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Evaluation of sustainable distribution network design decisions for essential medical products in Turkey

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Introduction: Optimization of distribution for essential medical products is important goal in health systems. For this purpose, the network design should consider economic, environmental, and social aspects together. This issue is especially serious in Türkiye, where regional disparities, infrastructure differences, and limited access to healthcare make pharmaceutical distribution more complicated.
Methods: This study develops a tri objective mathematical programming model for sustainable distribution network design of essential medical products in Türkiye. The model tries to minimize logistics cost and carbon emission at the same time, while it maximizes social benefit through regional job creation. Since the problem is NP hard, two multi objective metaheuristic algorithms, NSGA II and MOPSO, were applied for solving large scale instances. Their performance was evaluated by mean ideal distance, spacing metric, number of Pareto solutions, and computational time. Validation was done through comparison of metaheuristic results with exact MILP solutions in small scale instances.
Results: The results show that both algorithms produced near optimal solutions with good quality. MOPSO had faster convergence, lower mean ideal distance, and also more uniform Pareto front, while NSGA II gave wider spread of alternative solutions. No statistically significant difference was found in the number of non-dominated solutions. The case study results also show that the proposed model can help simultaneous improvement of economic, environmental, and social performance in Turkish healthcare distribution network.
Discussion: The proposed framework gives a practical decision support basis for sustainable and resilient healthcare distribution network design in Türkiye. Its contribution is that it brings together cost, carbon emissions, and regional employment generation in one unified multi echelon optimization structure, and also shows that metaheuristic solution methods can be useful for real world healthcare logistics planning.

KEYWORDS
medical product distribution, metaheuristic algorithms, multi-objective optimization, sustainable healthcare logistics, Turkey

1 Introduction

Logistics of essential medicines is a basic function of the global health infrastructure and a cornerstone for ensuring quality health care and health system stability (Bashirynejad et al., 2024). The management of the supply chain has to move away from the traditional cost reduction methods to a sustainable model that addresses various aspects in the current 'new normal' scenario (Tyagi, 2024). This has to be done especially in the distribution phase, which is the last connection between the production sites and the patients, while it remains the most vulnerable to the imbalances in the inventory levels (Zandkarimkhani et al., 2020). Recent studies have highlighted the need for sustainable optimization models that can handle high levels of uncertainty in perishable-product supply chains (Shiri and Ahmadizar, 2023; Truant et al., 2024; Rostamzadeh et al., 2025). Research done recently in 2025 has pointed out the need to have a sustainable optimization model that can handle high levels of uncertainty in the perishable products' supply chains (Shiri and Ahmadizar, 2023; Truant et al., 2024).

A truly sustainable health care supply chain is a balancing act that achieves competing priorities in a dynamic way, reflecting the Triple Bottom Line: economic, environmental and social considerations (Madani et al., 2024). The main purpose of the economic efficiency is to ensure the long-term sustainability of the logistics network. On the other hand, the environmental performance of a logistics network is aimed at reducing the carbon emissions in the logistics activities so as to achieve the global decarbonization of the network (Zhou et al., 2024). Social sustainability is the least quantified aspect and is focused on the improvement of health equity and regional economic development (Truant et al., 2024). Newly emerging studies on 2025 indicate that pharmaceutical SCM in developing countries is facing major challenges in terms of infrastructure and market access and requires more localized and comprehensive strategic frameworks (Alfaouri et al., 2025; Erdağ and Yeğenoğlu, 2025).

In the context of Turkey, regional differences in terms of infrastructure and geography result in a "spatial mismatch" between centers of supply and centers of demand (Acar and Bük, 2017; Erdağ and Yeğenoğlu, 2025). The Turkish pharmaceutical system is a complex multi-stage system that is heavily regulated and involves manufacturers, wholesalers, and thousands of retailers (Acar and Bük, 2017; Köse et al., 2022). Studies have shown that regional differences in Turkey have resulted in temporary shortages in the region, thus requiring structural interventions that bring services "closer to home" (Bravo et al., 2025; Erdoğan and Ayyildiz, 2022). In spite of these needs, existing optimization approaches for the Turkish context are either focused on robustness (Işık and Topaloglu Yildiz, 2023), without a unified mathematical perspective where job creation at the regional level is considered a major factor, together with economic and environmental aspects.

Addressing the gaps identified in the existing literature, this study contributes to healthcare logistics and sustainable supply chain design in several ways. It first proposes a tri-objective mathematical optimization model for the distribution of essential medical products that jointly captures economic cost, transportation-related carbon emissions, and social benefits in the form of regional employment generation. By doing so, the framework moves beyond the predominantly single-dimensional, or only partially integrated, approaches reported in much of the prior literature. The study also combines strategic facility location decisions with tactical product flow allocation in a unified multi-echelon optimization framework, which allows the network to be designed in a more coherent and realistic manner. Because the problem is NP-hard, two established multi-objective metaheuristic algorithms, Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO), are used to solve large-scale instances. Their performance is evaluated through mean ideal distance, number of Pareto solutions, spacing metric, and computational time. The framework is then applied to a real-world case study of Turkey's pharmaceutical distribution network, represented by aggregated demand zones, and the reliability of the resulting solutions is verified by comparison with exact MILP solutions for small-scale instances and with generated large-scale benchmark instances. Collectively, these contributions provide both methodological advancement and practical guidance for the design of more sustainable medical distribution systems.

