
$$+ \sum_{p}\sum_{m}\sum_{f}\sum_{h} amf_{pmfh} * man_{pm}$$
$$+ \sum_{p}\sum_{f}\sum_{r}\sum_{h} afr_{pfrh} * Pac_{pf}$$
$$+ \sum_{p}\sum_{m}\sum_{f}\sum_{h} Sc_{pm} * amf_{pmfh}$$
$$+ \sum_{p}\sum_{m}\sum_{f}\sum_{h} rc_{pm} * amf_{pmfh} * \delta_p * \left(1 - \gamma_p\right)$$
$$+ \sum_{p}\sum_{m}\sum_{r}\sum_{b}\sum_{h}\sum_{t} cg_{pb} * \left(aap_{pmbht} + arb_{prbth}\right)$$
$$+ \sum_{i}\sum_{s}\sum_{m} ors_{ism} * X_s + \sum_{i}\sum_{b}\sum_{m}\sum_{t} orb_{ibm} * RC_{bt}$$
$$+ \sum_{m}\sum_{f}\sum_{p}\sum_{h} Pum_{mfp} * amf_{pmfh}$$
$$+ \sum_{p}\sum_{f}\sum_{r}\sum_{h} Pud_{frp} * afr_{pfrh}$$
$$+ \sum_{p}\sum_{r}\sum_{b}\sum_{h}\sum_{t} Purb_{rbp} * arb_{prbth}$$
$$+ \sum_{p}\sum_{m}\sum_{b}\sum_{h}\sum_{t} Pumb_{mbp} * aap_{pmbht}$$

The objective function of the economic dimension includes 22 terms, as shown in Equation (1). Terms 1-5 compute the fixed opening cost of facilities, including suppliers, manufacturers, distribution centres, retailers, and recycling centres. Terms 6 to 11 define the transportation cost among different tiers of CLSC. The manufacturing cost is formulated in term 12, and the packaging cost is calculated in term 13. Terms 14 and 15 are related to the quality control process. Term 14 computes the screening cost of all products; however, term 15 gives information about the reworking cost that just calculates for those products that need reworking. Term 16 is about the recycling cost of the returned products to them. Terms 17 and 18 provide information about the fixed ordering cost of raw materials from suppliers and recycling centres. Remain terms compute the purchasing cost of products in the flow of them in all level of the designed supply chain.

$$Min\ Z2: \sum_{s} Es_s * X_s + \sum_{m} Ea_m * FA_m + \sum_{f} Ed_f * DC_f + \sum_{r} Er_r * RT_r$$
$$+ \sum_{b}\sum_{t} Erc_{bt} * RC_{bt} + \sum_{m}\sum_{p}\sum_{f}\sum_{h} Pe_{mp} * amf_{pmfh}$$
$$+ \sum_{f}\sum_{p}\sum_{r}\sum_{h} Pd_{fp} * afr_{pfrh} + \sum_{r}\sum_{p}\sum_{n} Pr_{rp} * Dem_n$$
$$+ \sum_{p}\sum_{r}\sum_{b}\sum_{t}\sum_{h} Pb_{btp} * arb_{prbth}$$
$$+ \sum_{i}\sum_{s}\sum_{m}\sum_{h} Etsm_{smih} * asm_{ismh}$$
$$+ \sum_{p}\sum_{m}\sum_{f}\sum_{h} Etmd_{mfph} * amf_{pmfh}$$
$$+ \sum_{p}\sum_{f}\sum_{r}\sum_{h} Etdr_{frph} * afr_{pfrh}$$
$$+ \sum_{p}\sum_{r}\sum_{b}\sum_{t}\sum_{h} Etrb_{rbph} * arb_{prbth}$$
$$+ \sum_{i}\sum_{b}\sum_{m}\sum_{t}\sum_{h} Etbm_{bmith} * abm_{ibmth}$$
$$+ \sum_{m}\sum_{b}\sum_{t}\sum_{p}\sum_{h} Etmb_{mbtph} * aap_{pmbht}$$
$$+ \sum_{t}\sum_{n}\sum_{p}\sum_{m}\sum_{b}\sum_{h} Pwp_t * \left(arb_{prbth} + aap_{pmbht}\right)$$
$$* dis_{bt} \qquad \textbf{(2)}$$

The objective function of the environmental dimension includes 16 terms, as seen in Equation (2). Terms 1 to 5 calculated the environmental impact of the working or opening facilities. The environmental impacts of operations of each level of the supply chain are computed in terms 6 to 9, including production, distribution, selling, and recycling operations. Environmental impacts of transportation are shown in terms 10 to 15, and term 16 gives information about the environmental impacts of disposing of.

3.2.3. Constraints

$$\sum_{h} amf_{pmfh} \leq \sum_{h}\sum_{i} (asm_{ismh} + abm_{ibmth}) * IM_{im} * \left(1 - \delta_p\right) \qquad \forall \boldsymbol{p,m,f,s,b,t} \qquad \textbf{(3)}$$
$$+ \sum_{h}\sum_{i} (asm_{ismh} + abm_{ibmth}) * IM_{im} * \delta_p$$
$$* \left(1 - \gamma_p\right)$$

Equation (3) illustrates the upper bound number of products that can be transferred from manufacturers to distribution centres. It is the flow constraint.

$$\sum_{h} afr_{pfrh} \leq \sum_{h} amf_{pmfh} \qquad \forall \boldsymbol{p,f,r,m} \qquad \textbf{(4)}$$

$$\sum_h afr_{pfrh} \le Dem_n \qquad \forall \boldsymbol{p,f,r,n} \qquad \textbf{(5)}$$

Equation (4) is also a flow constraint; however, the number of products transfer from distribution centre to retailers cannot be more than the demand of each customer zone noted in Equation (4).

$$\sum_h arb_{prbth} \le Dem_n * Ret_{pr} \qquad \forall \boldsymbol{p,r,b,m,t} \qquad \textbf{(6)}$$

Equation (6) shows that the amount of product transferred from retailers to recycling centres cannot be more than the returned products from customer zones.

$$\sum_h asm_{ismh} \le cas_s \qquad \forall\, \boldsymbol{i,s,m} \qquad \textbf{(7)}$$

$$\sum_h amf_{pmfh} + \sum_h aap_{pmbht} \le cam_{mp} \qquad \forall\, \boldsymbol{p,f,b,s,m} \qquad \textbf{(8)}$$

$$\sum_h afr_{pfrh} \le cad_{fp} \qquad \forall\, \boldsymbol{p,f,r} \qquad \textbf{(9)}$$

$$\sum_h arb_{prbth} \le car_{rp} \qquad \forall\, \boldsymbol{p,r,b,t} \qquad \textbf{(10)}$$

$$\sum_h abm_{ibmth} \le cacr_{bit} \qquad \forall\, \boldsymbol{i,b,m,t} \qquad \textbf{(11)}$$

Equations (7) to (11) illustrate that the capacity of facilities restricts the flow of products and raw materials.

$$\sum_h aap_{pmbht} \le \sum_h \sum_i (asm_{ismh} + abm_{ibmth}) * IM_{im} * \ \delta_p * \gamma_p \qquad \forall\, \boldsymbol{p,m,b,t} \qquad \textbf{(12)}$$

Equation (12) shows that just disposal products transfer from manufacturers to recycling centres.

$$\sum_h abm_{ibmth} \le \sum_h Pwp_t * \left(aap_{pmbht} + arb_{prbth}\right) \qquad \forall\, \boldsymbol{i,b,m,p,r} \qquad \textbf{(13)}$$

$$\sum_t RC_{bt} \le 1 \qquad \forall \boldsymbol{b} \qquad \textbf{(14)}$$

Equation. (14) shows that the amount of raw material that transfers from recycling centres to manufacturers does not include the amount of waste produced by technology. Equation. (14) determines that each recycling centre can employ one technology.

$$asm_{ismh} \le MM * X_s \qquad \forall\, \boldsymbol{i,s,m,h} \qquad \textbf{(15)}$$

$$asm_{ismh} \le MM * FA_m \qquad \forall\, \boldsymbol{i,s,m,h} \qquad \textbf{(16)}$$

$$abm_{ibmth} \le MM * RC_{bt} \qquad \forall\, \boldsymbol{i,b,m,t,h} \qquad \textbf{(17)}$$

$$abm_{ibmth} \le MM * FA_m \qquad \forall\, \boldsymbol{i,b,m,t,h} \qquad \textbf{(18)}$$

$$amf_{pmfh} \le MM * FA_m \qquad \forall\, \boldsymbol{p,m,f,h} \qquad \textbf{(19)}$$

$$amf_{pmfh} \le MM * DC_f \qquad \forall\, \boldsymbol{p,m,f,h} \qquad \textbf{(20)}$$

$$afr_{pfrh} \le MM * DC_f \qquad \forall\, \boldsymbol{p,f,r,h} \qquad \textbf{(21)}$$

$$afr_{pfrh} \le MM * RT_r \qquad \forall\, \boldsymbol{p,f,r,h} \qquad \textbf{(22)}$$

$$aap_{pmbht} \le MM * FA_m \qquad \forall\, \boldsymbol{p,m,b,t,h} \qquad \textbf{(23)}$$

$$aap_{pmbht} \le MM * RC_{bt} \qquad \forall\, \boldsymbol{p,m,b,t,h} \qquad \textbf{(24)}$$

$$arb_{prbth} \leq MM * RT_r \qquad \forall\, \boldsymbol{p, r, b, t, h} \qquad \textbf{(25)}$$

$$arb_{prbth} \leq MM * RC_{bt} \qquad \forall\, \boldsymbol{p, r, b, t, h} \qquad \textbf{(26)}$$

Equations (15) to (26) show that the flow of the products or raw materials exists between facilities if the supply chain work with a specific facility.

$$afr_{pfrh} \geq W * Dem_n \qquad \forall\, \boldsymbol{p, f, r, h, n} \qquad \textbf{(27)}$$

Equation (15) illustrates that the supply chain network should satisfy the least percentage of the demand.

$$\begin{array}{l} X_s, FA_m, DC_f, RT_r, RC_{bt} \in \{0,1\} \\ asm_{ismh}, abm_{ibmth}, amf_{pmfh}, afr_{pfrh}, aap_{pmbht}, and\, arb_{prbth} \geq 0 \end{array} \qquad \begin{array}{c} \forall\, \boldsymbol{s, m, f, r, b,} \\ \boldsymbol{t, i, h, b, p} \end{array} \qquad \textbf{(28)}$$

Eq. (28) represent sign constraints for decision variable.

