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Multi-objective planning for a multi-echelon supply chain using parameter-tuned meta-heuristics

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Abstract
Purpose: This study presents a tri-objective model for the integrated planning of production and distribution within a multi-level supply chain network that encompasses multiple product types and time periods.
Research methodology: The supply chain network includes manufacturer plants (MPs), distribution centers (DCs), retailers, and final customers. The proposed model aims to minimize total supply chain costs, ensure timely delivery of products to customers, and reduce the lost demand rate. Classified as a linear integer programming problem, which is NP-Hard, the model's complexity is addressed using two multi-objective meta-heuristic approaches based on the Pareto method: the Non-Dominated Sorting Genetic Algorithm (NSGA-II) and the Non-Dominated Ranking Genetic Algorithm (NRGA). The Taguchi method is employed to optimize the input parameters of these algorithms.
Results: The performance of the proposed solution methods is evaluated through various test problems of different dimensions. Statistical analyses confirm the effectiveness and reliability of both algorithms in achieving the defined objectives.
Conclusions: The findings highlight that multi-objective meta-heuristic approaches, when parameter-tuned appropriately, provide efficient and practical solutions for integrated supply chain planning, offering a balance among cost, service level, and demand fulfillment.
Limitations: The study acknowledges the inherent complexity of the problem and the dependency of meta-heuristic outputs on parameter settings, which may influence solution robustness.
Contribution: This research contributes to the literature by providing a robust framework for optimizing production and distribution in complex supply chain networks, delivering insights into the application of advanced algorithmic strategies in operational planning.

Keywords: *Multi Objective Procurement-production and Distribution Planning, Non-dominated Sorting Genetic Algorithm (NSGA-II), Non-dominated Ranking Genetic Algorithm (NRGA), Taguchi Method*

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1. Introduction

In today's world, industrial development and economic changes are occurring at an ever-increasing rate compared to the past. Increasing customer expectations and expanding global competition force organizations to pay more attention to customer satisfaction and investigate their logistics systems (Querin & Göbl, 2017). Supply chain management (SCM) has become an area of increasing interest for academics, consultants, and business managers in recent years (Khedr 2024). Moreover, market globalization compels firms to make more coordinated and integrated decisions to provide goods and services to customers at lower costs and higher service levels (Thomas & Griffin, 1996). Decision-making increasingly occurs at all levels of businesses, companies and organizations. There is a need to build a theory and develop normative tools and methods for successful SCM (Lee & Kim, 2002). Most of the proposed models in integrated SCM can be classified as follows: Integrated Buyer-Seller, Integrated Production-Distribution Planning, Integrated Production-Inventory Planning, and Location-Allocation Models. In an efficiently designed production/distribution system, products are produced and distributed in the right quantities, to the right customers, and at the right time, thereby minimizing system-wide costs while satisfying all required demands. Production and distribution models are operationally connected and closely related to each other. These two linked problems are considered production-distribution models in the supply chain (SC). To find an optimal solution for this problem, we need to propose an integrated model and solution method that simultaneously consider production and distribution characteristics (Farahani, Babaei, & Esfahani, 2024). In this study, a model was developed to plan production and distribution in a multilevel supply chain. In the next section, the literature on modeling a multilevel supply chain is reviewed, and considering the findings, a multi-objective model is developed to optimize the planning of production and distribution simultaneously in multiperiod and multiproduct situations.

2. Literature review

The modeling and analysis of production–distribution systems in SCM have been active areas of research for many years. Pasha, Kamalabadi, and Eydi (2021) and Joel, Oyewole, Odunaiya, and Soyombo (2024) provide excellent reviews of the SC literature. Bhattacharya, Govindan, Dastidar, and Sharma (2024) proposed multi heuristic algorithms to minimize production-distribution costs in the SC. Koutsokosta and Katsavounis (2024) presented a mixed integer production-distribution problem under stochastic demands and solved it using economic order quantity techniques. Bo et al. (2021) presented a production-distribution planning problem including a factory and multi warehouses. The proposed model minimizes the total transportation and inventory costs under production capacity and inventory balance constraints, respectively. Lee and Kim (2002) proposed an analytical technique to solve the integrated production-distribution planning in SCM. They developed a multi-plant, multi-product, and multi-period production-distribution problem by considering resource constraints. Tapia-Ubeda, Miranda-Gonzalez, and Gutiérrez-Jarpa (2024) designed a network including suppliers, manufacturers, distribution centers, and customers with mixed-integer programming according to material requirements. Biza, Montastruc, Negny, and Admassu (2024) presented a strategic planning problem for the three echelon supply chain network including suppliers, manufactures and distribution centers, in order to minimize production, distribution and transportation costs. Tsai, Tan, Truong, Tran, and Lin (2024) stated an optimization technique for the SC planning problem with uncertain demands by using valid and economic measures. They used a stochastic model for the SC problem to meet network demands on the expected delivery date. Goodarzian and Hosseini-Nasab (2021) proposed an optimal production allocation and distribution problem in the supply chain network as a mixed-integer linear programming (MILP) model. Their proposed objective was to determine the optimal configuration of a production-distribution network with operational and financial constraints. In this study, the operational constraints are quality, production, and supply constraints, which are related to the allocation of production and workload balance. Financial constraints include production costs, transportation costs, and duties for the material following within the network subject to exchange rates.

Many studies have used fuzzy logic to assess supply chain problems (Aliev, Fazlollahi, Guirimov, & Aliev, 2007; Forozandeh, 2021; Mbamalu, Chike, Oguanobi, & Egbunike, 2023; Zahedi, Abbasi, & Khanachah, 2020). In recent research, Liang (2012) proposed a fuzzy multi-objective production-distribution planning decision with a piecewise linear membership function in a multi-product and multi-period SC problem. The objective functions minimize the total costs and total delivery time of the network by considering inventory levels, labor levels at each source, available machine capacity, forecast demand, total budget, and available warehouse space at each destination. Razmi, Songhori, and Khakbaz (2009) presented an integrated framework consisting of two stages where suppliers and orders' allocations. They suggested a fuzzy TOPSIS model to evaluate suppliers, and then considered an integer programming model with fuzzy goals and constraints for the optimal allocation of order quantities assigned to the suppliers. Liang (2012) examined the application of fuzzy sets to manufacturing/distribution planning decisions in SCs. The objective function minimizes the total production costs, including regular and overtime production costs, inventory carrying cost, subcontracting cost, and backordering cost. In this study, a fuzzy mathematical programming methodology for solving MDPD integration problems in uncertain environments is considered.

In the real world, because the size of the problem is large and the computational time for solving this class of problems is high, meta-heuristic algorithms are suggested for solving the problem. In this regard, Rajabi-Kafshgar, Gholian-Jouybari, Seyedi, and Hajiaghaei-Keshteli (2023) developed a hybrid genetic algorithm (HGA) for designing a supply chain network with multiple products in multiple time periods. The suggested model determines the integration of production, distribution, and inventory systems so that products are produced and distributed in appropriate quantities by minimizing the system costs while meeting all demands. (Vishnu, Das, Sridharan, Ram Kumar, & Narahari, 2021) proposed a genetic algorithm for solving integrated production-distribution planning problems in the supply chain network. The proposed model is presented in three echelons of suppliers, manufacturers, and distribution centers, and minimizes total costs, including ordering, procurement, inventory, production, and transportation costs. Kazemi, Fazel Zarandi, and Moattar Husseini (2009) presented two scenarios to solve the production-distribution planning problem (PDPP). In the first scenario, a centralized method was applied, and a genetic algorithm (GA) was presented to solve the PDPP. Here, the crossover is a single point in the plant. In the second scenario, an agent-based system is developed to solve the PDPP. In this case, three GAs were assumed to be the agents of the model. Billal and Hossain (2020) suggested a multi-objective linear programming problem consisting of a manufacturer with multiple plants, products, distribution centers, retailers, and customers to integrate a production–distribution problem. They proposed three meta-heuristics: (1) a simple genetic algorithm, (2) a particle swarm optimization (PSO) algorithm with a new fitness function, and (3) an improved hybrid genetic algorithm. Hong, Diabat, Panicker, and Rajagopalan (2018) proposed a solution methodology using ant colony optimization (ACO) for a distribution-allocation problem. They used a two-stage supply chain with a fixed cost for the transportation route. S. Liu and Papageorgiou (2013) presented a production, distribution and capacity planning problem for the global SC. They considered three objectives: cost, responsiveness, and customer service level. In this model, the ε-constraint and lexicographic minimax methods are used as solution approaches to solve the multi-objective problem.