The rest of this paper is organized as follows: Section 2 presents the literature review and Section 3 introduces the research design. Section 4 formulates the mathematical model for the proposed sustainable distribution network design problem, while Section 5 presents the solution algorithms used to solve it. Section 6 describes the algorithmic implementation and parameter-tuning procedure. The case study and data setting are introduced in Section 7, followed by the computational experiments and results in Section 8. Section 9 discusses the main findings together with their managerial implications, and Section 10 concludes the paper by identifying directions for future research.

2 Literature review

2.1 Healthcare supply chain and distribution challenges

Pharmaceutical distribution in developing countries is faced with a number of challenges, including a highly fragmented, and often poorly developed, distribution structure (Alfaouri et al., 2025). Turkey has quite restrictive access to the market, and, as in the other countries, also a number of barriers exist for the distribution between warehouses and pharmacies (Erdoğan and Ayyildiz, 2022; Köse et al., 2022). Recent 2025 studies point to the fact that the "estimate-then-optimize" approach may lead to better service quality in the provinces and generally, in cases where the location of the logistics centre is not optimal in relation to the demand centres (Bravo et al., 2025). This is also confirmed by studies (Bilal et al., 2024; Erdoğan and Ayyildiz, 2022).

2.2 Sustainable supply chain network design

Sustainable design is not only about cost savings but also has to consider the environmental and social impacts (Govindan et al., 2016; Madani et al., 2024). For instance, the management of perishable products has to consider the environmental and uncertainty associated with product deterioration in order to limit waste (Rostamzadeh et al., 2025; Zandkarimkhani et al., 2020). While corporate social responsibility influences carbon reduction (Zhou et al., 2024), the integration of regional and rural development and job creation in a multi-tier health system is an important issue which is not covered in the current literature (Madani et al., 2024; Truant et al., 2024).

2.3 Social sustainability and optimization approaches

Social sustainability is often not incorporated within the framework of quantitative modeling (Govindan et al., 2019). There are many studies in the literature on vaccine equity during pandemics (Shiri and Ahmadizar, 2023) or job creation in medical waste recycling (El Liazidi and Dkhissi, 2024). In Turkey, studies on cold chain waste management (Işık and Topaloglu Yildiz, 2023) are available. However, for the healthcare distribution sector in Turkey, a systematic approach that balances the job creation potential of the regions with the carbon-based sustainability goals has not been identified in the literature yet.

2.4 Metaheuristics in logistics

The NP-hard location-allocation problems must be solved by meta-heuristic methods (Validi et al., 2021). Standard methods for multi-objective optimization such as NSGA-II and MOPSO are applied in order to explore the non-convex Pareto frontiers (Nikian et al., 2023; Rezaei and Liu, 2024). Although hybrid swarm intelligence has been used effectively in vehicle routing problems

TABLE 1 Comparative analysis of the proposed study with existing literature.

Author(s) and Year	Title of the work	Problem/ topic	Method/ model	Econ	Env	Soc	Multi-echelon	Key gap/ difference
Govindan et al. (2019)	Designing a sustainable supply chain network integrated with vehicle routing: A comparison of hybrid swarm intelligence metaheuristics	Sustainable SCM	Hybrid Swarm	✓	✓	✓	✓	Generic context; not specific to high-sensitivity medical logistics.
Zandkarimkhani et al. (2020)	A chance constrained fuzzy goal programming approach for perishable pharmaceutical supply chain network design	Perishable pharma	Fuzzy goal prog.	✓	–	–	✓	Lacks environmental impact and job creation metrics.
Shiri and Ahmadizar (2023)	An equitable and accessible vaccine supply chain network in the epidemic outbreak of COVID-19 under uncertainty	Vaccine equity	Mixed-integer	✓	–	✓	✓	Does not consider carbon emission or environmental sustainability.
Işık and Topaloglu Yildiz (2023)	Optimizing the COVID-19 cold chain vaccine distribution network with medical waste management: a robust optimization approach	Turkey cold chain	Robust MILP	✓	✓	–	✓	Focused on waste management; neglects regional job creation.
Goodarzian et al. (2021)	Designing a new medicine supply chain network considering production technology policy using two novel heuristic algorithms	Medicine SC	Meta-heuristics	✓	–	–	✓	Omitted environmental and social sustainability dimensions.