4. Solution Method

4.1. Non-Dominated Ranking Genetic Algorithm (NRGA)

The Non-Dominated Ranking Genetic Algorithm (NRGA) functions similarly to NSGA-II, except for their process for selecting parents and replicating them into the selection pool. A ranked-based roulette wheel (RBRW) selection operator and a Pareto-based population-ranking algorithm are combined in NRGA, which was initially proposed by Al Jadaan et al. (2008). The same process is then used to choose one solution from the candidate front. As a result, the solutions that belong to the best non-dominated set of the first front have the highest likelihood of being picked, but the solutions that are included within a set of the second front have a lower chance of being selected, and so forth. NRGA is an evolutionary method used for multi-objective optimisation. It combines the ideas of genetic algorithms with Pareto optimisation to identify optimum solutions for numerous goals. In a typical multi-objective optimisation issue, multiple competing objectives must be concurrently optimised (Moradi et al., 2011). NRGA does this by giving a non-dominated rank to each individual in the population based on its achievement of the goals. The non-dominated rank is a metric of an individual's performance compared to other individuals in the population. It is used to classify individuals into distinct groups depending on their degree of dominance. In NRGA, genetic operators (such as crossover and mutation) are utilised to produce new individuals. The best individuals are chosen to create the next generation after being appraised based on their non-dominated rank (Pasandideh et al., 2015). This procedure is continued until a suitable collection of non-dominated solutions is discovered. NRGA has the benefit over other multi-objective optimisation methods in that it is computationally efficient and can tackle large-scale problems with a high number of goals. Furthermore, NRGA can tackle situations with non-linear and non-convex objective functions.

4.2. NSGA-II

The NSGA is a widely used multi-objective optimisation method due to its effectiveness, ease of use, and minimal user involvement. Deb et al. (2002) introduced NSGA-II as an improved iteration of NSGA, which has demonstrated successful application in various engineering design optimisation scenarios. The algorithm in question is a highly efficient computational method that utilises a decision-making approach centred on the categorisation of solution dominance, employing Pareto dominance solutions. The algorithm in question exhibits a more advanced sorting methodology in comparison to NSGA, incorporates elitism, and does not require a pre-determined selection of the sharing parameter. The NSGA-II approach aims to tackle optimisation challenges that involve multiple objectives, with the objective of identifying a set of solutions that are non-dominated by any other solution. The algorithm endeavours to recognise the Pareto-optimal front, encompassing solutions that are optimally concurrent with all objectives. The NSGA-II algorithm employs a dual approach that involves non-dominated sorting and crowding distance as its primary strategies. The non-dominated sorting technique involves the ranking of solutions based on their respective dominance connections. The ranking of solutions is based on their degree of dominance over other solutions. Solutions that exhibit no dominance over any other solution are assigned the highest rank, followed by solutions that are dominated solely by solutions from the highest rank, and so forth. This process is iterated until all solutions have been ranked. The utilisation of the crowding distance approach maintains the diversity of solutions present in each individual rank. The concept of crowding distance pertains to the measurement of solution density within a specified region of the objective space. The proximity of solutions is inversely related to their reward, as closer solutions are penalised while those that are more distant are incentivized. This approach incentivizes the algorithm to explore a wider range of the objective space and mitigates the risk of premature convergence.

4.3. NSGA-III

Some changes have been made to the pairing and survival selection; however, the fundamental structure remains comparable to NSGA-II. In NSGA-III, the parents for recombination are chosen at random. Survival selection considers the multi-dimensional goal space utilising the idea of reference direction. The reference direction Z indicates objective value trade-offs among solutions (Yi et al., 2018). NSGA-III is a relatively recent MOEA. The fundamental NSGA-III method employs a constant mutation rate to tackle a variety of optimisation issues. Although NSGA-III is one of the most effective and typical MOEAs, it may provide unacceptable results in some complex situations due to the mutation operator's fixed rate (Cui et al., 2019). Using a reference point-based strategy, NSGA-III generates a diversified group of equally dispersed solutions throughout the Pareto front. The procedure begins by partitioning the goal space into a collection of reference points selected to include the full Pareto front. Each reference point is paired with a weight matrix which is employed to build a collection of candidate solutions. The candidate solutions are then ranked according to their dominance relationship and crowding distances, and the non-dominated solutions are chosen for the subsequent generation. NSGA-III additionally employs a crowding distance metric to promote solution variety. In contrast to NSGA-II, which utilises a fixed crowding distance value, NSGA-III dynamically modifies the crowding distance according to the solution density in the objective space. This ensures that the solutions are dispersed uniformly over the Pareto front and prevents overcrowding in regions with a high density of solutions. NSGA-III also includes a new crossover operator known as the differential evolution crossover operator, which is more successful at dealing with situations involving multiple goals. The differential evolution crossover operator yields offspring solutions by integrating the parent solutions according to their variations in the feasible region. This enables the algorithm to search a larger portion of the goal space and identify difficult answers for other operators to locate.

4.4. MOSA

The MOSA identifies non-dominated solutions by implementing a simple probability function that aids in generating solutions on the non-dominated frontier. To further maximise the number of non-dominated and unique solutions, the probability function is modified to uniformly cover the whole range of goal functions (Varadharajan and Rajendran, 2005).

The MOSA algorithm starts with an initial collection of potential solutions called "individuals". These individuals symbolise various trade-offs among the aims. The approach then iteratively performs simulated annealing to enhance the candidate solution set. During each iteration, MOSA produces a new set of people by perturbing the present solutions and then assesses each person based on their performance across all goals. The algorithm then chooses a new group of people as the starting point for the subsequent iteration.

MOSA has greatly succeeded in resolving various complicated optimisation challenges, including engineering design, financial portfolio optimisation, and transportation planning. The adaptability and durability of this metaheuristic algorithm in managing multiple, frequently competing goals make it an interesting alternative for solving real-world issues requiring simultaneous optimisation of many objectives. MOSA is thus a vital weapon in the armoury of optimisation methods since it may offer a collection of Pareto frontier of optimal solutions that can assist decision-makers in making informed judgements in complicated problem domains.

4.5. MOPSO

The MOPSO method is based on Pareto optimality, in which a solution is deemed optimal if it is impossible to improve one goal without compromising progress in at least another goal. MOPSO does this by preserving a set of non-dominated solutions in the Pareto front, which consists of the best solutions discovered to date. The method evaluates the quality of each solution in the search space using a set of fitness functions. It changes the location and velocity of the particles depending on the fitness values and the swarm behaviour.

MOPSO incorporates a variety of crucial strategies to increase the algorithm's search efficiency and convergence speed. One of these techniques is using a global best position, the optimal solution discovered by every particle in the swarm. The particles are drawn to the global best region, which pushes the swarm to investigate the search space in more detail. A second process uses a local best position, which is the optimal solution discovered by the particles in a particular region. The best local location prevents the swarm from abruptly converging on an inferior solution.

MOPSO also includes a diversity management mechanism to guarantee that the swarm successfully searches the search space without getting mired in a local optimum. This technique employs a crowding distance metric, which estimates the distance between each Pareto front solution and its closest neighbours. Solutions with a large crowding distance are favoured over those with a small crowding distance because they provide more variety to the Pareto front.

4.6. Dynamic Switched Crowding (DSC-MOAGDE)

This method uses the power of dynamic space combinations (DSC) to augment the functionality of MOEAs. It integrates a pareto strategy and a crowd-distance-centric technique in order to ensure diversity preservation within the decision and objective spaces. Reference spaces, the development of methodologies for enhancing crowding-distance evaluations, and the dynamic utilization of these methodologies via a transition mechanism are combined to create this methodology. The dynamic transition mechanism facilitates the selection of space vectors, which are subsequently used as a reference in crowding-distance computations. This, in turn, allows the efficient adoption of devised strategies. The effectiveness of this algorithm has been verified across numerous optimization challenges and practical engineering tasks, exhibiting a significant leap in performance (Kahraman et al., 2022). For example, Qin et al. (2023) applied DSC-MOAGDE to improve the searching process for the optimal parameters of blind deconvolution (BD).

4.7. Multi-objective slime mould algorithm (MOSMA)

MOSMA is an improved version of the slime mould algorithm (SMA) tailored for multi-objective optimization problems. Traditional optimization approaches often fall short in dealing with multi-objective optimization, while the SMA has shown remarkable effectiveness, because of its design inspired by the oscillation behaviors of slime moulds in laboratory settings. MOSMA utilizes SMA's convergence mechanisms and an elitist non-dominated sorting method to identify pareto optimal solutions (Premkumar et al., 2020). This method has proved its capacity; for example, Peng et al. (2023) employed MOSMA to optimize the support vector regression (SVR) hyperparameters through an intelligent optimization algorithm.

4.8. Multi-objective sunflower optimization (MOSFO)

MOSFO is a constrained multi-objective meta-heuristic, taking inspiration from the sun-following life cycle of sunflowers. The structure of that is more straightforward programming model than many of its evolutionary algorithm counterparts. It illustrated perfect performance according to the metrics such as inverted general distance, spacing, maximum spread, and hyper volume to assess their respective capabilities (Pereira and Gomes, 2023). MOSFO regularly shone through with excellent convergence and coverage capabilities. This method also shows its application. For instance, Kashyap et al. (2022) employed MOSFO to improve the hybridized controller.

4.9. MOEA/D

Introduced to solve various optimization problems, MOEA/D is a decomposition-based metaheuristic algorithm, as documented by Zhang and Li (2007). This evolutionary optimization strategy has proven to excel in achieving rapid attainment of global optima and convergence rate, as confirmed by Zhang et al. (2009). Nevertheless, the effectiveness, limitations, and applicability of MOEA/D in various fields remain under active research. This paper investigates the application of MOEA/D as a novel algorithm for solving the SCLP. Further information regarding the algorithm's implementation can be found in (Zhang and Li, 2007). The main steps of the algorithm are summarized in **Algorithm 1**.