In this study, an integrated procurement, production, and distribution planning problem model for designing f four-level SC with multiple product types and multiple time periods is suggested to minimize the total supply chain costs, the due date of the products to the customers, and the last demand rate of customers. To solve the problem, two tuned multi-objective meta-heuristic algorithms, NSGA-II and NRGA based on the Pareto method, are proposed. The Taguchi method was used to tune the algorithm parameters. The remainder of this paper is organized as follows: the problem definition and detailed mathematical formulation are presented in Section 2. The proposed solution method is discussed in Section 3. In Section 4, the obtained optimization results are analyzed. Finally, the conclusions and suggestions for future research are presented in Section 5.

3. Research methodology

3.1 Problem Definition

A supply chain consisting of multiple manufacturers (MPs), distribution centers (DCs), retailers, and customers is considered in this study. In the studied supply chain, products produced by each manufacturer are shipped to distribution centers. Here, a distributor can be established as a logistics warehouse in potential centers to deliver products from manufacturers to retailers. Therefore, retailers at these potential centers supply products to customers during each period.

Figure 1 illustrates the proposed supply chain network. Three key factors are required in this supply chain: reduced costs, improved responsiveness, and increased service levels for customers. In the proposed research, reduced costs are achieved by minimizing the total costs of the supply chain, improved responsiveness is attained by minimizing the due dates of products to customers, and increased service levels are accomplished by minimizing the lost demand rate of products. The proposed Supply Chain Network Design (SCND) problem is formulated as a multi-objective mixed-integer linear programming (MILP) model. In this model, one of the objectives is a function of time, whereas the other two objectives conflict with each other. In other words, on one hand, retailers aim to maximize service levels for customers; on the other hand, maximizing service levels may lead to an increase in the total cost of the supply chain

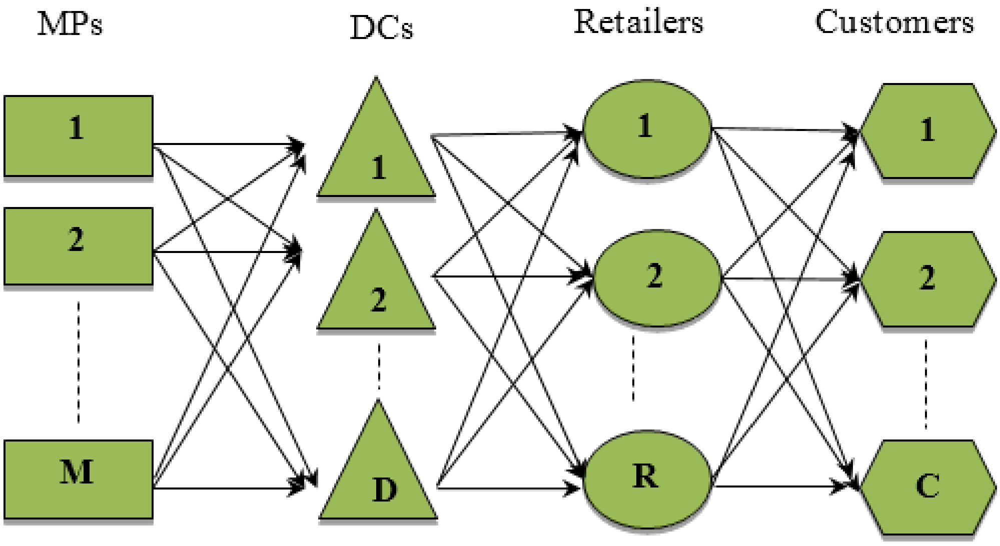

Figure 1. Proposed supply chain network

In the following subsections, the assumptions and nominations are presented. The indices, parameters, decision variables, objective function, and constraints are then introduced.

3.2 Assumptions and nominations

The assumptions and nominations for formulating the problem are as follows:

- We have *P* MPs, *D* DCs, *R* retailers, and *C* customers.
- Each MP can produce various products and can manufacture all the ordered products within each period.
- The production capacity for MPs was considered.
- The holding capacity of products for DCs and retailers in each period is considered.
- The location of MPs is fixed, and the potential centers for DCs and retailers are known.
- The minimum fill rate must be maintained.

3.2.1 Indices and parameters

m: index of MPs ($m=1, 2, ..., M$)
d: index of DCs ($d=1, 2, ..., D$)
r: index of retailers ($r=1, 2, ..., R$)
c: index of customers ($c=1, 2, ..., C$)
p: index of products ($p=1, 2, ..., P$)
t: index of periods ($t=1, 2, ..., T$)
C_d: Fixed cost of establishing the DC d
C_r: Fixed cost of establishing the retailer r
D_{cpt}: Demand of product p by customer c in period t
C_{mdpt}: Unit cost of making and transportation of product p to DC d by MP m in period t
C_{drpt}: Unit cost of transportation of product p to retailer r by DC d in period t
C_{rcpt}: Unit cost of transportation of product p to customer c by retailer r in period t
H_{dpt}: Holding cost of product p for DC d in period t

H_{rpt}: Holding cost of product p for retailer r in period t
UCM_{mpt}: Upper capacity of MP m for product p in period t
LCM_{mpt}: Lower capacity of MP m for product p in period t
CD_{dpt}: Capacity of DC d for product p in period t
CR_{rpt}: Capacity of retailer r for product p in period t
DU_{rct}: Due date of products from retailer r to customer c in period t

3.2.2 Decision Variables
Q_{mdpt}: Quantity of product p shipped from MP m to DC d in period t
Q_{drpt}: Quantity of product p shipped from DC d to retailer r in period t
Q_{rcpt}: Quantity of product p shipped from retailer r to customer c in period t
I_{dpt}: Inventory of product p for DC d in period t
I_{rpt}: Inventory of product p for retailer r in period t

$$Y_d: \begin{cases} 1 & \textit{if DC d is to be established} \\ 0 & \textit{otherwise} \end{cases}$$

$$Y_r: \begin{cases} 1 & \textit{if retailer r is to be established} \\ 0 & \textit{otherwise} \end{cases}$$

3.2.3 Formulated problem
The first objective function of the proposed model is given by Eq. 1 minimizes the total costs of the supply chain (SC). This includes the sum of transportation costs between SC echelons, inventory costs of products for distribution centers (DCs), and retailers in each period, and the costs associated with establishing the DCs and retailers. The second objective function is given by Eq. 2 minimizes the due dates of products delivered to customers by retailers. The third objective function is given by Eq. 3 minimizes the lost demand rate of products to customers.