(Continued)

TABLE 1 (Continued)

Author(s) and Year	Title of the work	Problem/ topic	Method/ model	Econ	Env	Soc	Multi-echelon	Key gap/ difference
El Liazidi and Dkhissi (2024)	A genetic artificial bee colony algorithm for investigating job creation and economic enhancement in medical waste recycling	Medical recycling	Genetic ABC	–	✓	✓	✓	Focused strictly on waste recycling; not pharmaceutical flow.
Bravo et al. (2025)	Closer to home: a structural estimate-then-optimize approach to improve access to healthcare services	Healthcare access	Estimate-then-opt.	✓	–	✓	–	Qualitative focus on access; lacks tri-objective mathematical model.
Bouchenine and Almaraj (2024)	A robust optimization approach model for a multi-vaccine multi-echelon supply chain	Multi-vaccine SC	Robust MILP	✓	–	–	✓	Single-objective focus on cost/ robustness; lacks TBL.
Karakostas and Sifaleras (2025)	Modeling of sustainable integrated supply chains under the consideration of European Union regulations	Sustainable logistics	Multi-obj. MILP	✓	✓	✓	✓	Restricted to EU regulations; lacks national meta-heuristic comparison.
This study	Evaluation of sustainable distribution network design decisions.	Turkey pharma	Tri-obj. MILP	✓	✓	✓	✓	Unified Tri-obj. (Cost, CO2, and regional job creation under aggregated demand-zone representation) with meta-heuristic comparison.

(Govindan et al., 2019), applying these algorithms to a tri-objective model of Turkey's national distribution network provides a useful benchmark for decision-making at the national level. Table 1 summarizes representative studies in the literature and clarifies the methodological contribution of the proposed model.

3 Methodology

The purpose of this research is to develop a quantitative model for design of sustainable distribution network of essential medical products, with focus on locating upstream and mid-level distribution centers, and also planning of product flows between different parts of network. In this model, network design is carried out by considering sustainability dimensions at same time, so that decisions are not only acceptable from economic view, but also from environmental and social viewpoints.

Within framework of proposed model, three main objective functions are considered, which include minimization of total distribution costs, reduction of environmental impacts caused by logistics activities, and strengthening positive social effects of distribution network. The population studied in this research includes companies active in field of medical product distribution in Turkey, which are responsible for transferring products from upstream centers to demand points.

Main activities in medical product distribution network mainly include storage and spatial movement of products. Decision making complexity at this level of supply chain depends on factors such as geographic dispersion of supply and demand centers, diversity of service regions, and demographic and regional characteristics of final customers. For example, providing stable access to medical products in less developed or low-density areas usually faces more challenges compared to urban regions.

One of basic considerations in distribution network design is environmental impacts related to transportation and logistics activities. Different transportation modes used in network can have different effects on environment, including consumption of natural resources, air pollution, noise pollution, and emission of greenhouse gases. In recent years, controlling and reducing these impacts has become one of important concerns in logistics industries.

Besides environmental aspects, design of medical product distribution network also has notable social and economic impacts. In present model, creating job opportunities in less developed regions is considered as one of social sustainability indicators. From economic perspective, efforts are made to design network structure in way that operational distribution costs at whole network level are minimized.

Based on these considerations, the model for designing essential medical product distribution network is developed under following assumptions.

1. At network level, shortage of medical products at any demand point is not allowed.
2. Direct exchange of products between upstream distribution centers is not allowed.
3. Direct transfer of products between mid-level distribution centers is not considered.
4. Calculation of carbon dioxide emissions is limited only to transportation activities between network levels.
5. Human resource capacity used in transportation and distribution activities is assumed to be fixed.

4 Mathematical model

In following, indexes (Table 2), parameters (Table 3), and decision variables (Table 4) of model are introduced, and then mathematical structure of model is explained through set of Equations 1–10.

TABLE 2 Model indexes.

Indexes	Description
$p\epsilon\{1,\ldots,P\}$	Candidate locations of main distribution centers for essential medical products
$m\epsilon\{1,\ldots,M\}$	Candidate locations of local or regional distribution centers for essential medical products
$d\epsilon\{1,\ldots,D\}$	Demand regions including health service providers and consumption points, such as hospitals, clinics, and pharmacies.

TABLE 3 Model parameters.

Parameters	Description
c_{pm}	Transportation and transfer cost of essential medical product shipments from main distribution center p to local distribution center m.
$\acute{c}_{md}$	Distribution and delivery cost of essential medical products from local distribution center m to demand region d.
D_d	Amount of demand for essential medical products in demand region d.
F_p	Fixed cost for opening or activating main distribution center p for covering essential medical products.
$\grave{F}_m$	Fixed cost for opening or activating local distribution center m for covering essential medical products.
H_p	Holding and storage cost of essential medical products at distribution center p.
$\grave{H}_m$	Holding and storage cost of essential medical products at distribution center m.
Cap_p	Operational and storage capacity of main distribution center p related to essential medical products.
$C\grave{a}p_m$	Operational and storage capacity of local distribution center m related to essential medical products.
e_{pm}	CO_2 emission coefficient caused by transportation of essential medical products on route from p to m.
$\grave{e}_{md}$	CO_2 emission coefficient caused by distribution of essential medical products on route from m to d.
ω_p	Social dimension parameter related to regional conditions and social responsibility for locating main distribution center p.
$\grave{\omega}_m$	Social dimension parameter related to regional conditions and social responsibility for locating local distribution center m.
J_p	Number of jobs created by establishing main distribution center p.
$\grave{J}_m$	Number of jobs created by establishing local distribution center m.

TABLE 4 Model variables.