Algorithm 1. Proposed MOEA/D

Input: Algorithm parameters: $(nPop, t, ns, nr, MaxIt)$, Problem parameters
Output: P_f (Nondominated set)

$w \leftarrow (w_1, w_2, \dots, w_{nPop})$,
assign w to S randomly
measure the Euclidean distance between weights
determine ns neighboring weights $\mathcal{B}(w_i)$ of w_i and identify the associated neighboring solutions $B(S_i)$ of S_i
Define pool $Q \leftarrow \emptyset$, set the probability of mating restriction $\delta \leftarrow 0.7$
while $t \leq MaxIt$
  for $i \leftarrow 1$ to $nPop$
    if $rand() < \delta$
      $Q \leftarrow \mathcal{B}(S_i)$
    else
      $Q \leftarrow P_f$
    end

```
        Apply crossover and mutation operators and generate new solution S_new
        Evaluate the objective value of S_new;
        Compute g^c(S|w) for all nPops using Eqs (34) or (35)
        c ← 0
        while c ≤ nr|| Q = ∅
            randomly chose solution j from Q;
            If g^c(S_new|w_i) < g^c(S_i|w_i)
                S_j ← S_new
                c ← c + 1
            End
            Remove S_j from Q
        End
    End
End
```

The reference point is a crucial element in MOEA that greatly affects the quality of solutions. This section delves into the impact of different reference point strategies on solution quality, algorithm convergence, and Pareto solution coverage in MOEA/D. The most prominent scalarizing technique, the Chebyshev approach, is widely acknowledged. To properly discuss the various reference point strategies, it is essential to provide a detailed presentation of the Chebyshev approach.

$$g^c(x|w) = \max_i \left\{ \lambda_i \frac{\mathcal{F}_i - z_i^*}{z_i^{max} - z_i^*} \right\} \tag{29}$$

$$z_i^* = z_i^{min} - \epsilon_i \tag{30}$$

$$\lambda_i = \left(\frac{1}{w_i} \right) \tag{31}$$

The weight vector, w_i, is used to indicate the importance of the i_{th} objective function in multi-objective optimisation. It is imperative to acknowledge that the total of every weight vector must be equivalent to one, as represented by the mathematical symbol $\sum_{i=1}^{m} w_i = 1$. The representation of the objective function's value for a given solution is denoted as $\mathcal{F}_i$, while the ideal point for the i_{th} objective function is symbolised as z_i^*. Furthermore, the upper and lower bounds of the ith objective function are denoted as z_i^{max} and z_i^{min}, correspondingly.

The ideal point, z_i^*, for the ith objective function is frequently unknown in real-world scenarios. To address this, equation (29) has been modified in the following manner:

$$g^c(x|w) = \max_i \left\{ \lambda_i \frac{\mathcal{F}_i - z_i^{min}}{z_i^{max} - z_i^{min}} - \epsilon_i \right\} \tag{32}$$

We can express the difference between the minimum value of z_i and the ideal point as ϵ_i. Therefore, the statement can be written as:

$$\begin{aligned} z_i^* &= z_i^{min} - \epsilon_i \\ \epsilon_i &= (\epsilon_i^s - \epsilon_i^e) \left(\frac{MaxIt - t}{MaxIt - 1} \right) + \epsilon_i^e \end{aligned} \tag{33}$$

The algorithm being proposed employs estimates of ϵ_i, specifically ϵ_i^s and ϵ_i^e, for the initial and final iterations, respectively. The maximum number of iterations for MOEA/D is denoted as MaxIt, while the current iteration is indicated by t. Initially, ϵ_i^s and ϵ_i^e are set to 1 and 0.001, respectively. The algorithm applies a formula to implement different strategies.

$$g^c(x|w) = \max_i \left\{ \lambda_i \frac{\mathcal{F}_i - z_i^{min}}{z_i^{max} - z_i^{min}} - (\epsilon_i^s - \epsilon_i^e) \left(\frac{MaxIt - t}{MaxIt - 1} \right) - \epsilon_i^e \right\} \tag{34}$$

In this research, we suggested three approaches for the MOEA/D framework based on reference points: pessimistic, optimistic, and dynamic. To apply the pessimistic and optimistic approaches, we utilized Equation (32) with predetermined values of ϵ_i. Specifically, $\epsilon_i$was set to 0.001 for the pessimistic approach and 1 for the optimistic approach. This led to the introduction of MOEA/D-v1 and MOEA/D-v2. Moreover, we incorporated Equation (34) to implement the dynamic process, which allows for a linear variation of ϵ_i during the optimization process. Additionally, we modified Equation (35) to incorporate non-linear variations into the MOEA/D framework.

$$g^c(x|w) = \max_i\left\{\lambda_i \frac{\mathcal{F}_i - z_i^{min}}{z_i^{max} - z_i^{min}} - (\epsilon_i^s - \epsilon_i^e)\left(\frac{MaxIt - t}{MaxIt - 1}\right)^v - \epsilon_i^e\right\}, v \in \{0.2, 0.5, 2, 5\} \tag{35}$$

The focus of this study was to evaluate the effectiveness of four different dynamic strategies, namely MOEA/D-v3, MOEA/D-v4, MOEA/D-v5, and MOEA/D-v6. The primary objective was to assess the performance of these strategies in tackling various multi-objective optimization problems. The study was designed to examine each strategy thoroughly, which involved an in-depth evaluation of its features, capabilities, and limitations. The assessment aimed to determine which strategies were most suitable for specific optimization problems and under what conditions.

The determination of the time complexity associated with the MOEA/D is of paramount significance, given its implications for the efficiency and practical applicability of the algorithm in addressing large-scale problems (Zhang and Li, 2007). Central to MOEA/D's functioning is its ability to reduce the original problem space into a series of subproblems(Goh and Tan, 2009).

We denote the time complexity of this decomposition process—wherein each multi-objective issue is transformed into scalar subproblems, often utilizing methods such as the weighted sum or the Tchebycheff approach—by D. Furthermore, the complexity associated with updating each solution's neighborhood is represented by U. The algorithm's iterations, or generations, are represented by T, while N denotes the size of the population in consideration. The number of objectives and the complexity of the genetic operators, encompassing mutation and crossover, are depicted by F and G respectively. Given these notations, the time complexity of the MOEA/D algorithm can be approximated as follows:

$$O(T \times N \times (F + G + D + U)) \tag{36}$$

This provides an approximate measure of the algorithm's efficiency and can be used to predict its performance in the context of large-scale problems.

4.10. Multi-objective Performance metric

In their study, Audet et al. (2020) suggested that MOEAs should be evaluated based on four different aspects encompassing a wide range of properties. These aspects were categorized into four groups: cardinality indicators, convergence indicators, distribution and spread indicators, and convergence and distribution indicators. To evaluate the performance of a proposed approach, several metrics were identified.

The error Ratio (ER) is a metric that represents the ratio of non-dominated objective vectors relative to the Pareto front, with a desired minimum. The number of pareto solutions (NPS) determines the number of non-dominated solutions generated, with a desired maximum. The diversity metric (Δ) reports the diversity of Pareto solutions produced by each algorithm, with a desired minimum. The inverted generation distance (IGD) measures the average minimum distance between a discrete Pareto front element and its nearest point, with a desired minimum. The hyper-volume (HV) calculates the coverage area between the reference point and the Pareto solutions with a desired maximum. The mean ideal distance (MID) calculates the difference between the ideal and Pareto points, with a desired minimum. For further details on these metrics, readers may refer to (Audet et al., 2020)

5. Computational Experiments

In order to evaluate the effectiveness of optimizers, it is necessary to utilise a collection of benchmark problems that exhibit varying degrees of complexity. The present study involves the design of 30 test problems that are categorised into three levels of difficulty, namely small, medium, and large. Table 1 displays the test problems that were created for the purpose of this study. These experiments are detailed in Table 1. The selection of benchmark suits utilised in these experiments was predicated upon various factors, such as their extensive range of sizes and heterogeneity, rendering them highly appropriate for this investigation. By utilising datasets of diverse sizes and types, the scholars achieved a more comprehensive comprehension of the efficacy of the suggested tactics across a broad spectrum of situations. This practise aids in enhancing the reliability and generalizability of the study findings to a diverse range of practical contexts.

Table 1. The general data of the test problems.

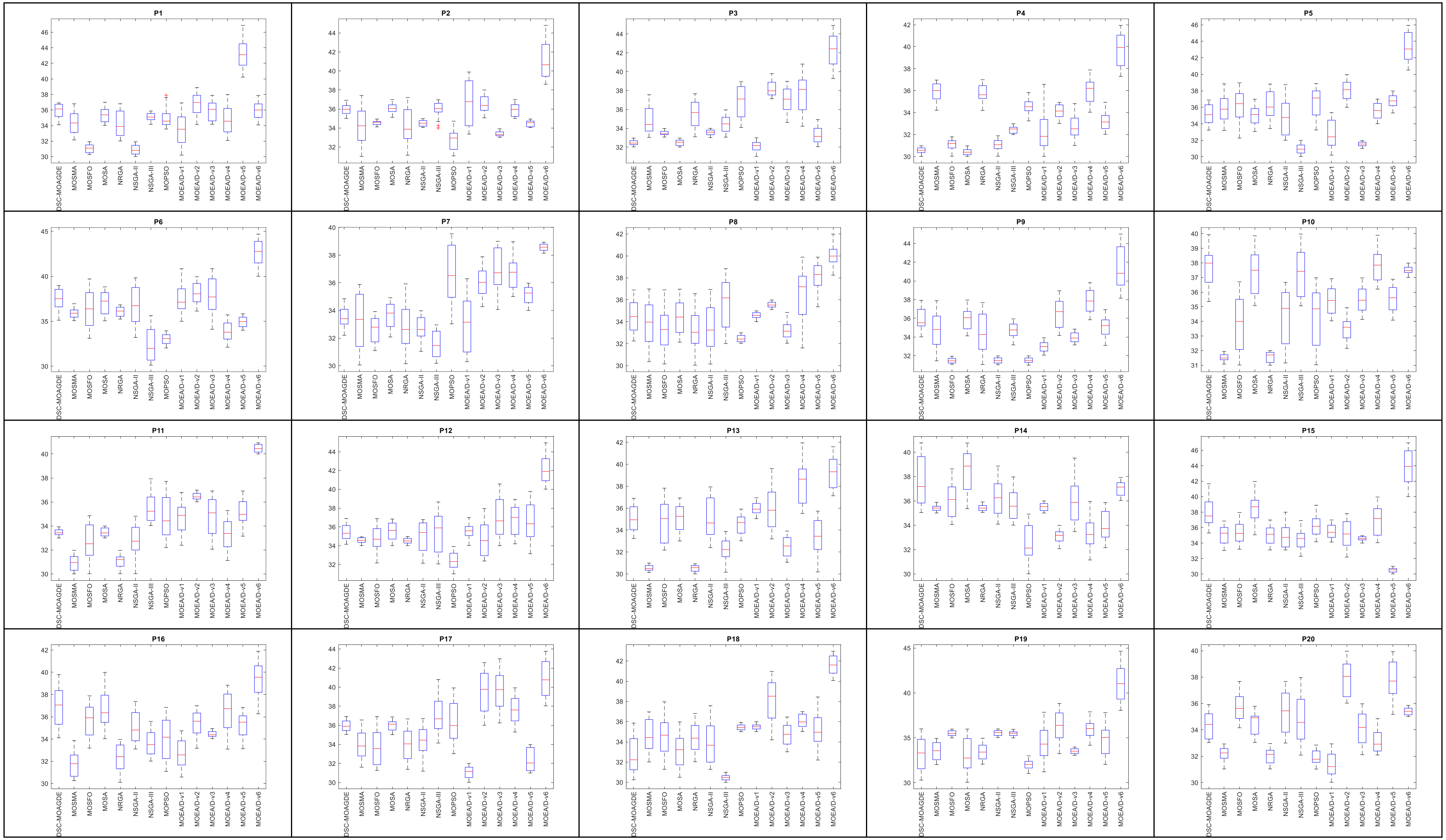
Problem Level	Problem Name	$D, S, M, F, R, B, P, N, H, T, I$	Number of variables	Number of constraints	MOEA/D-v6 (Run time)
Small	P1	[3 7 2 4 2 2 4 6 8 6 5]	3595	13088	245
	P2	[9 2 6 7 9 2 1 7 3 2 4]	955	5606	320
	P3	[9 2 3 7 8 2 9 2 8 4 9]	14068	53660	360
	P4	[6 5 3 3 8 5 6 2 5 5 5]	11534	43409	379
	P5	[3 8 7 2 8 4 4 6 1 3 9]	2137	25448	392
	P6	[1 3 6 7 6 1 5 7 6 4 3]	4742	27229	401
	P7	[9 2 9 5 9 8 5 7 3 5 1]	13349	80819	375
	P8	[9 9 3 6 8 5 6 7 1 3 9]	2075	39263	410
	P9	[8 7 1 5 3 4 3 4 3 3 1]	697	4274	388
	P10	[3 6 1 9 1 5 9 1 4 4 8]	2957	19994	296
Medium	P11	[17 19 14 10 14 19 14 15 11 16 16]	2150201	18591851	1022
	P12	[19 10 19 17 12 16 19 17 18 12 11]	2553549	19925202	1060
	P13	[14 10 12 18 18 11 16 15 17 13 12]	1688505	11295131	851
	P14	[19 14 17 13 10 17 15 17 11 16 14]	2018749	19382431	1120
	P15	[16 12 19 10 17 19 11 13 16 15 18]	3494647	17535702	1110
	P16	[19 11 12 10 15 15 14 11 14 13 11]	1465791	8223213	1201
	P17	[10 11 13 18 18 13 16 15 10 15 16]	1485215	14164381	1325
	P18	[13 13 19 12 11 17 11 16 15 17 17]	2953484	17827391	1365
	P19	[11 11 14 14 18 19 15 16 12 10 13]	1614271	12655069	1453
	P20	[13 10 12 13 11 10 12 19 14 18 12]	1129018	6902026	1344
Large	P21	[20 22 22 20 22 23 24 20 22 20 24]	16750818	163539575	1604
	P22	[20 20 21 21 21 22 24 21 22 20 21]	14686579	142939210	1606
	P23	[24 23 21 23 21 23 20 21 23 20 20]	13997888	149314643	1595
	P24	[24 21 22 23 20 24 20 20 21 21 23]	14875520	156395054	1746