$$Min\ Z_1 = \sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{p=1}^{P}\sum_{t=1}^{T}(C_{mdpt}.Q_{mdpt}) + \sum_{d=1}^{D}\sum_{r=1}^{R}\sum_{p=1}^{P}\sum_{t=1}^{T}(C_{drpt}.Q_{drpt}) + \sum_{r=1}^{R}\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{t=1}^{T}(C_{rcpt}.Q_{rcpt})$$
$$+\sum_{d=1}^{D}\sum_{p=1}^{P}\sum_{t=1}^{T}(H_{dpt}.I_{dpt}) + \sum_{r=1}^{R}\sum_{p=1}^{P}\sum_{t=1}^{T}(H_{rpt}.I_{rpt}) + \sum_{d=1}^{D}(C_d.Y_d) + \sum_{r=1}^{R}(C_r.Y_r) \tag{1}$$

$$Min\ Z_2 = \sum_{r=1}^{R}\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{t=1}^{T}(DU_{rct}.Q_{rcpt}) \tag{2}$$

$$Min\ Z_3 = \frac{\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{t=1}^{T}D_{cpt} - \sum_{r=1}^{R}\sum_{c=1}^{C}\sum_{p=}^{P}\sum_{t=1}^{T}Q_{rcpt}}{\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{t=1}^{T}D_{cpt}} \tag{3}$$

S.t.

$$LCM_{mpt} \le \sum_{d=1}^{D}Q_{mdpt} \le UCM_{mpt} \qquad \forall m,p,t \tag{4}$$

$$\sum_{m=1}^{M}Q_{mdpt} + I_{dpt} \le CD_{dpt} \qquad \forall d,p,t \tag{5}$$

$$\sum_{r=1}^{R}Q_{drpt} \le CD_{dpt}.Y_d \qquad \forall d,p,t \tag{6}$$

$$\sum_{d=1}^{D}Q_{drpt} + I_{rpt} \le CR_{rpt} \qquad \forall r,p,t \tag{7}$$

$$\sum_{c=1}^{C} Q_{rcpt} \le CR_{rpt}.Y_r \qquad \forall r,p,t \tag{8}$$

$$I_{dpt} - I_{dpt-1} = \sum_{m=1}^{M} Q_{mdpt} - \sum_{r=1}^{R} Q_{drpt} \qquad \forall d,p,t \tag{9}$$

$$I_{rpt} - I_{rpt-1} = \sum_{d=1}^{D} Q_{drpt} - \sum_{c=1}^{C} Q_{rcpt} \qquad \forall r,p,t \tag{10}$$

$$\sum_{r=1}^{R} Q_{rcpt} \le D_{cpt} \qquad \forall c,p,t \tag{11}$$

$$0.85 \le \frac{\sum_{r=1}^{R}\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{t=1}^{T} Q_{rcpt}}{\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{t=1}^{T} D_{cpt}} \le 1 \tag{12}$$

$$Q_{mdpt},\ Q_{drpt},\ Q_{rcpt}, I_{dpt},\ I_{rpt} \ge 0 \qquad \forall m,d,r,c,p,t \tag{13}$$

$$Y_d, Y_r \in \{0,1\} \qquad \forall d,r \tag{14}$$

$$I_{dp0}, I_{rp0} = 0 \qquad \forall d,r,p \tag{15}$$

Constraint (4) indicates the lower and upper capacity of the MP that can be shipped to the DCs. Equation (5) states that the total quantity of each product shipped from the MPs to a DC plus the inventory of products in period *t* cannot exceed the DC's capacity. Equation (6) specifies that the total quantity of each product shipped to retailers by each DC in period *t* is limited to its corresponding capacity if DC *d* is established. Constraint (7) indicates that the total quantity of each product shipped from DCs to retailer *r* plus the inventory of the product in period *t* is limited to the retailer's capacity. Equation (8) shows that the total quantity of each product shipped from each retailer to customers in period *t* cannot exceed the retailer's capacity if retailer *r* is established. Constraints (9) and (10) are the inventory balance equations for each product for DCs and retailers. For example, Equation (9) means that the inventory of product *p* for DC *d* in period *t* is equal to the inventory of product *p* in the previous period plus the quantity of product *p* shipped from MPs to DC *d* in period *t* minus the quantity of product *p* shipped from DC *d* to retailers in period *t*. Constraint (11) ensures that the quantity of a product shipped by retailer *r* to a customer in period *t* cannot exceed the customer demand if retailer *r* is assigned to the customer. Constraint (12) indicates that the fill rate can vary from 85% to 100%. Finally, Constraints (13) and (14) ensure the non-negativity and binary states of the variables. Note that the initial states of the inventories are shown in Equation (15).

3.3 Solution methodology

Multi-objective problems are concerned with mathematical optimization problems involving more than one objective function to be optimized simultaneously. Multi-objective optimization has been applied in many fields of science, including engineering, economics, and logistics, where optimal decisions must be made in the presence of trade-offs between two or more conflicting objectives. In a multi-objective optimization problem, there is no single solution that simultaneously optimizes each objective. In this case, the objective functions are said to be conflicting, and there exists a possibility of an infinite number of optimal solutions.

In this study, two multi-objective algorithms based on Pareto were suggested for solving the integrated production-distribution model. The proposed algorithms are called the non-dominated Sorting Genetic Algorithm (NSGA-II) and non-dominated Ranking Genetic Algorithm (NRGA).

3.3.1 Non-dominated Sorting Genetic Algorithm (NSGA-II)
The Non-dominated Sorting Genetic Algorithm (NSGA-II) is one of the most successful and widely used multi-objective evolutionary algorithms introduced by Bouali, Abi, Benhala, and Guerbaoui (2025).

In single-objective problems, finding the solution is based on an objective, whereas in multi-objective problems, there is no single solution that simultaneously optimizes each objective; thus, there will be a set of optimal solutions called non-dominated solutions. The set of all efficient points for a multiple-objective optimization problem is known as the efficient frontier. A solution is called non-dominated, Pareto optimal, Pareto efficient, or no inferior, if none of the objective functions can be improved in value without degrading some of the other objective values. Without additional subjective preference information, all Pareto-optimal solutions are considered equally good. Pareto-based algorithms are a new generation of multi-objective algorithms that mostly work in accordance with the domination concept. In a multi-objective model with m minimization objective functions, that is,

1) $F(x)$ =[$f(x)$, ..., $fm(x)$] subject to $g_i(x) \leq 0$, i =1, 2, ..., m, in which $x \varepsilon X$ is a n-dimensional vector that can gets real, integer, or even Boolean value and X is the feasible region, domination concept is defined as follows

$$1)\ f_a(\vec{x}) \leq f_b(\vec{x}), \quad i = 1, 2, ..., m$$
$$2)\ \exists i \in \{1, 2, ..., m\} : f_a(\vec{x}) < f_b(\vec{x})$$

According to these conditions, solution ‘a’ dominates solution ‘b’ under the simultaneous existence of the two conditions mentioned above. Based on this definition, the Pareto optimal front is a set of solutions that cannot dominate each other. This front has two main features: 1) good convergence and 2) good diversity within the solutions of the Pareto front.

Note that the initial population size (*nPop*), crossover probability (P_c), and mutation probability (P_m) are required to start the NSGA-II. The parameter values were obtained using the Taguchi method.

3.3.1.1 Chromosome representation
The structure of the problem’s chromosomes includes three parts. The first part of the chromosome indicates decisions about establishing potential DCs and retailers. The second part of the chromosome is an array with dimensions of MPs, DCs, customers, products, and time periods. The array indicates the number of products shipped from MPs to DCs, from DCs to retailers, and from retailers to customers in each time period. The third part includes the amount of product inventory for DCs and retailers. An example of the aforementioned structure is shown in Fig.2.