Variables	Description
X_{pm}	Amount of flow of essential medical products from p to m.
X'_{md}	Amount of flow of essential medical products from m to d.
I_p	Inventory level of essential medical products at main distribution centers.
I'_m	Inventory level of essential medical products at local distribution centers
Y_p	Equals 1 if main distribution center p is opened, otherwise 0.
Z_m	Equals 1 if local distribution center m is opened, otherwise 0.

4.1 Model

$$\min w_1 = \sum_p F_p Y_p + \sum_m F'_m Z_m + \sum_p \sum_m C_{pm} X_{pm} + \sum_m \sum_d C'_{md} X'_{md} + \sum_p H_p I_p + \sum_m H'_m I'_m \tag{1}$$

$$\min w_2 = \sum_p \sum_m e_{pm} X_{pm} + \sum_m \sum_d e'_{md} X'_{md} \tag{2}$$

$$\max w_3 = \sum_p w_p J_p Y_p + \sum_p w'_m J'_m Z_m \tag{3}$$

Subject to:

$$I'_m = \sum_p X_{pm} - \sum_d X'_{md} \qquad \forall m \tag{4}$$

$$I_p \le Cap_p Y_p \qquad \forall p \tag{5}$$

$$I'_m \le Cap'_m Z_m \qquad \forall m \tag{6}$$

$$\sum_m X'_{md} = D_d \qquad \forall d \tag{7}$$

$$\sum_m X_{pm} \le Cap_p Y_p \qquad \forall p \tag{8}$$

$$Y_p, Z_m \in \{0,1\} \qquad \forall p,m \tag{9}$$

$$X_{pm}, X'_{md}, I_p, I'_m \ge 0 \qquad \forall p,m,d \tag{10}$$

The mathematical formulation of the proposed model is presented in Equations 1–10. Specifically, Equations 1–3 define the objective functions, while Equations 4–10 represent the operational constraints of the distribution network. In order to optimize distribution network of essential medical products with emphasis on economic dimension of sustainability and based on views of experts in health and logistics field, this research considers minimization of total costs of distribution network. The costs considered in model include a set of strategic and operational costs of medical product distribution network. These costs specifically include fixed costs for opening main distribution centers and local distribution centers, costs of transportation and movement of medical products from main distribution centers to local distribution centers, costs of transferring medical products from local distribution centers to demand regions, and also holding and storage costs of medical products at both main and local distribution center levels.

The economic objective function of the proposed model is formulated in Equation 1 and consists of several main components. The first and second components represent total fixed costs related to opening main distribution centers and local distribution centers, respectively. The third component covers total transportation costs of medical products from main distribution centers to local distribution centers, while the fourth component is related to costs of transferring medical products from local distribution centers to demand regions. Finally, the fifth component of objective function reflects total holding costs of medical products at main and local distribution centers. In this way, economic objective function of model, by aggregating all costs related to network structure and product flows, makes possible a comprehensive evaluation of economic performance of essential medical product distribution network and provides basis for simultaneous comparison with environmental and social objectives of model. These costs are considered in model through parameters c_{pm} and c_{md}.

The environmental objective function, which minimizes total carbon dioxide emissions generated by transportation activities in the network, is defined in Equation 2. Its aim is minimizing negative environmental impacts caused by logistics activities in distribution network of essential medical products. More specifically, this objective function considers amount of carbon dioxide emissions resulting from movement and transportation of products at different levels of distribution network and tries to minimize total emissions across whole network. This objective function includes two main components. The first component reflects total carbon dioxide emissions caused by transferring products from main distribution centers to local distribution centers. The second component covers amount of carbon dioxide emissions resulting from movement of products from local distribution centers to demand regions. In this way, this objective function comprehensively captures direct environmental impacts of transportation activities in distribution network. It should be noted that in this model, calculation of carbon dioxide emissions is limited only to transportation activities between different levels of network, and other components of distribution network, such as internal processes of distribution centers, are not included in environmental calculations.

International organizations active in health and sustainable development define social dimension of sustainability as a set of impacts resulting from organizational activities on social systems, which can include areas such as labor force, local community, human rights, and product responsibility (Saygili et al., 2023). Despite importance of this dimension, its systematic inclusion into quantitative supply chain models still faces challenges, so that significant part of existing studies either focus on economic and environmental aspects or consider social dimension in limited and unstructured way (Azab et al., 2023). Social sustainability reference frameworks usually divide this dimension into components such as employment and decent work, rights of employees and suppliers, social impacts on local community, and safety and access of consumers to vital products, each of which can provide basis for defining measurable indicators in strategic decision making (Bianchini et al., 2022). In context of essential medical product distribution networks, which are directly related to public health and social welfare, paying attention to social components in location and network design decisions can lead to reduction of regional inequalities, improvement of fair access to health services, and creation of employment opportunities in less developed regions, an issue that has been emphasized in recent studies related to health supply chains and emerging economies, including Turkey (Piffari et al., 2026).

The social objective function, which maximizes employment opportunities generated by establishing distribution centers, is presented in Equation 3. The first part of this function considers social impacts resulting from opening main distribution centers in regions with higher social priority, while the second part reflects employment created in local distribution centers.