	P25	[22 23 24 21 24 20 20 23 23 20 21]	14199588	141862604	1695
	P26	[23 22 21 22 21 20 21 23 21 22 24]	13447498	139545650	1758
	P27	[21 23 20 23 22 24 24 21 22 21 23]	17020584	186399324	1833
	P28	[20 23 21 23 24 24 24 22 23 23 23]	20671318	216731163	1855
	P29	[24 23 24 24 24 21 22 21 20 22 23]	15619277	190899933	1939
	P30	[24 21 20 22 21 23 24 20 23 20 24]	16219408	156242423	2097

The approaches that were discussed in Section 4 were created using the Matlab 2018b software. The programs were executed on a laptop with an AMD Ryzen 7 4800H CPU, which ran at 2.90 GHz, and 32 GB of RAM. The laptop's operating system was Windows 11 Pro. In order to ensure that the results were reliable, each algorithm was run independently 30 times.

5.1. Computation

In this section, we have conducted a detailed and thorough evaluation of our proposed algorithm's performance compared to other existing algorithms. Our analysis was carried out using two different approaches. Firstly, we examined the impact of using our proposed approaches on various metrics. We analysed the results of our proposed algorithm against those of existing algorithms and compared the differences in various performance indicators. We analysed the efficiency of our algorithm, the accuracy of its predictions, and its ability to handle large data sets. Secondly, we applied sensitivity analysis to evaluate the performance of our algorithm in the presence of various sustainable factors. We assessed the changes in the algorithm's performance when different sustainable factors were introduced. This helped us to determine how well our algorithm performs under different conditions and its robustness in real-world scenarios.


P1
P2
P3
P4
P5
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P8
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P10
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P13
P14
P15
P16
P17
P18
P19
P20
DSC-MOAGDE
MOSMA
MOSFO
MOSA
NRGA
NSGA-II
NSGA-III
MOPSO
MOEA/D-v1
MOEA/D-v2
MOEA/D-v3
MOEA/D-v4
MOEA/D-v5
MOEA/D-v6

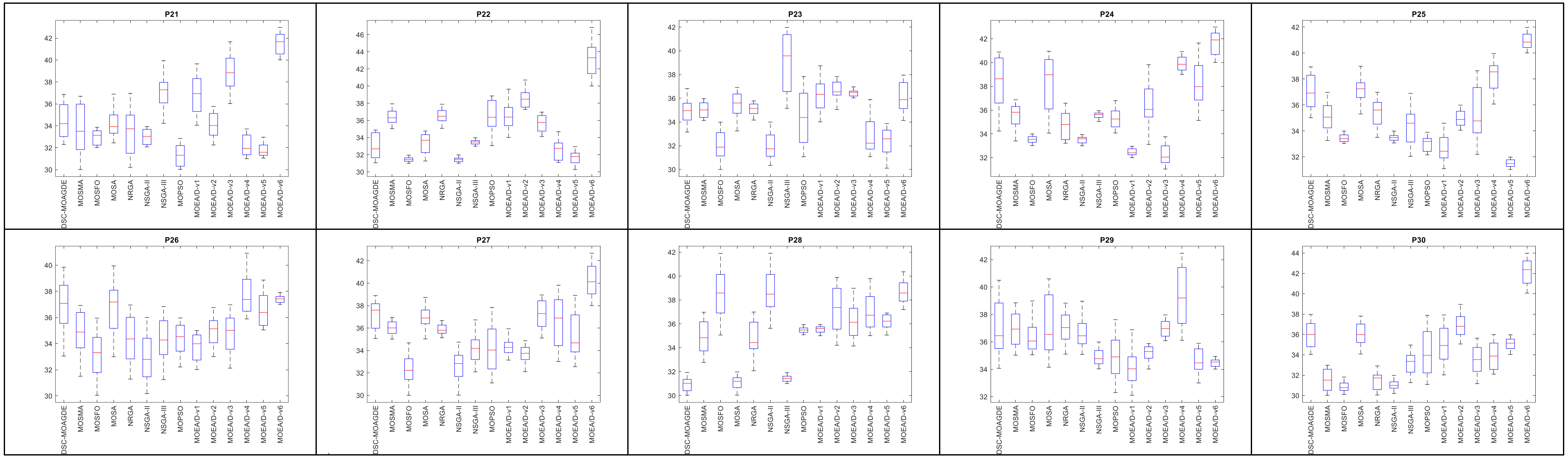


Figure 2. Boxplot of NPS metric for test problems based on various approaches

Table 2. Statistical rank sum test for NPS metrics

MOEA/D-v6 vs #		DSC-MOAGDE	MOSMA	MOSFO	MOSA	NRGA	NSGA-II	NSGA-III	MOPSO	MOEA/D-v1	MOEA/D-v2	MOEA/D-v3	MOEA/D-v4	MOEA/D-v5
P1	R	1128	1270	1234	1130	1275	1365	1234	1088	1273	880	1028	1084	465
	h	1	1	1	1	1	1	1	1	1	0	0	1	1
	p	1.62E-03	1.09E-07	2.02E-11	1.52E-03	1.07E-07	3.02E-11	2.49E-06	1.08E-02	1.25E-07	6.10E-01	9.63E-02	1.27E-02	3.02E-11
P2	R	1365	1365	1365	1365	1365	1365	1365	1365	1330	1365	1365	1365	1365
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	8.89E-10	3.02E-11	3.02E-11	3.02E-11	3.02E-11
P3	R	1365	1365	1365	1365	1365	1365	1365	1365	1365	1350	1365	1319	1365
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	1.33E-10	3.02E-11	2.44E-09	3.02E-11
P4	R	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1296	1365
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	1.85E-08	3.02E-11
P5	R	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11
P6	R	1365	1365	1365	1365	1365	1365	1365	1365	1358	1365	1346	1365	1365
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	6.066E-11	3.02E-11	1.957E-10	3.02E-11	3.02E-11
P7	R	1.37E+03	1.37E+03	1.37E+03	1.37E+03	1.37E+03	1.37E+03	1.37E+03	1.18E+03	1.37E+03	1.37E+03	1.31E+03	1.29E+03	1.37E+03
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	9.79E-05	3.02E-11	3.02E-11	6.52E-09	4.69E-08	3.02E-11
P8	R	1365	1365	1365	1365	1365	1365	1341	1365	1365	1365	1365	1309	1247
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.16E-10	3.02E-11	3.02E-11	3.02E-11	3.02E-11	5.97E-09	9.53E-07
P9	R	1365	1365	1365	1365	1365	1365	1365	1365	1365	1337	1365	1283	1365
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	4.62E-10	3.02E-11	5.53E-08	3.02E-11
P10	R	934	1365	1365	934	1365	1365	885	1365	1365	1365	1365	706	1365
	h	0	1	1	0	1	1	0	1	1	1	1	1	1
	p	7.54E-01	3.02E-11	3.02E-11	7.84E-01	3.02E-11	3.02E-11	6.63E-01	3.02E-11	3.02E-11	3.02E-11	3.02E-11	2.05E-03	3.02E-11
P11	R	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11
P12	R	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1334	1365	1365
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	6.12E-10	3.02E-11	3.02E-11