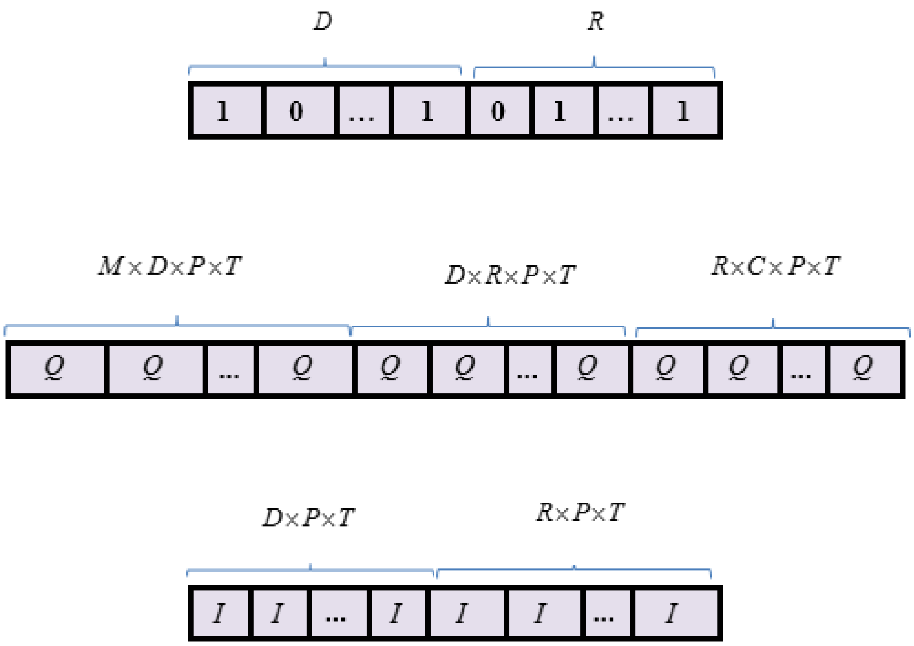

Figure 2. The proposed chromosome structure

In the proposed solution method, the assignments are based on the problem constraints. For example, the product shipped from MP *p* to DC *d* is not greater than the production capacity of manufacturer *p* in period *t*. This assignment for each random manufacturer is repeated until the capacity constraints are satisfied.

In the proposed algorithm, the penalty is defined as the positive coefficient. When a chromosome is feasible, the penalty value is selected as zero. Even if one of the constraints is not satisfied, it will be considered a nonzero value. According to the general form of constraints as $g(x) \leq b$, the penalty value of a chromosome is obtained as follow (Yeniay, 2005):

$$P(x) = M \times Max\left\{\left(\frac{g(x)}{b} - 1\right), 0\right\} \tag{16}$$

where *P(x)*, *M*, and *g(x)* indicate the penalty value of chromosome x, a large number, and constraint, respectively. When a chromosome is feasible, the penalty value is zero; otherwise, the penalty value is multiplied by the function value. In addition, we consider the normalization policy within the penalty function framework to normalize all constraints. It should be noted that when the penalty is large, the coefficient is considered large, and the average of the violation is considered for each type of constraint.

3.3.1.2 A fast non-dominated sorting approach

To sort a population of size N according to the level of non-domination, each solution must be compared with every other solution in the population to determine whether it is dominated.

This requires O (MN) comparisons for each solution, where M is the number of objectives. When this process is continued to find the members of the first non-dominated class for all population members, the total complexity is O (MN^2). At this stage, all individuals in the first nondominated front are found. To find the individuals in the next front, the solutions of the first front are temporarily discounted, and the above procedure is repeated. In the worst case, the task of finding the second front also requires O (MN^2) computations. The procedure is repeated to determine the subsequent fronts.

To estimate the density of solutions surrounding a particular point in the population, we consider the average distance of the two points on either side of this point along each of the objectives. This quantity *i* distance serves as an estimate of the size of the largest cuboid enclosing point *i* without including any other point in the population (the crowding distance). In Figure 3, the crowding distance of the *i*-th solution in its front (marked with solid circles) is the average side length of the cuboid (shown with a dashed box).

Between two solutions with differing crowding distances, we prefer the point with the lower density. Otherwise, if both points belong to the same front, we prefer the point located in a region with less crowding distance (Bouali et al., 2025).

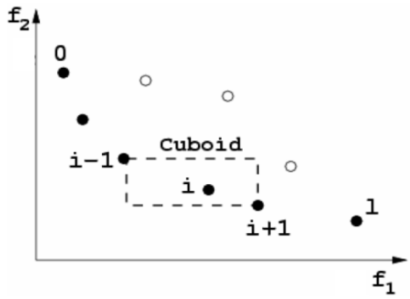

Figure 3. Crowding distance calculation (Bouali et al., 2025)

3.3.1.3 Parent and selection strategy

The crowded tournament selection operator is used for parent population selection by applying crossover and mutation. This operator compares two solutions and selects the better one (i). We assume that every individual i in the population has two attributes.

1. Non-domination rank (r_i)
2. Local crowding distance (d_i)

That is, between two solutions with differing non-domination ranks, we prefer the point with the lower rank. Otherwise, if both points belong to the same front, we prefer the point located in a region with a lesser number of points (Bouali et al., 2025).

3.3.1.4 Crossover structure

During the iterations of the algorithm, a uniform crossover operator was implemented to produce new offspring. Generally, this method is used for situations in which the appropriate characteristics of genes are scattered throughout the chromosome (Bate & Jones, 2008). In this crossover operator, some genes are swapped within the chromosomes of the parents to produce offspring. Figure 4 illustrates a scheme of this operator.

Parent 1	884	914	1854	1104	...	573
Parent 2	954	1374	2025	1197	...	853

Random Number	0	1	1	0	...	1

Offspring 1	954	914	1854	1197	...	573
Offspring 2	884	1374	2025	1104	...	853

Figure 4. A sample of the uniform crossover operator for Quantity of product shipped from MP m to DC d

3.3.1.5 Mutation operation

The movement from the present population to the new population causes an increase in population variation. This diversity is based on the evaluation and progress made in reaching the final solution. Thus, to prevent local optimum solutions, mutation is performed after a crossover is applied. To obtain a new offspring using mutation, at least one chromosome part is considered. Then, based on to the rate of mutation (P_m), the number $p_m \times popsize$ chromosomes are randomly selected. Moreover, two genes from one chromosome are selected, and their positions are swapped (Hassanat et al., 2019). Figure 5 illustrates this operation for a binary-variable decision.

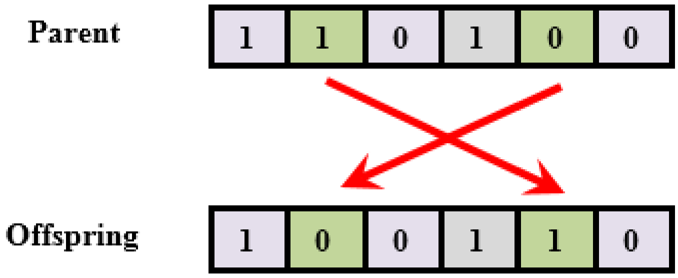

Figure 5. An example of the mutation operator

3.3.1.6 Evaluation of children and creation of next generation

In this part of the algorithm, the populations of parents and children are combined, and a population twice the initial size of the population is formed. This combination of solutions retains the best solutions among the parent and child populations, and elitism is also ensured. In this case, non-dominated ranking is used so that each solution is evaluated based on its non-domination (Bouali et al., 2025). Then, a fast non-dominated sorting approach and crowding distance are applied, and the element of each population is ranked based on crowding distance and non-dominated respectively (non-dominated fronts).

3.3.1.7 Stopping criteria

The last step of the genetic algorithm is the stopping criterion. There are no specific stopping criteria for multi-objective optimization problems. Consequently, the algorithm stops when it reaches the maximum number of defined iterations.