The weighting coefficients ω_p and $\grave{\omega}_m$ represent relative importance of regions from perspective of unemployment and social justice, and parameters J_p and J_m are considered as number of job opportunities created by opening main and local distribution centers. This structure is fully aligned with objectives of sustainable development policies and regional justice in medical product distribution system.

The model constraints are presented in Equations 4–10. Equation 4 represents the inventory balance at local distribution centers, where inflow from main distribution centers equals outbound shipments to demand regions plus ending inventory. Equations 5, 6 impose capacity constraints on the main and local distribution centers, respectively. Equation 7 enforces exact demand satisfaction in each demand region. Equation 8 limits the total outbound flow from each main distribution center. In the present formulation, main distribution centers are treated as upstream supply origins; therefore, a separate inflow balance for I_p is not modeled. Under the empirical case-study assumptions of zero initial and ending inventories and positive holding cost, I_p takes a zero value in the implemented solution. Finally, Equations 9, 10 define the binary and non-negativity conditions of the decision variables.

5 Solution algorithms

5.1 Solving the medical product distribution network model

To solve the proposed three-objective model, the linear weighted-sum approach was used for small- and medium-sized instances, and the resulting single-objective formulation was solved as a mixed-integer linear programming (MILP) model. The implementation and exact solution of this reformulated model were carried out using the Gurobi 10.0 solver within the MATLAB R2023a environment. Gurobi was selected because of its strong computational capability and reliable performance in solving network design problems, and it was used to obtain benchmark optimal solutions for validation and comparison purposes.

With increase of problem size and due to NP-hard nature of sustainable distribution network design model, solution time of exact methods increased significantly. Therefore, to solve model at large scales, multi objective metaheuristic algorithms were used. In this research, two algorithms NSGA-II and MOPSO were fully implemented and executed to generate a set of non dominated optimal solutions (Pareto front).

NSGA-II was employed because of its strong capability to preserve solution diversity and achieve gradual convergence toward the Pareto front, whereas MOPSO was selected due to its high convergence speed and stable performance. The implementation of both algorithms and the computational experiments were carried out in MATLAB R2023a, while the statistical analysis of performance indicators was conducted using the Statistical Package for the Social Sciences (SPSS) version 20. The parameter settings of both algorithms were determined based on standard recommendations reported in recent multi-objective optimization studies, as well as the parameter levels listed in Table 5 and the experimental combinations presented in Table 6. Finally, the obtained Pareto solution set was used as basis for analysis and selection of final solution, and final decision making was carried out by creating balance among economic, environmental, and social objectives.

5.2 Solving the model using NSGA-II algorithm

To solve large scale multi objective design model of sustainable distribution network of essential medical products, NSGA-II algorithm was applied. Considering NP-hard nature of distribution network design problem and existence of conflicting economic, environmental, and social objectives, use of classical exact methods is not efficient at realistic scales. Therefore, evolutionary algorithms were selected as suitable solution tools.

In first stage of algorithm, initial population is generated randomly. Each solution vector includes four main decision components that simultaneously determine spatial structure and flows of medical product distribution network:

1. The amount of product flow transferred from main distribution centers to local distribution centers, represented by variables X_{pm};

TABLE 5 Control parameters and their levels for the optimization algorithms.

Algorithm	Parameter	Symbol	Number of levels	Level 1	Level 2	Level 3
NSGA-II	Population size	POP_{NS}	3	100	200	300
NSGA-II	Number of generations	Gen_{NS}	3	100	200	300
NSGA-II	Crossover probability	P^{C}	3	0.60	0.75	0.85
MOPSO	Swarm size	POP^{PS}	3	100	200	400
MOPSO	Maximum iterations	$Iter^{PS}$	3	100	200	300
MOPSO	Inertia weight	w^{PS}	3	0.40	0.50	0.60

TABLE 6 Taguchi L9 experimental design for algorithm parameter tuning.

Experiment	POP_{NS}	Gen_{NS}	P^{c}	POP^{ps}	$Iter^{ps}$	w^{ps}
1	POP_1	Gen_1	P^1	POP^1	$Iter^1$	w^1
2	POP_1	Gen_2	P^2	POP^1	$Iter^2$	w^2
3	POP_1	Gen_3	P^3	POP^1	$Iter^3$	w^3
4	POP_2	Gen_1	P^2	POP^2	$Iter^1$	w^2
5	POP_2	Gen_2	P^3	POP^2	$Iter^2$	w^3
6	POP_2	Gen_3	P^1	POP^2	$Iter^3$	w^1
7	POP_3	Gen_1	P^3	POP^3	$Iter^1$	w^3
8	POP_3	Gen_2	P^1	POP^3	$Iter^2$	w^1
9	POP_3	Gen_3	P^2	POP^3	$Iter^3$	w^2

2. The amount of product flow transferred from local distribution centers to demand regions, represented by variables X_{md};
3. The active or inactive status of main distribution centers, represented by binary variablesY_p;
4. The active or inactive status of local distribution centers, represented by binary variables Z_m.

Values of these variables in initial population are generated randomly within allowable ranges defined in model. Each chromosome represents a complete configuration of medical product distribution network that simultaneously includes information related to flow allocation and selection of active centers (Figure 1).