P13	R	1365	1365	1357	1365	1365	1357	1365	1365	1365	1258	1365	1022	1365
	h	1	1	1	1	1	1	1	1	1	1	1	0	1
	p	3.04E-11	2.02E-11	5.70E-11	3.02E-11	3.02E-11	6.70E-11	3.02E-11	3.02E-11	3.02E-11	4.11E-07	3.02E-11	1.15E-01	3.02E-11
P14	R	690	1365	1006	690	1365	1006	1163	1365	1365	1365	854	1365	1365
	h	1	1	0	1	1	0	1	1	1	1	0	1	1
	p	9.03E-04	3.02E-11	1.81E-01	9.03E-04	3.02E-11	1.81E-01	2.53E-04	3.02E-11	3.02E-11	3.02E-11	3.71E-01	3.02E-11	3.02E-11
P15	R	1337	1365	1365	1337	1365	1365	1365	1365	1365	1365	1365	1365	1365
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	4.62E-10	3.02E-11	3.02E-11	4.62E-10	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11
P16	R	1095	1365	1292	1095	1365	1292	1365	1330	1365	1329	1365	1212	1307
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	7.96E-03	3.02E-11	2.60E-08	7.96E-03	3.02E-11	2.60E-08	3.02E-11	8.89E-10	3.02E-11	9.76E-10	3.02E-11	1.17E-05	7.12E-09
P17	R	1365	1365	1365	1365	1365	1365	1298	1311	1365	1028	1019	1337	1365
	h	1	1	1	1	1	1	1	1	1	0	0	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	1.56E-08	5.00E-09	3.02E-11	9.63E-02	1.26E-01	4.62E-10	3.02E-11
P18	R	1365	1365	1365	1365	1365	1365	1365	1365	1365	1328	1365	1365	1365
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	1.07E-09	3.02E-11	3.02E-11	3.02E-11
P19	R	1365	1365	1365	1365	1365	1365	1365	1365	1365	1358	1365	1365	1365
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	6.07E-11	3.02E-11	3.02E-11	3.02E-11
P20	R	1260	1365	946	1260	1365	946	1024	1365	1365	465	1263	1365	556
	h	1	1	0	1	1	0	0	1	1	1	1	1	1
	p	3.52E-07	3.02E-11	6.52E-01	3.52E-07	3.02E-11	6.52E-01	1.09E-01	3.02E-11	3.02E-11	3.02E-11	2.78E-07	3.02E-11	1.16E-07
P21	R	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1300	1365	1365
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	1.31E-08	3.02E-11	3.02E-11
P22	R	1365	1365	1365	1365	1365	1365	1365	1365	1365	1322	1365	1365	1365
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	1.86E-09	3.02E-11	3.02E-11	3.02E-11
P23	R	986	1127	1365	986	1127	1365	606	1062	771	770	752	1231	1365
	h	0	1	1	0	1	1	1	1	1	1	1	1	1
	p	2.97E-01	1.77E-03	3.02E-11	2.97E-01	1.77E-03	3.02E-11	5.09E-06	3.03E-02	3.39E-02	3.27E-02	1.63E-02	3.09E-06	3.02E-11
P24	R	1347	1365	1365	1347	1365	1365	1365	1365	1365	1365	1365	1317	1297
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	1.78E-10	3.02E-11	3.02E-11	1.78E-10	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	2.92E-09	1.70E-08
P25	R	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11
P26	R	949	1365	1365	947	1365	1365	1365	1365	1365	1365	1365	618	1054
	h	0	1	1	0	1	1	1	1	1	1	1	1	1

	p	6.41E-01	3.02E-11	3.02E-11	6.41E-01	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	1.17E-05	4.06E-02
P27	R	1357	1365	1365	1357	1365	1365	1365	1365	1365	1365	1357	1331	1361
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	6.70E-11	3.02E-11	3.02E-11	6.70E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	6.70E-11	8.10E-10	4.50E-11
P28	R	1365	1365	965	1365	1365	965	1365	1365	1365	1237	1259	1119	1365
	h	1	1	0	1	1	0	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	4.64E-01	3.02E-11	3.02E-11	4.64E-01	3.02E-11	3.02E-11	3.02E-11	2.00E-06	3.81E-07	2.62E-03	3.02E-11
P29	R	516	465	465	513	465	465	653	848	882	595	465	465	968
	h	1	1	1	1	1	1	1	0	0	1	1	1	0
	p	2.92E-09	3.02E-11	3.02E-11	2.92E-09	3.02E-11	3.02E-11	1.11E-04	3.26E-01	6.31E-01	2.32E-06	3.02E-11	3.02E-11	4.38E-01
P30	R	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365	1365
	h	1	1	1	1	1	1	1	1	1	1	1	1	1
	p	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11
	The number of hypotheses is equal 1	27	30	27	27	30	27	28	29	29	28	27	29	29
	Percentage of win	90%	100%	90%	90%	100%	90%	93%	97%	97%	93%	90%	97%	97%

The information from Figure 2 and Table 2, which includes data on the NPS metric, serves as a canvas of contrast between MOEA/D-v6 and a baker's dozen of other metaheuristic methodologies, with individual rows (from $P1$ to $P30$) being reflective of distinct problem sets. The tools utilized for this juxtaposition is the rank-sum test, a statistical apparatus. For every algorithm and problem pair, a rank-sum or 'R' is allocated. The hypothesis (the Wilcoxon signed-rank test p-value) of nullity or $H = 0$ postulates an absence of a substantial disparity in the performance output between MOEA/D-v6 and its counterparts. The P-value, or 'p', stands as the gauge for the possibility of stumbling upon the given data under the umbrella of the null hypothesis being factual. In an event where the P-value shrinks to a tiny figure (generally $\leq$ 0.05), the null hypothesis finds itself being shunned. This is often construed as hinting at the probability of its alternative being valid. Moreover, an element worth taking into account is that the h factor in the proffered table follows the binary format and seemingly symbolizes the rejection (1) or acceptance (0) of the null hypothesis.

Rankings: it is preferable to have lower ranks. The data presented demonstrates that MOEA/D-v6 consistently maintains the topmost position in all problem scenarios. This suggests that, among the considered options, MOEA/D-v6 is the optimum algorithm for this specific array of problems.

Hypothesis Indicator ($\boldsymbol{h}$): When 'h' equals 1, it denotes that the performance disparity is statistically relevant at the specified significance level. On the contrary, if 'h' equals 0, the discrepancy lacks statistical significance. In all problem cases, MOEA/D-v6 shows 'h' equal to 1, implying that its superior performance isn't coincidental but statistically significant.

p-value ($\boldsymbol{p}$): The p-value denotes the likelihood of the observed results occurring by sheer chance under the assumption that the null hypothesis is correct. A smaller p-value signals more potent evidence disputing the null hypothesis. In most scientific settings, a p-value lesser than 0.05 is deemed statistically significant. For MOEA/D-v6, all p-values are much lower than 0.05, strengthening the claim that the performance differences are statistically meaningful.

Analysing these results, it is evident that, statistically, MOEA/D-v6 outclasses the other MOEA/D iterations and the additional algorithms (DSC-MOAGDE, MOSMA, MOSFO, MOSA, NRGA, NSGA-II, NSGA-III, MOPSO) when dealing with this specific problem set.

Table 3. Wining percentage of various approaches in competition with others based on NPS metric

	DSC-MOAGDE	MOSMA	MOSFO	MOSA	NRGA	NSGA-II	NSGA-III	MOPSO	MOEA/D-v1	MOEA/D-v2	MOEA/D-v3	MOEA/D-v4	MOEA/D-v5	MOEA/D-v6	Average
DSC-MOAGDE	0%	40%	47%	41%	48%	35%	30%	30%	50%	40%	31%	41%	43%	41%	40%
MOSMA	43%	0%	38%	30%	46%	30%	40%	47%	42%	44%	47%	31%	34%	39%	39%
MOSFO	20%	10%	0%	30%	54%	66%	50%	70%	53%	37%	50%	40%	57%	7%	42%
MOSA	11%	23%	32%	0%	77%	73%	57%	70%	53%	37%	50%	40%	57%	7%	45%
NRGA	32%	29%	34%	23%	0%	60%	40%	57%	43%	17%	27%	23%	43%	3%	33%
NSGA-II	19%	36%	30%	27%	40%	0%	37%	43%	40%	20%	33%	17%	33%	3%	29%
NSGA-III	36%	23%	40%	43%	60%	63%	0%	60%	63%	27%	33%	23%	43%	10%	40%
MOPSO	31%	27%	18%	30%	43%	57%	40%	0%	53%	17%	30%	17%	40%	3%	31%
MOEA/D-v1	24%	21%	38%	47%	57%	60%	37%	47%	0%	27%	40%	27%	40%	7%	36%
MOEA/D-v2	30%	22%	35%	63%	83%	80%	73%	83%	73%	0%	67%	43%	73%	13%	57%
MOEA/D-v3	11%	22%	16%	50%	73%	67%	67%	70%	60%	33%	0%	37%	57%	10%	44%
MOEA/D-v4	17%	27%	15%	60%	77%	83%	77%	83%	73%	57%	63%	0%	73%	10%	55%
MOEA/D-v5	33%	38%	27%	43%	57%	67%	57%	60%	60%	27%	43%	27%	0%	7%	42%
MOEA/D-v6	90%	100%	90%	90%	100%	90%	93%	97%	97%	93%	90%	97%	97%	0%	94%

Table 3 presents a comparative analysis of the efficacy of 14 distinct metaheuristic optimization algorithms, utilizing winning rates as the key determinant. These algorithms have been benchmarked for their prowess in refining complex issues. As per the resultant data, the standout performer is MOEA/D-v6, commanding an impressive winning rate of 94%. This illustrates the high efficiency and dependability of MOEA/D-v6, qualifying it as a potent tool for enhancing an array of intricate dilemmas. Nonetheless, it's vital to underline that MOEA/D-v6's performance may vary contingent upon the nature of the problem under consideration, and certain other algorithms may prove superior under specific circumstances.

The NSGA-II algorithm demonstrates a noticeably limited success rate, with its victories amounting to a mere 29% on average. This consistent shortfall against other algorithms suggests that NSGA-II could benefit from enhancements or perhaps it excels under more specialized conditions. Interesting variations are also observed among different versions of the MOEA/D algorithm. Specifically, MOEA/D-v2 and MOEA/D-v4 have demonstrated relatively admirable performances, boasting average winning rates of 57% and 55% respectively. Despite their solid showings, these figures still lag notably behind MOEA/D-v6, indicating that significant adjustments or upgrades in the sixth version have bolstered its superior performance. Further granularity is revealed when scrutinizing individual matchups between algorithms. An illustrative example can be seen in the direct comparison of MOEA/D-v1 and NSGA-III. The latter algorithm emerges victorious 63% of the time, suggesting that under particular circumstances or when pitted against certain algorithms, one method might prove more effective. This highlights the multifaceted nature of these algorithms' dynamics.

Dominance of MOEA/D-v6: In line with prior observations, MOEA/D-v6 continues to stand out with an imposing average winning rate of 94%. This superior track record provokes curiosity about which algorithm fares best against it. Notably, the MOSA and MOEA/D-v5 emerge as the most successful challengers, each securing a win rate of 7%.