3.3.2 Non-dominated ranking genetic algorithm (NRGA)

A new multi-objective evolutionary algorithm based on population and non-dominated ranking genetic algorithms was proposed by Zhu et al. (2024). This successful algorithm was proposed to optimize non-convex, discrete, and non-linear problems (Zhu et al., 2024). In NRGA, roulette wheel selection (RWS) is utilized instead of BTS. In this RWS, two tiers of rank-based roulette wheel selections are used. One tire is used for front selection based on FNDSs, and one tire is used for selecting solutions from the front based on CDs (Zhang & Gu, 2024). The procedure is defined such that better elements have a higher chance of reproduction and a higher chance of forming the next generation. The flowchart of the NRGA and NSGA-II algorithms is shown in Figure 6.

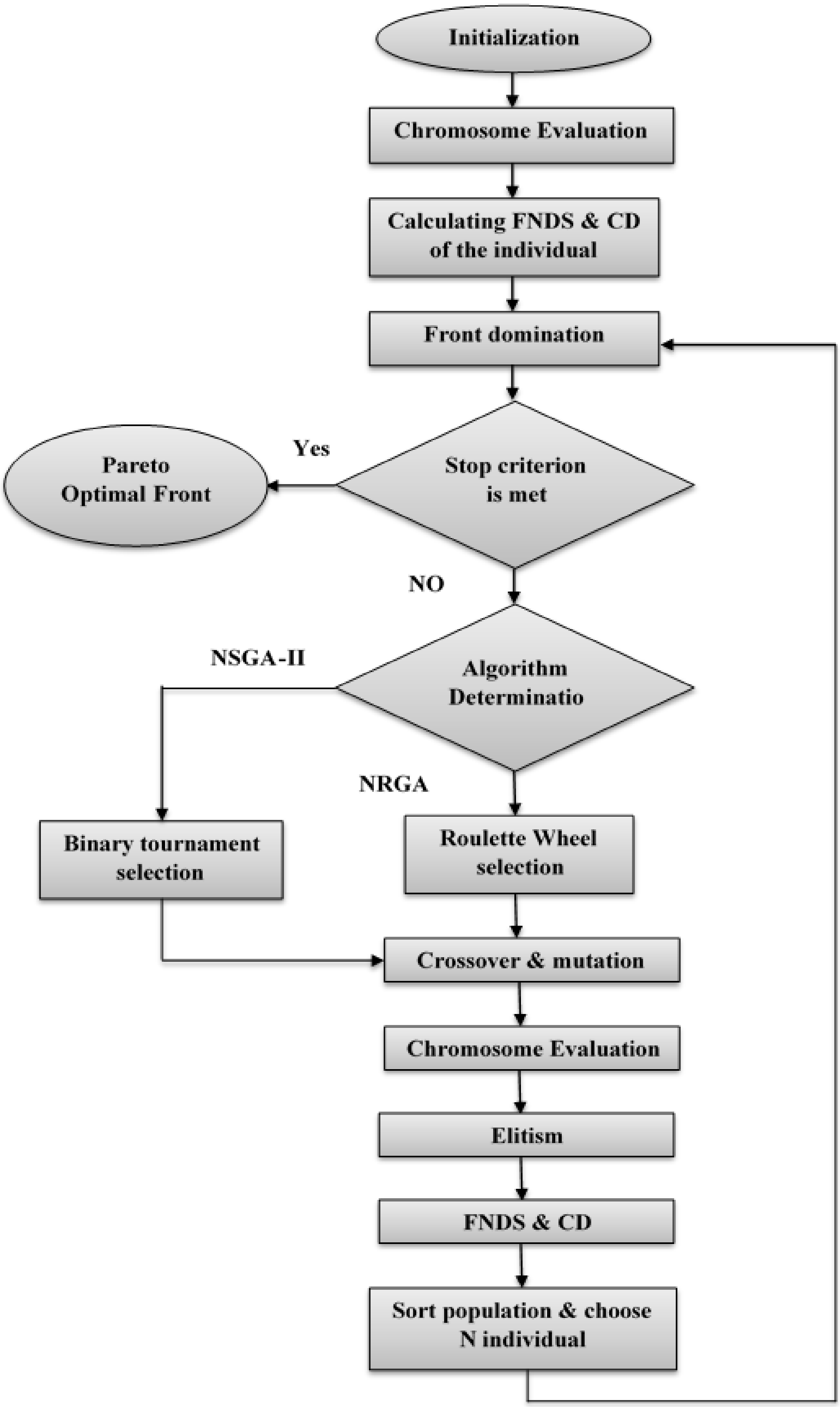

Figure 6. Flowchart of the NRGA and NSGA-II algorithms

4. Result and discussion

This section presents the experimental outputs of the algorithms. To do so, the parameters of the algorithms are first tuned via the Taguchi method. Subsequently, some popular multi-objective metrics were introduced. Finally, the defined metrics are calculated on the outputs of the metrics, and the outputs are compared using different statistical tests.

4.1 Taguchi method

Because the output of the problems relies heavily on the proposed algorithm parameters, the Taguchi method was used to adjust these parameters. An advantage of the Taguchi method compared to other experimental design methods is that optimum tuned parameters are obtained in less time (Jung & Lee, 2024). One of the most important steps of this method is the selection of an orthogonal array that estimates the effective changes in the mean response. In this study, three-level experiments were identified as the best design. Considering Taguchi's standard orthogonal array, the L9 array was selected as an appropriate experimental design for tuning the algorithm parameters. A statistical measure called the signal-to-noise (S/N) ratio was considered for setting the optimal parameters. This ratio involves means and deviations, and a high level is the suitable value of the parameters. The considered response variable is the Mean Ideal Distance (MID), a standard metric ratio for multi-objective algorithms. Because this standard indicator is a "less is better" type, equation (17) is considered as its S/N ratio. A proposed meta-heuristic algorithm for each Taguchi experiment was performed, and the S/N ratio was calculated using Minitab 16 software. The experimental design and L9 orthogonal arrays are shown in Tables (2) and (3).

$$S/_N \, Ratio = -10\log\left(sum\left(y^2\right) /_n \right) \tag{17}$$

Table 1. Factors and levels for parameters tuning of both algorithm

Algorithm	Parameters	Levels	Low (1)	Medium (2)	High (3)
NSGA-II	nPop (A)	75-125	75	100	125
	P_c (B)	0.75-0.95	0.75	0.85	0.95
	P_m (C)	0.1-0.2	0.1	0.15	0.2
NRGA	nPop (A)	75-125	75	100	125
	P_c (B)	0.75-0.95	0.75	0.85	0.95
	P_m (C)	0.1-0.2	0.1	0.15	0.2

Table 2. Experimental design for the L9 orthogonal arrays L9 for NSGA-II

Run Order	**Algorithm Parameters**			**Response Value of NSGA-II (MID)**
	nPop	P_c	P_m	
1	1	1	1	35181787
2	1	2	2	22817843
3	1	3	3	27143002
4	2	1	2	17664478
5	2	2	3	23477538
6	2	3	1	49640563
7	3	1	3	43718346
8	3	2	1	42838449
9	3	3	2	26331484

Table 3. Experimental design for the L9 orthogonal arrays L9 for NRGA

Run Order	Algorithm Parameters			Response Value of NRGA MID
	nPop	P_c	P_m	
1	1	1	1	41183352
2	1	2	2	26835710
3	1	3	3	32956834
4	2	1	2	19936731
5	2	2	3	20473546
6	2	3	1	35935034
7	3	1	3	39538733
8	3	2	1	40180460
9	3	3	2	28353934

The optimum combinations of the parameters have the red values are shown in Figs. 7 and 8, and also are reported in Table 4 for each algorithm