5.2.1 Stage two: evaluation of initial population

At this stage, the initial population generated is evaluated using economic, environmental, and social objective functions defined in model, and value of each objective function is calculated for all solutions.

5.2.2 Stage three: non dominated sorting

Members of population are sorted based on Pareto dominance concept, in such way that non dominated solutions are placed in first front and other solutions are classified into next fronts according to level of dominance.

5.2.3 Stage four: crowding distance calculation

For each solution in each front, crowding distance index is calculated. This index shows level of spread of solutions in objective space and helps keeping diversity of population, so larger values indicate more uniform distribution of solutions.

5.2.4 Stage five: parent selection and generation of new population

Parent selection is performed using binary selection operator based on non dominance rank and crowding distance. In this process, if two solutions belong to different fronts, solution with better rank is selected, and if they belong to same front, solution with higher crowding distance is chosen. Then, by applying crossover and mutation operators, new generation is produced.

5.2.5 Stage six: applying crossover and mutation

In this stage, new offspring solutions are generated by applying Simulated Binary Crossover (SBX) and polynomial mutation to the parent population. SBX is used to recombine pairs of parent solutions and generate new candidate network configurations, whereas polynomial mutation introduces controlled stochastic perturbations into the decision variables in order to enhance search diversity and prevent premature convergence. Because these operators may occasionally produce infeasible solutions, a repair mechanism is applied after each operation to restore feasibility with respect to the model constraints.

5.3 Solving the model using MOPSO algorithm

In this research, to solve multi objective optimization model, MOPSO algorithm is used. In this algorithm, each potential solution is represented as a particle, and search process is performed through collective movement of particles in decision space. Each particle at each iteration has a position vector and a velocity vector, which, respectively, show current status of solution and its movement direction in search space.

5.4 Algorithm symbols

To avoid conflict with symbols of optimization model, following symbols are defined only at algorithm level and only these symbols are used in algorithm:

- $x_s(t)$: position of particle s at iteration t
- $v_s(t)$: velocity of particle s at iteration t
- $p_s(t)$: best recorded position of particle s until iteration t (personal best)
- $g(t)$: selected non dominated best solution from archive at iteration t (leader)

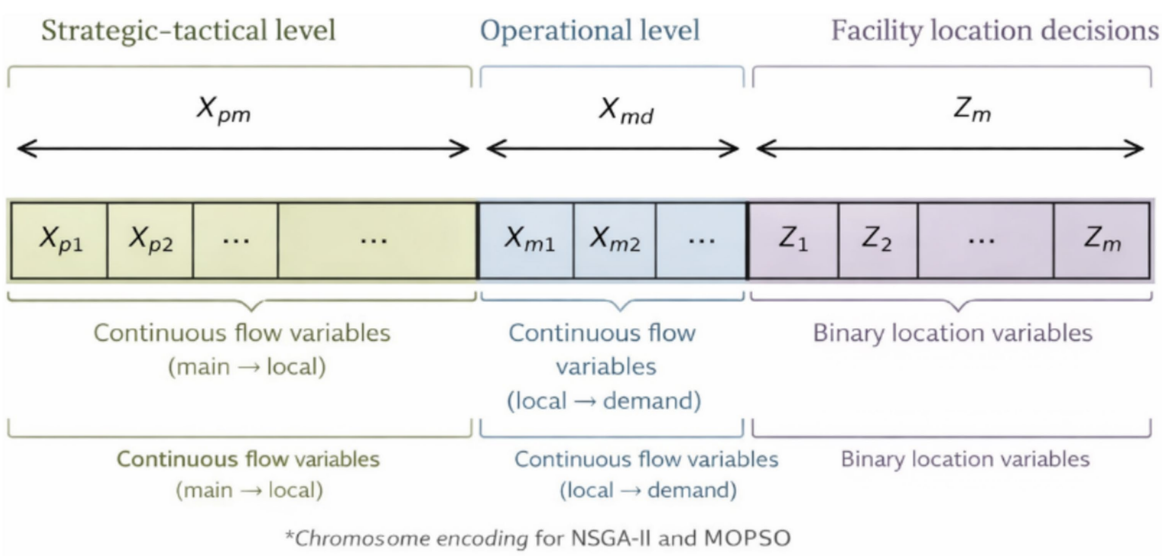

FIGURE 1
Chromosome-based structure of the decision vector used in NSGA-II and MOPSO, integrating continuous flow variables across strategic–tactical and operational levels with binary facility location decision variables.

- w: inertia weight
- c_1, c_2: individual and social learning coefficients
- r_1, r_2: random numbers uniformly distributed in range [0,1]

5.5 Updating position and velocity of particles

Movement mechanism of particles in search space is carried out based on following relations, the velocity and position update rules of the particles are defined in Equations 11, 12:

$$x_s(t+1) = x_s(t) + v_s(t+1) \tag{11}$$

$$v_s(t+1) = wv_s(t) + c_1 r_1 \left(p_s(t) - x_s(t)\right) + c_2 r_2 \left(g(t) - x_s(t)\right) \tag{12}$$

These relations create balance between personal memory of particle and collective experience of whole population.