Identification of Rivals: Revealing insights can be gleaned by identifying the most formidable and weakest competitors for each algorithm. For instance, DSC-MOAGDE finds MOEA/D-v6 insurmountable, failing to secure a win, but it manages a commendable 50% success rate against MOEA/D-v1. It's worth highlighting that MOEA/D-v6 poses the most significant challenge for a majority of the algorithms.

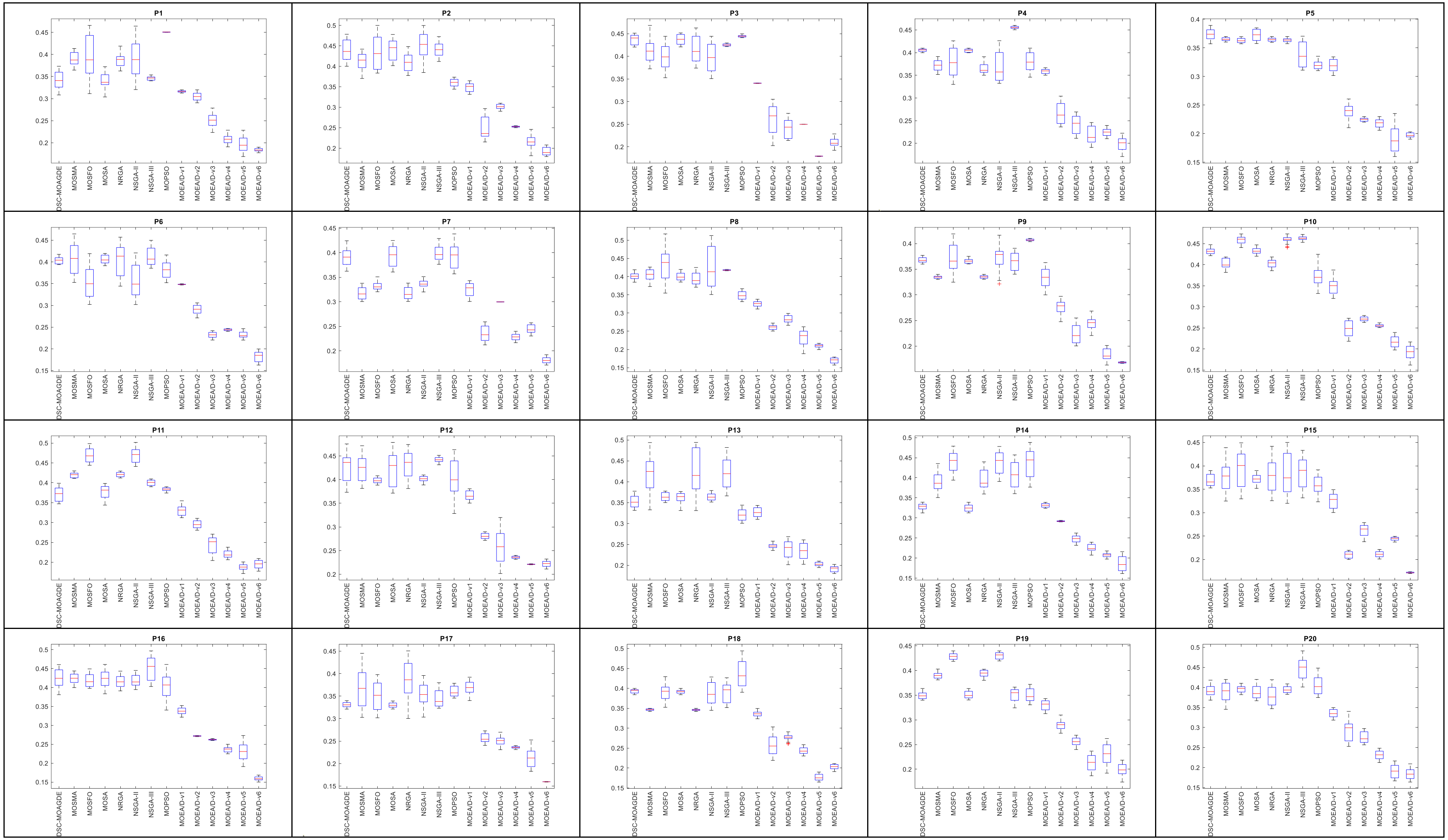
Variability in MOEA/D Iterations: The MOEA/D algorithm iterations demonstrate a considerable range in effectiveness. MOEA/D-v2, v4, and v6 display commendable win averages above 50%, whereas other versions exhibit more modest to poor performance levels, with v1 recording an average win rate of just 36%.

Performance of MOSFO and MOSA: Intriguingly, although MOSFO and MOSA possess average win rates of 42% and 45% respectively, they, alongside MOEA/D-v6, are the only algorithms to achieve an over 70% win rate in any direct competition (specifically against MOPSO).

Complex Mosaic of Strengths and Weaknesses: The data paints a multifaceted picture of relative strengths and weaknesses. For example, despite NRGA's overall low average of 33%, it secures a 60% win rate against NSGA-II, itself a modest performer at 29% on average.

Similarly, MOSMA, with a fair average of 39%, delivers a strong performance of 47% against MOPSO, which generally achieves a win rate of 31%.

ER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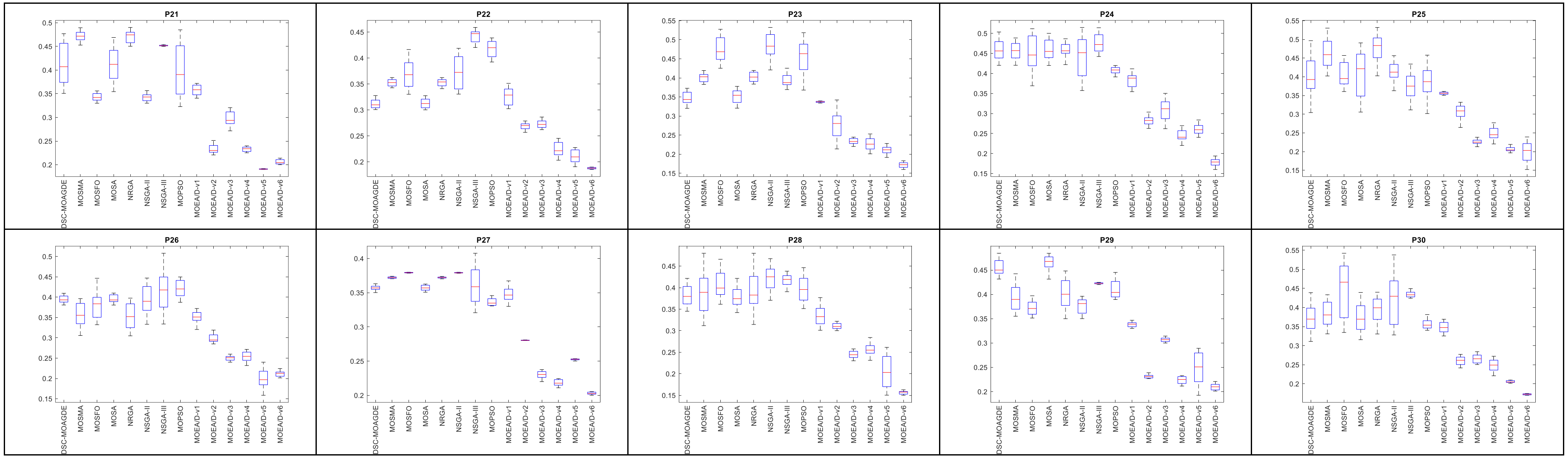


Figure 3. Boxplot of ER metric for test problems based on various approaches

Table 4. Wining percentage of various approaches in competition with others based on ER metric

ER	DSC-MOAGDE	MOSMA	MOSFO	MOSA	NRGA	NSGA-II	NSGA-III	MOPSO	MOEA/D-v1	MOEA/D-v2	MOEA/D-v3	MOEA/D-v4	MOEA/D-v5	MOEA/D-v6	Avg
DSC-MOAGDE	0%	23%	15%	23%	29%	23%	23%	24%	13%	39%	36%	21%	27%	39%	26%
MOSMA	21%	0%	31%	22%	16%	14%	27%	14%	11%	30%	36%	12%	20%	15%	21%
MOSFO	26%	16%	0%	16%	13%	16%	22%	16%	19%	11%	31%	35%	23%	24%	21%
MOSA	15%	36%	40%	0%	53%	57%	77%	43%	10%	0%	0%	0%	0%	0%	25%
NRGA	20%	33%	16%	47%	0%	57%	70%	43%	3%	0%	0%	0%	0%	0%	22%
NSGA-II	38%	31%	21%	43%	43%	0%	57%	40%	7%	0%	0%	0%	0%	0%	22%
NSGA-III	12%	24%	18%	23%	30%	43%	0%	33%	3%	0%	0%	0%	0%	0%	14%
MOPSO	11%	28%	10%	57%	57%	60%	67%	0%	10%	0%	0%	0%	0%	0%	23%
MOEA/D-v1	29%	33%	10%	90%	97%	93%	97%	90%	0%	0%	0%	0%	0%	0%	41%
MOEA/D-v2	18%	28%	13%	100%	100%	100%	100%	100%	100%	0%	37%	7%	10%	0%	55%
MOEA/D-v3	100%	100%	100%	100%	100%	100%	100%	100%	100%	63%	0%	20%	3%	0%	76%
MOEA/D-v4	100%	100%	100%	100%	100%	100%	100%	100%	100%	93%	80%	0%	27%	0%	85%
MOEA/D-v5	100%	100%	100%	100%	100%	100%	100%	100%	100%	90%	97%	73%	0%	17%	91%
MOEA/D-v6	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	83%	0%	99%

Figure 3 and Table 4 present intriguing insights into the ER metric. In Table 4, each row reveals the victory rate of a given metaheuristic over its counterparts based on the ER metric. Taking the first row as an example, we compare DSC-MOAGDE with MOSMA, MOSFO, NRGA, NSGA-II, NSGA-III, MOPSO, MOEA/D-v1 through v6. Securing a standout victory rate of 99% on average, MOEA/D-v6 indisputably leads the race among all tested algorithms. Even its lowest win rate against MOEA/D-v5 clocks in at a high 83%, indicating a fierce rivalry between these two iterations. The substantial lead of MOEA/D-v6 over other versions likely points to significant upgrades incorporated into this release, contributing to its exceptional results.

Other strong contenders, MOEA/D-v5 and v4, put up commendable performances, with average victory rates of 91% and 85% in turn. These versions boast a perfect 100% win rate against numerous algorithms but face difficulties when pitched against each other or MOEA/D-v6. This supports the notion that the latter iterations of MOEA/D have seen advanced enhancements making them superior.