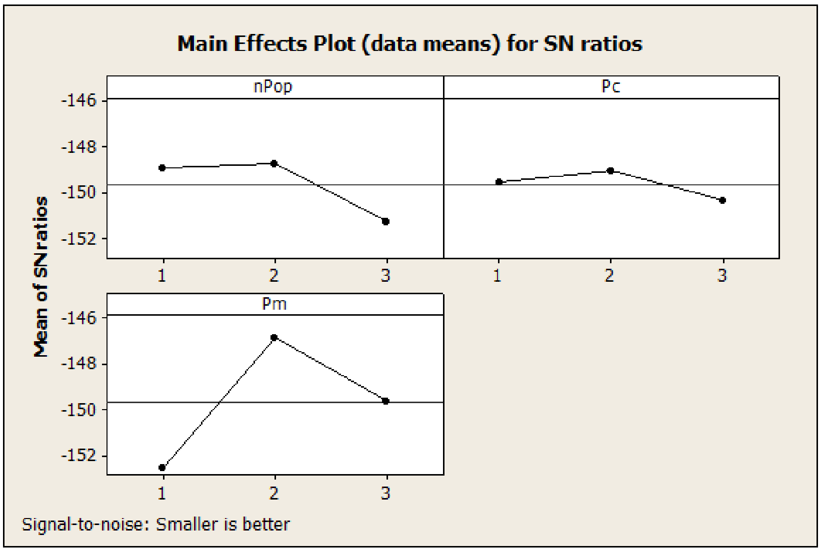

Figure 7. S/N ratio’s plot of the parameters of NSGA-II

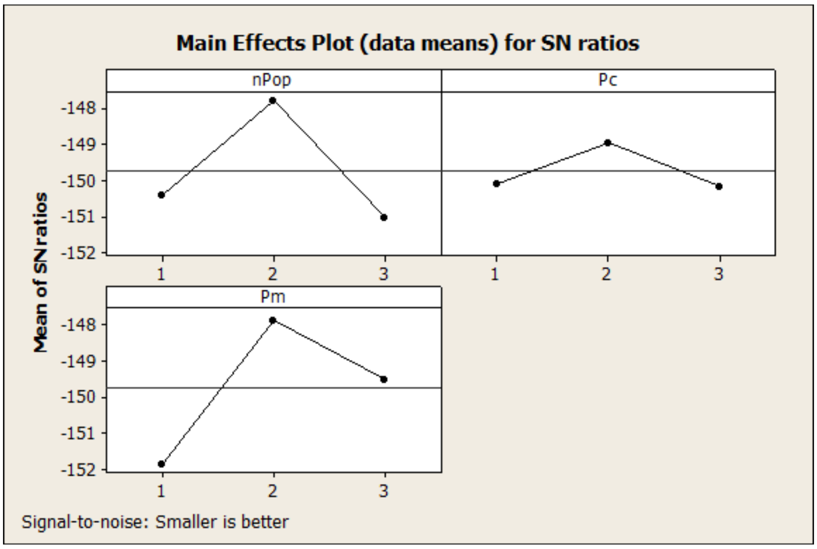

Figure 8. S/N ratio’s plot of the parameters of NRGA

Table 4. Optimum parameter levels

Methodology	Parameter	Optimum value
NSGA-II	nPop (A)	100
	P_c (B)	0.85
	P_m (C)	0.15
NRGA	nPop (A)	100
	P_c (B)	0.85
	P_m (C)	0.15

In the next section, the performances of both algorithms considering the tuned parameters for various problems are analyzed.

4.2 The multi-objective standard metrics

The following standard criteria are presented for evaluating a multi-objective algorithm using the Pareto approach. Unlike single-objective optimization, multi-objective optimization modeling involves two main criteria to maintain the diversity of the solutions and convergence to the Pareto set solutions (Bouali et al., 2025). In this section, four criteria for evaluating multi-objective optimization algorithms are presented.

4.2.1 Maximum Spread or Diversity

Equation 18 shows the calculation of this indicator.

$$D = \sqrt{\sum_{j=1}^{m} \left(\max_i f_i^j - \min_i f_i^j \right)^2} \tag{18}$$

In the presented bi-objective model, this measure is equal to the Euclidean distance between the two boundary solutions in the objective space. The larger this measure, the better (J. Liu, Sarker, Elsayed, Essam, & Siswanto, 2024).

4.2.2 Spacing

The spacing criteria were proposed by Schott in 1995 (Schott, 1995), in which the relative distance of the sequential responses is calculated based on Equation 19.

$$S = \sqrt{\frac{1}{|n-1|} \sum_{i=1}^{n} \left(d_i - \bar{d} \right)^2} \tag{19}$$

In which $\bar{d} = \sum_{i=1}^{n} \frac{d_i}{|n|}$ and, $d_i = \min_{k \in n \,\wedge\, k \neq 1} \sum_{m=1}^{2} \left| f_m^i - f_m^k \right|$.

The minimum distance is equal to the sum of the absolute difference between the measured values of the objective functions between the *i* th response and the response of the final non-dominated. Notably, this distance measure criterion differs from the minimum Euclidean distance.

4.2.3 Number of Pareto Solution (NOS)

The NOS measure represents the number of Pareto-optimal solutions that can be found in each algorithm. In the case of the multi-objective Pareto-based approach, one of the objectives is to search for a closer front to the origin of the coordinates. Therefore, this measure calculates the front distance from (J. Liu et al., 2024).

4.2.4 CPU Time

The time required to solve the model using the considered algorithms.

4.3 Result analysis

In this section, the performances of the proposed algorithms with different sizes are evaluated and analyzed. Test problems were implemented using the proposed NSGA-II and NRGA algorithms for 20 problems of different sizes. The parameters were generated from the distributions listed in Table 5.

Table 5. Parameters for test problems

Parameter	**Distribution**	**Parameter**	**Distribution**
D_{cpt}	Norm(400,20)	LCM_{mpt}	**Uniform(1000,1500)**
C_{mdpt}	Uniform(90,100)	UCM_{mpt}	**Uniform(3000,3500)**
H_{dpt}	Uniform(10,15)	C_{drpt}	**Uniform(120,130)**
C_{rcpt}	Uniform(140,150)	CD_{dpt}	**3000**
H_{rpt}	Uniform(10,15)	CR_{rpt}	**1000**
C_d	100000	DU_{rct}	**Uniform(48,72) hour**
C_r	100000	C_{mdpt}	**Uniform(90,100)**

Here, two classes of problems (small and large sizes) are considered. In the small-size case, to ensure the integrity and accuracy of the model, the optimal solutions are obtained using the developed mathematical programming and Lp-metric method (p=∞) in GAMS software (Stadler, 1988). Table 6 demonstrates the objective function value for each problem with various indicators that *T*=6 and *P*=4 parameters in small size. For large sizes, experiments were conducted on 20 test problems, and the solution methods were compared. The generated test problems, including the number of manufacturing plants (*M*), distribution centers (*D*), retailers (*R*), and clients (*C*), are different. Four product types and six time periods were considered in this problem, and the values are shown in Table 7. In addition, to decrease the uncertainties of the solutions, the average of three runs for each problem was considered as the final response. To solve the model, 120 problems were run and analyzed.