5.6 Execution steps of MOPSO algorithm

5.6.1 Stage 1: generation of initial population

At first, a population of particles is generated randomly. This stage is similar to initialization process in NSGA-II algorithm.

5.6.2 Stage 2: evaluation and archive formation

Initial particles are evaluated and non dominated solutions are stored in an external archive.

5.6.3 Stage 3: sorting in objective space

Non dominated solutions are classified and sorted based on objective function values to preserve diversity in Pareto space.

5.6.4 Stage 4: leader selection for each particle

To guide the movement of particles, a leader is selected for each particle from the archive members. The leader selection probability is determined through a density-based roulette wheel mechanism, as calculated by Equation 13:

$$Pr_s = \frac{\left(1/n_s\right)^{\beta}}{\sum_j \left(1/n_j\right)^{\beta}} \tag{13}$$

where:

- n_s: number of solutions located in neighborhood of particle s
- β: selection pressure parameter

Stage 5: updating personal best.

After computing new position, the personal best position of each particle is updated according to Equation 14:

$$p_s(t+1) = \begin{cases} p_s(t) & \text{if } p_s(t)\ dom\ x_s(t+1) \\ x_s(t+1) & \text{if } x_s(t+1)\ dom\ p_s(t) \\ \text{random}\left\{p_s(t), x_s(t+1)\right\} & \text{otherwise} \end{cases} \tag{14}$$

In this relation, operator "dom" represents Pareto dominance concept.

5.6.5 Stage 6: archive updating

New non dominated members are added to archive and dominated solutions are removed.

5.6.6 Stage 7: archive size control

If the number of archive members exceeds the predefined limit, an archive pruning mechanism is activated. In this step, solutions located in highly crowded regions of the objective space are removed using crowding distance measures, so that the archive preserves a well-distributed set of non-dominated solutions.

5.6.7 Stage 8: stopping condition check

If stopping condition, such as reaching maximum number of iterations, is satisfied, algorithm stops; otherwise, process is repeated from objective space sorting stage.

For setting parameters of metaheuristic algorithms, Taguchi method is applied in order to reach suitable combination of parameters. For this reason, parameter notation is used as follows:

- POP_{NS} represents population size in NSGA-II.
- Gen_{NS} is number of generations in NSGA-II.
- P^{c} shows crossover probability in NSGA-II.
- POP^{ps} is swarm size in MOPSO.
- $Iter^{ps}$ means number of iterations in MOPSO.
- w is inertia weight in MOPSO.

Accordingly, Gurobi 10.0 in MATLAB R2023a was used for all exact MILP runs, including the weighted-sum benchmark solution and the small-scale validation instances, whereas NSGA-II and MOPSO were implemented in MATLAB R2023a for large-scale multi-objective solution generation.

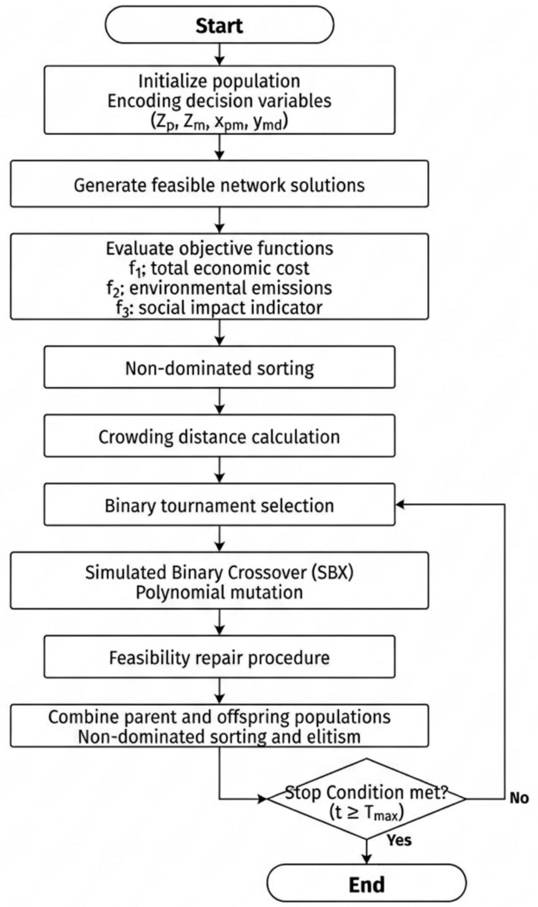

FIGURE 2
Flowchart of the NSGA-II algorithm used for solving the proposed multi-objective distribution network design model.

6 Algorithmic implementation, constraint handling, and reproducibility details

To enhance transparency and ensure reproducibility of the proposed solution procedures, the implementation logic of the adopted metaheuristic algorithms is explicitly described in this section. The algorithmic structures presented in this section are developed based on the mathematical formulation introduced in Section 4, including the defined sets, parameters, and decision variables of the sustainable distribution network design model.

The overall execution procedures of the two applied multi-objective metaheuristic algorithms are illustrated in Figures 2, 3. Specifically, Figure 2 presents the operational flow of the NSGA-II algorithm, while Figure 3 illustrates the MOPSO-based search procedure. The flowcharts depict the complete sequence through which candidate network configurations are generated, evaluated, and updated during the search process.