Contrastingly, MOEA/D-v1 trails behind with an average win rate of a mere 41%. Despite scoring a flawless 100% win rate against certain algorithms, it falls flat when pitted against subsequent MOEA/D iterations. This could suggest that while MOEA/D-v1 has potential, the refinements in the later versions offer significant performance boosts. Paying attention outside of the MOEA/D family, both NRGA and NSGA-II, variations of genetic algorithms, display similar average win rates of 22%. However, NRGA has a slight upper hand when directly facing NSGA-II. Meanwhile, NSGA-III lags a bit further behind with a lower average win rate of 14%, which might suggest some modifications in this iteration did not contribute effectively to error reduction in this study. Lastly, MOPSO, a version of the well-known Particle Swarm Optimization algorithm, positions itself mid-tier with an average victory rate of 23%. This indicates that while it may hold its own in some cases, it typically falls short when compared to the MOEA/D versions, and is closely matched with the genetic algorithm variations. This comprehensive overview of the competition between these metaheuristic algorithms emphasizes the dominance of the later MOEA/D versions.

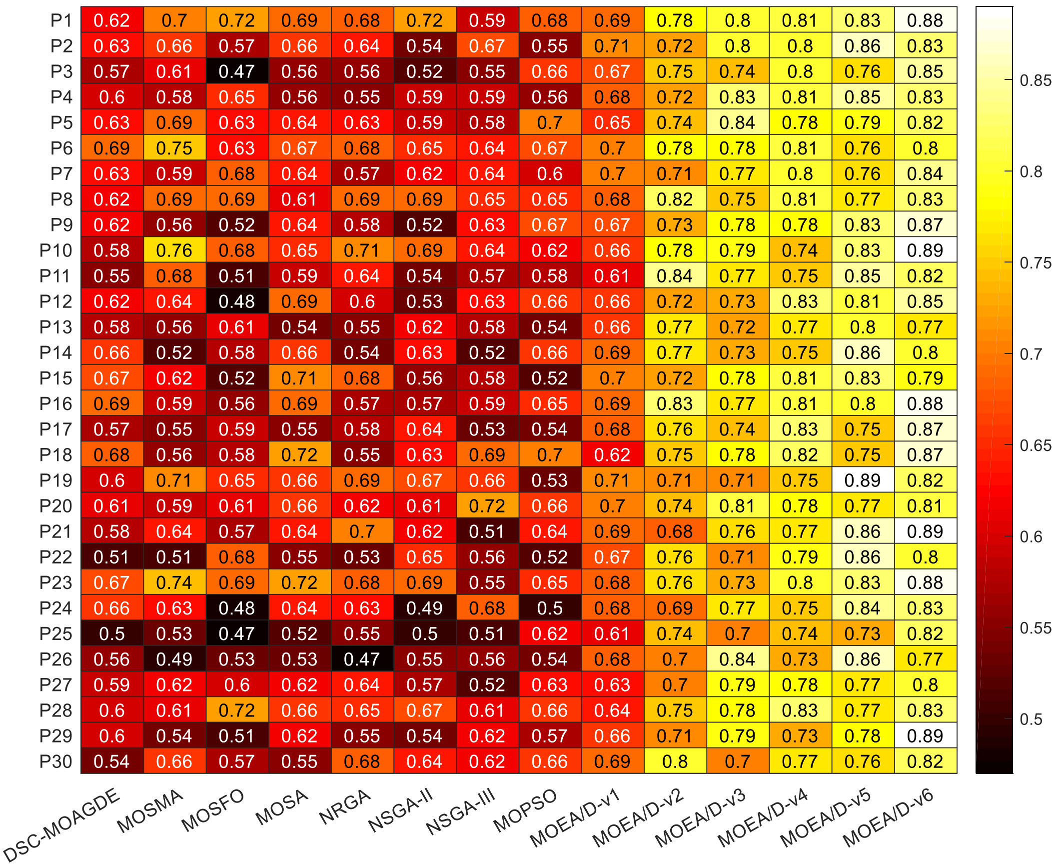


Figure 4. The average score of using various approaches for thirty test problems

Table 5. Wining percentage of various approaches in competition with others based on HV metric

	DSC-MOAGDE	MOSMA	MOSFO	MOSA	NRGA	NSGA-II	NSGA-III	MOPSO	MOEA/D-v1	MOEA/D-v2	MOEA/D-v3	MOEA/D-v4	MOEA/D-v5	MOEA/D-v6	Average
DSC-MOAGDE	11%	14%	23%	23%	29%	16%	36%	30%	36%	27%	18%	11%	24%	28%	25%
MOSMA	30%	35%	16%	34%	13%	19%	11%	19%	31%	10%	19%	11%	29%	38%	24%
MOSFO	22%	23%	15%	23%	29%	39%	30%	36%	24%	20%	12%	11%	32%	39%	27%
MOSA	24%	34%	25%	0%	63%	67%	63%	60%	20%	0%	0%	0%	0%	0%	27%
NRGA	21%	14%	40%	37%	0%	60%	57%	50%	20%	3%	0%	0%	0%	0%	23%
NSGA-II	26%	19%	14%	33%	40%	0%	53%	43%	20%	0%	0%	0%	0%	0%	19%
NSGA-III	38%	39%	26%	37%	43%	47%	0%	43%	7%	0%	0%	0%	0%	0%	22%
MOPSO	17%	11%	34%	40%	50%	57%	57%	0%	13%	0%	0%	0%	0%	0%	21%
MOEA/D-v1	16%	30%	21%	80%	80%	80%	93%	87%	0%	3%	0%	0%	0%	0%	38%
MOEA/D-v2	100%	100%	100%	100%	97%	100%	100%	100%	97%	0%	40%	23%	20%	3%	75%
MOEA/D-v3	100%	100%	100%	100%	100%	100%	100%	100%	100%	60%	0%	33%	27%	7%	79%
MOEA/D-v4	100%	100%	100%	100%	100%	100%	100%	100%	100%	77%	67%	0%	43%	10%	84%
MOEA/D-v5	100%	100%	100%	100%	100%	100%	100%	100%	100%	80%	73%	57%	0%	33%	88%
MOEA/D-v6	100%	100%	100%	100%	100%	100%	100%	100%	100%	97%	93%	90%	67%	0%	96%

Figure 4 and Table 5 furnish an understanding of the performance of all 14 metaheuristics, as evaluated by the HV metric. Winning percentages serve to illustrate the frequency with which one algorithm outperforms the rest, all gauged using the Hypervolume (HV) indicator.

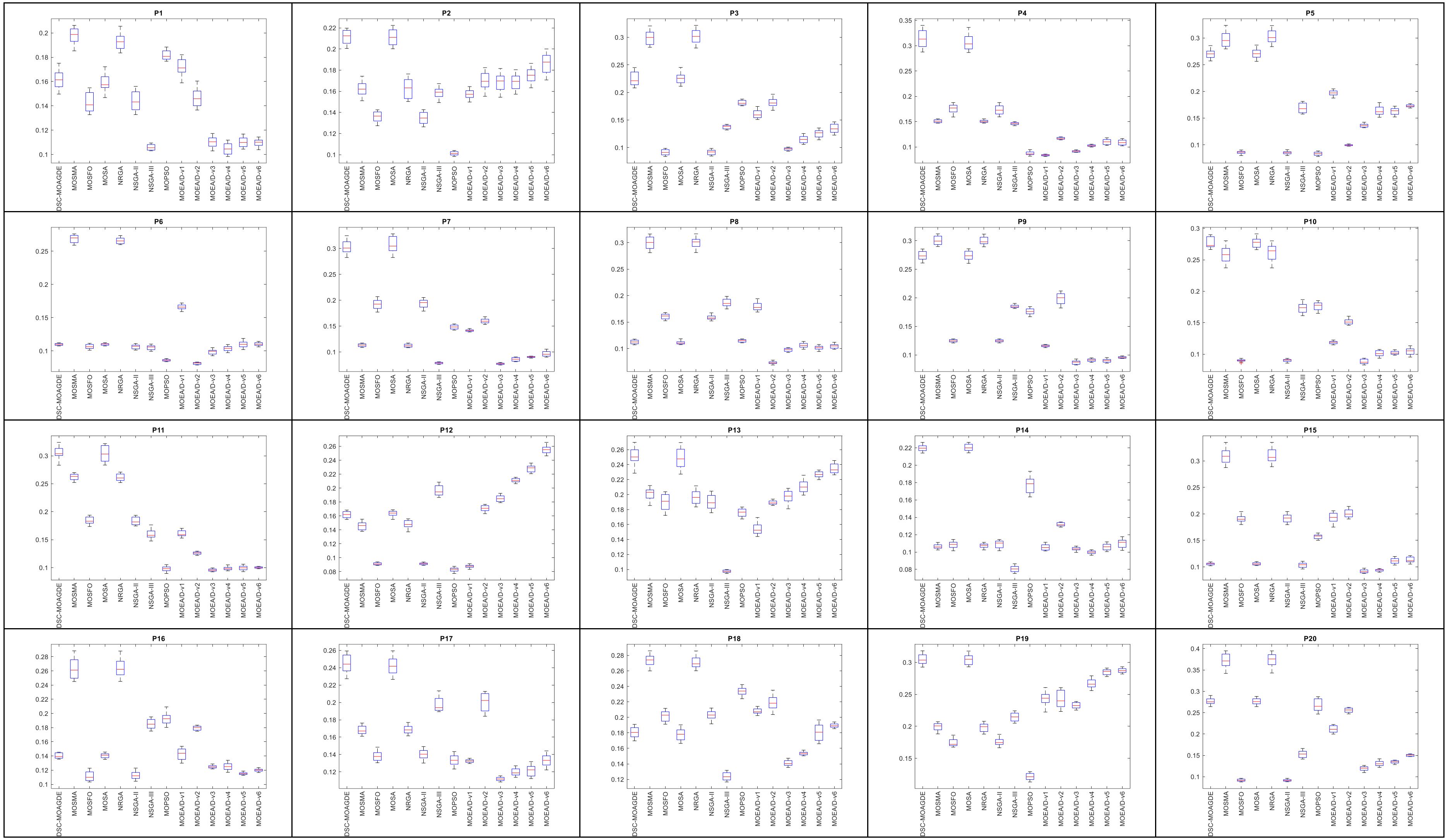
Several enlightening patterns and tendencies can be deduced from the presented data:

Primarily, it becomes apparent that more recent iterations of MOEA/D consistently excel, outshining not only other metaheuristic algorithms but also its preceding versions. MOEA/D-v6, the most current version, showcases the most impressive average win rate, standing at a hefty 96%. It consistently garners a perfect 100% score against all competing algorithms except its own variants, implying that it universally, or near universally, emerges as the superior performer in the Hypervolume evaluation.