Table 6. The results evaluation of proposed model for small size problems

Num	**Problem Size**				**Optimal Solution**	**GA**
	M	D	R	C		
1	1	1	1	1	0.431	**0.431**
2	1	2	1	2	0.326	**0.326**
3	1	2	2	2	0.225	**0.227**
4	1	2	2	3	0.518	**0.584**
5	2	2	3	3	0.061	**0.095**
6	2	3	3	4	0.249	**0.253**
7	2	3	4	5	0.425	**0.431**
8	3	4	5	6	0.583	**0.588**
9	3	5	6	7	0.102	**0.109**
10	3	6	7	8	0.297	**0.304**

Table 7. Different levels in the proposed SC problem

Test Problem Number	**M**	**D**	**R**	**C**
1	2	2	4	**5**
2	2	3	5	**8**
3	4	6	8	**10**
4	5	8	12	**15**
5	8	10	12	**17**
6	10	12	15	**20**
7	12	15	18	**25**
8	15	18	20	**25**
9	15	20	24	**30**
10	18	22	25	**35**
11	20	25	30	**40**

12	22	28	33	**45**
13	25	30	35	**45**
14	25	33	38	**48**
15	30	35	40	**50**
16	30	40	45	**60**
17	35	45	50	**70**
18	35	50	60	**80**
19	40	55	65	**90**
20	40	60	70	**100**

After defining the standard criteria for comparing multi-objective problems based on Pareto, the measuring criteria for the generated test problems were calculated, as shown in Table 8.

Table 8. Multi-objective metrics obtained for each algorithm

Num	**Proposed NSGA-II**					**Proposed MOPSO**				
	Spacing	Diversity	NOS	MID	Time (sec)	Spacing	Diversity	NOS	MID	**Time (sec)**
1	53582.67	159352.57	3	27047731.89	130.88	404583.737	7052592.12	8	53077294.36	**130.28**
2	4234.5	286989.59	4	27659963.64	132.08	362259.677	7665648.60	7	55544626.27	**133.28**
3	61804.01	403565.99	4	26083752.08	135.12	749974.898	5642766.07	9	52693287.52	**134.91**
4	70107.53	684178.22	6	24753574.26	150.32	546059.149	4329299.79	6	51951224.40	**147.95**
5	11260.95	35859.92	3	28812866.87	158.24	831716.329	6292739.85	7	58125511.31	**155.63**
6	16309063.4	98211449.1	10	110735040.7	183.36	762593.175	6284132.05	8	210189916.5	**172.20**
7	3687778.37	29575559.1	11	84745194.10	204.05	374058.18	7648330.62	14	189581296.2	**192.55**
8	1582765.46	21596358.2	11	83719919.44	216.30	733065.661	11159132.4	17	164537385.1	**200.1**
9	6476841.91	80136785.2	12	108540647.7	262.33	242036.519	7870903.01	14	179443233.0	**233.25**
10	1210476.68	43924367.2	13	110188445.3	325.22	860090.488	8297269.60	10	204986828.6	**285.36**
11	1888569.29	26022749.2	10	184867409.6	299.65	323959.871	13347687.4	16	389773548.8	**336.3**
12	14802524.8	101476246.	15	216622076.4	386.24	1072897.60	20581617.6	16	411413791.1	**294.3**
13	3235168.96	142446988.	18	262767759.9	402.74	1118861.11	25500747.2	18	426082315.1	**326.5**
14	5531732.81	53043953.0	11	241884110.7	462.52	909567.976	14998093.7	13	470068733.3	**371.5**
15	3492480.96	91496788.8	21	231137231.0	509.62	664486.484	20336705.6	19	430496595.9	**417.8**
16	471378.004	1095898.15	14	37556688.02	639.3	67063.48	36488.287	20	163647791.7	**499.3**
17	1324199.48	4002021.0	15	32218026.67	864.3	78128.228	4021222.41	20	151290165.0	**594.3**
18	1551738.01	11823226.0	12	36914954	1166.5	134797.79	3156200.93	18	133620114.2	**866.5**

19	1743211.32	11023679.0	16	37947757.67	1371.5	14174.403	275337.057	21	147167026.2	**1071.5**
20	5200117.29	7069687.05	14	35282222.72	1475.8	230579.44	311701.038	17	176148392.6	**1137.8**
Ave	3435451.82	36225785.1	11.2	97474268.65	473.80	524047.710	8740430.77	13.9	205991953.9	**385.06**

In figure 9, the performances of the proposed algorithms based on the five metrics are depicted graphically. The algorithms were then studied based on their outputs using statistical methods and analysis of variance. Figure 10 shows the statistical performance of the algorithms in the form of interval plots.

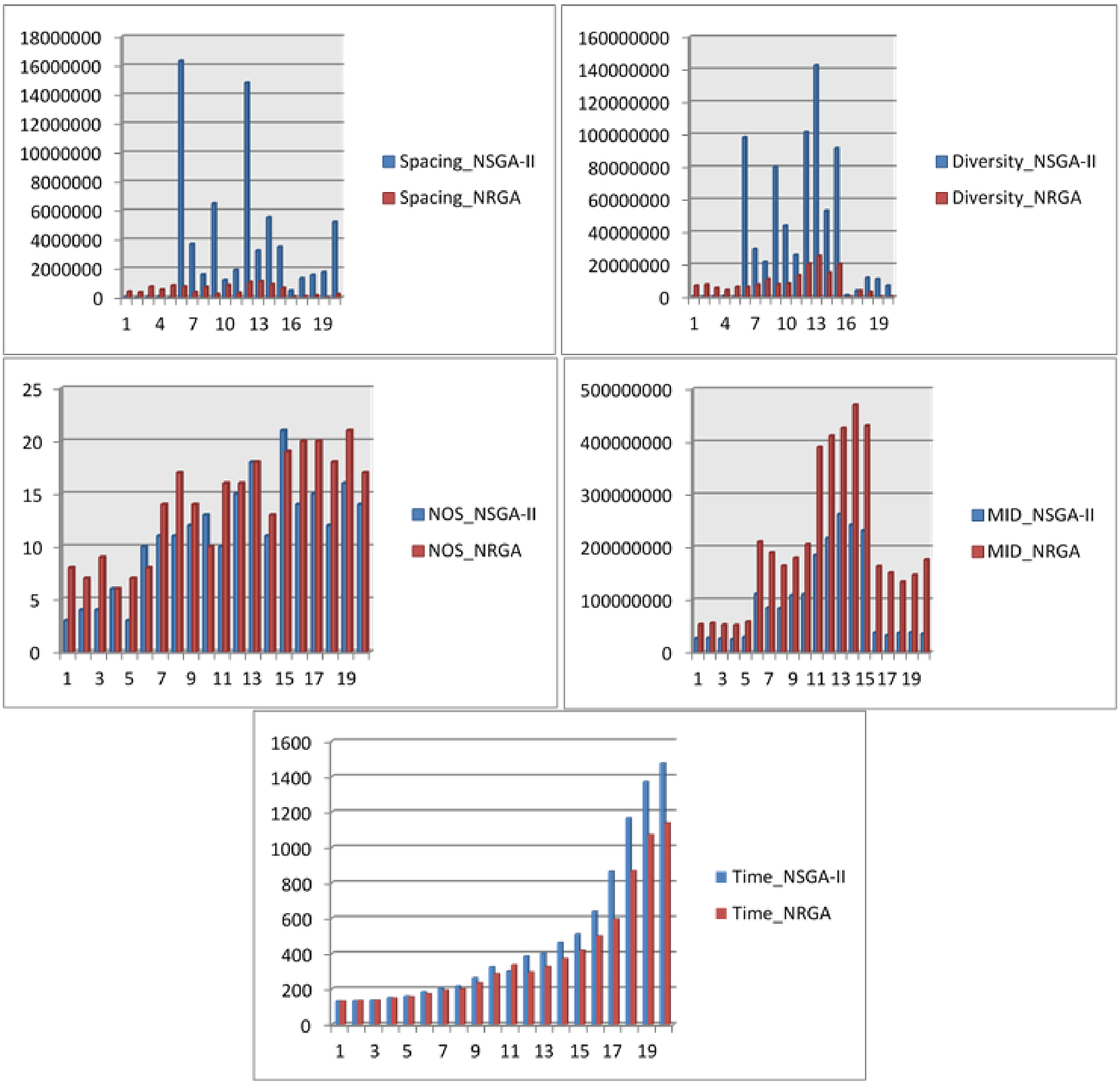

Figure 9. Graphical plots of NSGA-II and NRGA algorithms based on metrics

In the above-defined metrics, MID and Spacing and Time metrics have lower values as desirable. In addition, NOS and Diversity have higher values as desirable. As shown in the bottom row of Table 8, the Diversity and MID metrics in the NSGA-II algorithm and Spacing, MID and Time metrics in the NRGA have better performance. Statistical analysis and t-tests were used to investigate and compare the problem more precisely. The p-values and test results are shown in Table 9. The confidence intervals are shown in Figure 10. Therefore, the statistical output indicates that there is a difference between the algorithms in terms of spacing, diversity, and MID metrics. For spacing NRGA and diversity and MID NSGA-II, the superior algorithms are the superior algorithms. For NOS and time was no significant difference in the NOS and time among the algorithms.

Table 9. Statistical comparison of NSGA-II with NRGA

Metric	P-Value	Test Results
Spacing	0.011	**H_0 is rejected**
Diversity	0.012	**H_0 is rejected**
NOS	0.092	**H_0 is not rejected**
MID	0.006	**H_0 is rejected**
Time	0.451	**H_0 is not rejected**

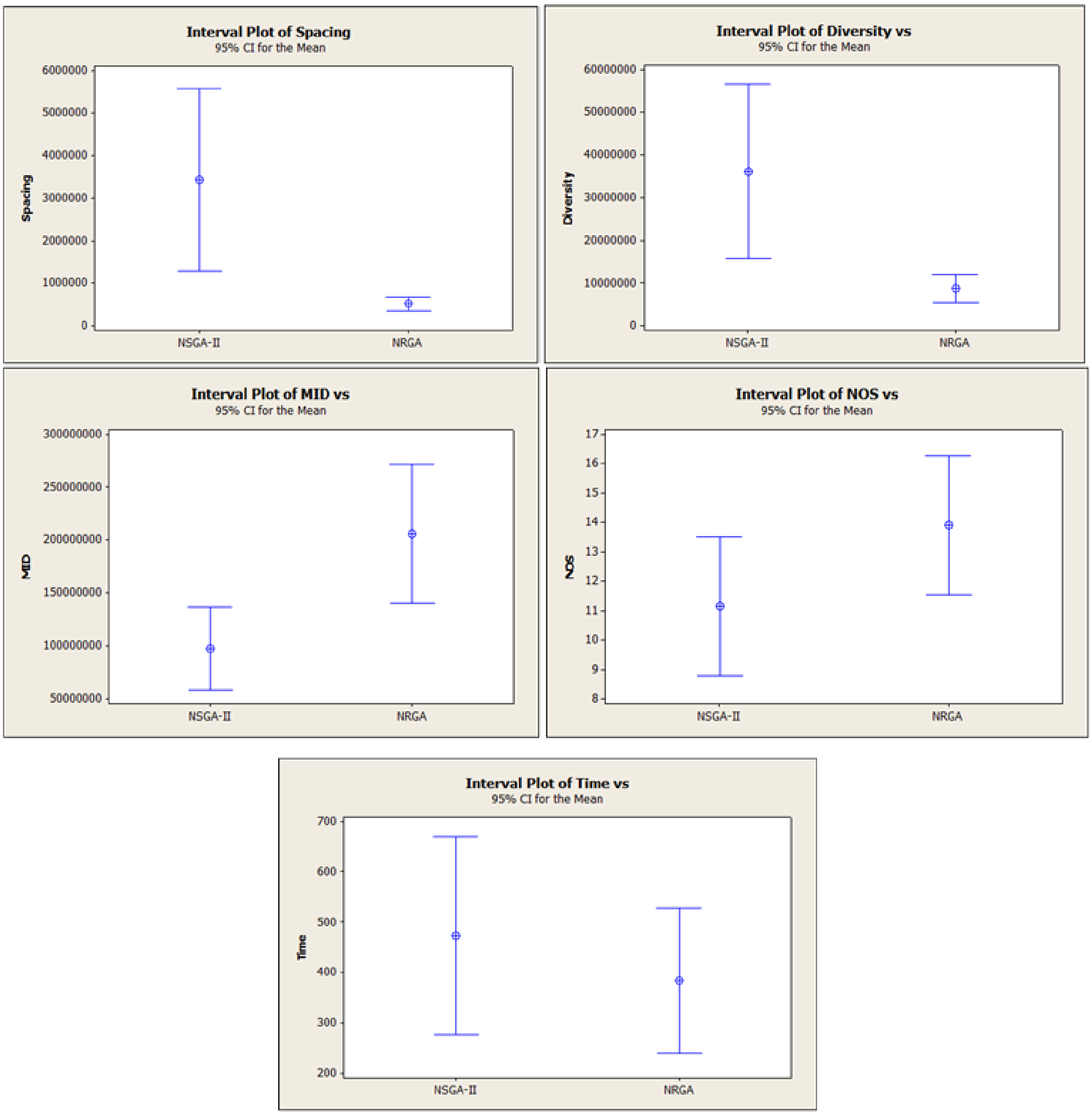

Figure 10 Interval Plot of the statistical test on all metrics

5. Conclusion

5.1 Conclusion

In this study, an integrated procurement, production, and distribution planning problem for designing f four-level supply chain with multiple product types and multiple periods was presented. In addition to minimizing the total supply chain costs, the due date and lost demand rate of the products for customers have also been minimized. Because the multi-objective supply chain network design problem is NP-Hard, two multi objective meta- heuristic algorithms were developed to solve the problem. The NSGA-II and NRGA algorithms were created based on the Pareto method, and their performances were compared. Selecting the algorithm parameter is a critical task; therefore, the Taguchi method was used for tuning the parameter. Finally, statistical analysis was used to choose the most efficient method among the presented models.

5.2 Limitation

In today's business world, there are a wide range of supply chain types with various characteristics. This study focuses on a typical supply chain. Therefore, modeling decision-making in a supply chain, considering specific constraints, considerations, and features, requires a broad scope of research. For example, the potential perishability of goods, the existence of time windows for delivering goods to customers, and, most importantly, the uncertainty of demand information have not been addressed in this study.

The proposed model includes a large number of variables; consequently, the feasible solution space is concave, highly dispersed, and discontinuous. In this study, no alternative methods were used to solve the model, and the efficiency of the proposed algorithm was evaluated. Furthermore, hybrid heuristic algorithms have not been used to improve the search for optimal solutions in this context. In the hybrid approach, some heuristic algorithms generate initial solutions, whereas others explore nearby solutions to enhance the search for viable options.

Moreover, a large number of variables were used in the proposed model. Consequently, the feasible solution space is concave, highly dispersed, and discontinuous. Therefore, employing other methods to solve the model and utilizing hybrid heuristic algorithms can be beneficial for better searching the feasible solution space.

5.3 Suggestion

In the real world, some parameters are not precisely defined. Therefore, they are sometimes expressed linguistically. It is recommended that future research utilize fuzzy variables to incorporate this type of information into models and make decisions accordingly. For future research, it would be beneficial to consider discounts on product prices in both all-unit and incremental formats.

Today, the concepts of collaboration and strategic partnerships have gained significant attention from researchers. Collaboration with key suppliers can impact supply chain design, inventory levels, and distribution systems. Therefore, the concept of strategic alliances should be considered in modeling and determining inventory levels across different layers of the supply chain.

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