The preceding MOEA/D versions, v5, v4, and v3, each display commendable performance, albeit with a gradual decline, achieving respectable average win rates of 88%, 84%, and 79% in that order. This consistent decline hints at the ongoing refinement and progressive performance enhancement of the MOEA/D series.

The non-MOEA/D algorithms display considerable fluctuation in their win rates. Algorithms such as DSC-MOAGDE, MOSMA, and MOSFO clock in with average win rates of approximately 25%, 24%, and 27% respectively. MOSA and NRGA consistently outperform NSGA-II, NSGA-III, and MOPSO, but fail to match up to any MOEA/D version, suggesting a distinct performance divide.

Interestingly, MOEA/D-v1 showcases an average win rate of 38%, outperforming many non-MOEA/D algorithms but falling significantly short of its later counterparts. This indicates substantial improvements in the MOEA/D algorithm over its subsequent iterations.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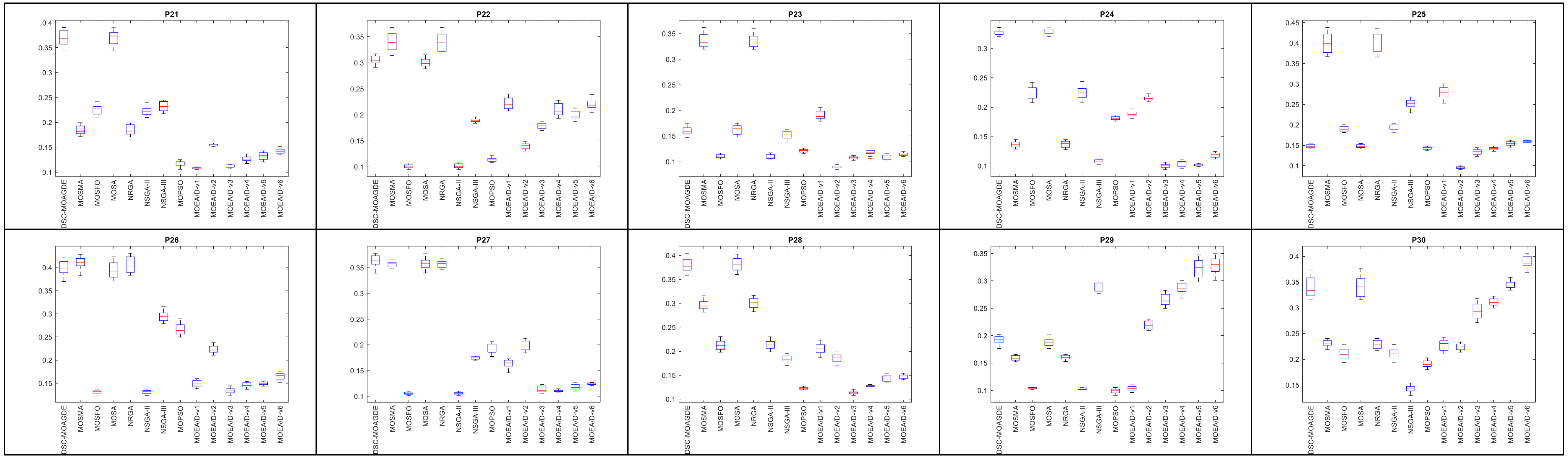

Figure 5. Boxplot of DM metric for test problems based on various approaches

Table 6. Wining percentage of various approaches in competition with others based on DM metric

	DSC-MOAGDE	MOSMA	MOSFO	MOSA	NRGA	NSGA-II	NSGA-III	MOPSO	MOEA/D-v1	MOEA/D-v2	MOEA/D-v3	MOEA/D-v4	MOEA/D-v5	MOEA/D-v6	Average
DSC-MOAGDE	0%	13%	39%	22%	27%	14%	18%	28%	13%	26%	12%	12%	35%	19%	21%
MOSMA	40%	0%	33%	35%	38%	23%	22%	33%	19%	18%	32%	26%	25%	31%	29%
MOSFO	34%	39%	0%	22%	21%	24%	20%	36%	25%	27%	14%	34%	30%	12%	26%
MOSA	31%	30%	14%	0%	53%	57%	13%	17%	7%	27%	17%	20%	20%	23%	25%
NRGA	30%	19%	16%	47%	0%	50%	13%	17%	17%	27%	17%	7%	7%	20%	22%
NSGA-II	26%	22%	23%	43%	50%	0%	17%	17%	10%	13%	27%	17%	20%	20%	23%
NSGA-III	21%	21%	25%	87%	87%	83%	0%	60%	40%	60%	67%	43%	50%	50%	53%
MOPSO	31%	12%	29%	83%	83%	83%	40%	0%	40%	60%	50%	23%	30%	43%	47%
MOEA/D-v1	39%	15%	27%	93%	83%	90%	60%	60%	0%	50%	60%	33%	43%	47%	54%
MOEA/D-v2	25%	37%	21%	73%	73%	87%	40%	40%	50%	0%	67%	23%	27%	27%	45%
MOEA/D-v3	100%	100%	100%	83%	83%	73%	33%	50%	40%	33%	0%	33%	37%	40%	62%
MOEA/D-v4	100%	100%	100%	80%	93%	83%	57%	77%	67%	77%	67%	0%	90%	93%	83%
MOEA/D-v5	100%	100%	100%	80%	93%	80%	50%	70%	57%	73%	63%	10%	0%	77%	73%
MOEA/D-v6	100%	100%	100%	77%	80%	80%	50%	57%	53%	73%	60%	7%	23%	0%	66%

Figure 5 and Table 6 provide a comprehensive view of metaheuristics' performance measured by the DM metric. The table under analysis provides an intriguing breakdown of various algorithms' performances. Emerging as the unrivalled frontrunner, MOEA/D-v4 has an impressive 83% average success rate, signifying its ability to consistently outmatch other competitors across various scenarios or challenges. In matchups with DSC-MOAGDE, MOSMA, MOSFO, MOEA/D-v3, MOEA/D-v5, and MOEA/D-v6, it boasts an unbroken record of triumph, indicating its broad adaptability and effective approach. Trailing behind, but still packing a punch, are MOEA/D-v5 and MOEA/D-v6 with their commendable averages of 73% and 66% respectively. These stats highlight the efficacy of MOEA/D versions from v3 onwards, underlining their relative superiority in the given context.

Contrastingly, DSC-MOAGDE appears to struggle with an average success rate of a mere 21%, performing worst against MOEA/D-v3, MOEA/D-v4, MOEA/D-v5, and MOEA/D-v6. This could be indicative of either DSC-MOAGDE's limited adaptability across different problem types, or an avenue for potential enhancements and optimisation. With slightly higher averages of 29% and 25% respectively, MOSMA and MOSA also showcase several weak performances, suggesting they could greatly benefit from further refinement.

It is also worth noting that NSGA-II and NSGA-III, despite their widespread acclaim in the academic domain, fail to put up a strong show in this evaluation. This could either be reflective of the niche nature of the tackled problems, or suggest that these algorithms have limitations when applied under certain conditions.

In a broader sense, all algorithms under scrutiny have registered at least one absolute defeat against MOEA/D-v3, MOEA/D-v4, MOEA/D-v5, and MOEA/D-v6. This pattern could be interpreted as a testament to the relative robustness and superiority of these four MOEA/D versions in this context.

However, without further information about the DM metric, specific problem instances, or more context about the comparison, these findings should be interpreted with a grain of salt. Deeper investigation would provide a more robust understanding and allow for more detailed and meaningful insights.

6. Conclusion

The present study introduces a new model for designing a closed-loop tire supply chain network that takes into account both economic and environmental factors. This model represents a noteworthy contribution to the current body of literature. The literature review revealed a number of gaps in the research, specifically in regard to sustainability dimensions, model types, solution methods, and product types. Prior studies have primarily emphasised economic variables while affording comparatively less consideration to environmental aspects.

In light of the computational complexity of the problem at hand, scholars have put forth and devised metaheuristic algorithms with the aim of acquiring viable solutions. The research conducted an assessment of the algorithms' efficacy and devised six novel metaheuristics MOEA algorithms grounded on MOEA/D that exhibited proficiency in addressing problems of considerable magnitude. In order to assess the efficacy and effectiveness of the suggested algorithms, a variety of evaluation metrics were employed, such as NPS, HV, ER, and DM. Besides, the effectiveness of six newly developed metaheuristics is juxtaposed with the performance of eight well-established metaheuristic algorithms in this comparison. The study's findings indicate that the suggested algorithms were notably more efficient in producing non-dominated solutions, as per the Pareto optimal set metrics.

In order to provide additional verification for the multi-objective model under consideration, a set of thirty standardised benchmark functions were randomly generated and subsequently compared to the outcomes produced by the MOSA, NRGA, NSGA-II, NSGA-III, MOPSO, DSC-MOAGDE, MOSMA, and MOSFO algorithms. The MOEA/D-v6 algorithm exhibited superior performance in terms of the majority of metrics used to evaluate MOEAs.

Future research can expand upon the hybrid metaheuristic algorithms that have been suggested to address additional extensive predicaments within worldwide supply chain networks. Furthermore, researchers have the potential to adapt the operators of contemporary individual algorithms, such as volleyball premier league algorithm (Moghdani and Salimifard, 2018) and the coati optimization algorithm (Dehghani et al., 2023), in order to enhance their efficacy and efficiency. Incorporating heuristic rules derived from variable neighbourhood descent or implementing selection methods such as a tournament or roulette wheel mechanisms during the competition phase may potentially improve the efficacy of inter-phase interactions.

Additional quantitative factors could be suggested to enhance the proposed sustainability model, including consumer risk and the value of local development. These factors would more effectively demonstrate the model's capacity and relevance. Ultimately, the suggested network has the potential to be further investigated in additional contexts involving scrap tires and repurposed materials through empirical case studies.

The proposed model for designing a closed-loop tyre supply chain network contributes to the existing literature on sustainable supply chain management by integrating both economic and environmental considerations. The development of six novel metaheuristic algorithms for MOEA presents a promising approach for achieving enhanced efficacy in addressing this intricate problem. Future research may investigate the model's suitability for alternative global supply chain networks and enhance its effectiveness and efficacy. Furthermore, the potential application of hybrid methodologies, integrating evolutionary algorithms with exact methods or other heuristic or metaheuristic techniques tailored for MILP problems, is suggested. This could represent a worthwhile avenue for future research exploration.

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