6.1 Solution encoding

To represent candidate solutions in both algorithms, a multi-segment encoding structure is adopted. Each solution, defined as a chromosome in NSGA-II and as a particle in MOPSO, comprises two groups of decision variables associated with facility location and product flow decisions. The first segment captures the binary facility activation decisions, including Z_p, which denotes the activation status of main distribution centers, and Z_m, which denotes the activation status of local distribution centers. The second segment contains the continuous shipment variables that represent product flows within the network, namely x_{pm}, the quantity shipped from main distribution center p to local distribution center m, and y_{md}, the quantity shipped from local distribution center m to demand zone d. This hybrid encoding structure allows the algorithms to determine facility activation decisions and distribution flow allocations simultaneously, thereby reflecting the integrated nature of the proposed distribution network design problem.

6.2 Genetic operators in NSGA-II

In the NSGA-II implementation, the parent solutions are selected by using a binary tournament selection. The candidates are compared based on their non-domination rank and crowding distance. This ensures that the diversity of the Pareto front and the quality of the solution were addressed in the selection process. The offspring were produced using two genetic operators:

- Simulated Binary Crossover (SBX) is used to cross over two parent solutions to yield two offspring solutions for the network topology.
- Polynomial mutation introduces controlled stochastic perturbations into the decision variables to enhance the diversity of the search process and avoid getting stuck at the local optimum.

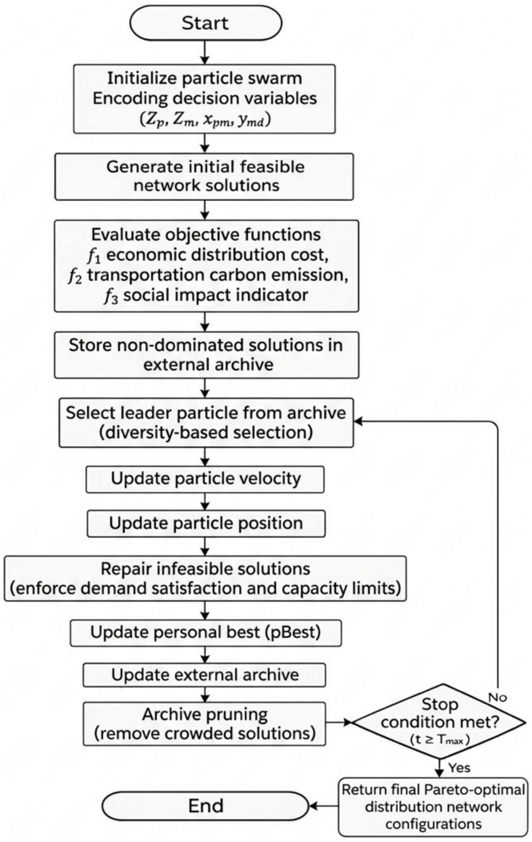

FIGURE 3
Flowchart of the MOPSO algorithm used for solving the proposed multi-objective distribution network design model.

Because crossover and mutation may produce infeasible network configurations, a feasibility repair mechanism is applied after each genetic operation. This repair process is ensured to guarantee that each and every possible solution within the population complies with the structural and operational constraints of the distribution network before we perform the objective assessment. The implementation of the NSGA-II algorithm has a computational complexity of $O\left(MN^2\right)$, where M is the number of objectives and N is the population size.

6.3 Archive management and leader selection in MOPSO

The MOPSO algorithm has an external archive that stores all non-dominated solutions encountered during the search process. The leader selection process of MOPSO chooses a leader particle for every iteration from the solutions stored in the external archive. The leader selection mechanism in the proposed multi-objective DE algorithm employs a density-based method to select the leader from the less crowded area in the objective space. This maintains the diversity on the Pareto fronts approximated by the evolution process. When the archive size exceeds its limit, pruning is activated. In this case, solutions that are found in densely packed regions of objective space are removed using crowding distance criteria to ensure that a spread set of Pareto optimal solutions is maintained.

6.4 Constraint handling mechanism

Maintaining the feasibility of candidate solutions is critical in the distribution network design problem considered here. Accordingly, a repair-based constraint-handling strategy is applied during both the initialization phase and the iterative search process. This repair mechanism ensures that candidate solutions satisfy the following conditions:

- Demand satisfaction constraints for each demand zone d
- capacity limitations of activated main distribution centers $p$and local distribution centers m
- Logical consistency between facility activation variables $\left(Z_p, Z_m\right)$ and shipment variables $\left(x_{pm}, y_{md}\right)$

Crossover, mutation and particle updates can result in infeasible solutions. If that is the case, the repair mechanism is applied to decision variables in order to obtain a feasible solution before evaluating the objective function.

6.5 Stopping criterion

Both NSGA-II and MOPSO terminate when the maximum iteration criterion, $T_{\max}$, is reached. All the parameters to be tuned, namely the population size, mutation rate, crossover rate, inertia weight, and acceleration coefficients, are tuned using the Taguchi design of experiments, as will be elaborated on in the next subsection. In order to improve transparency of the paper and ease of replication of the proposed metaheuristics, the structure of the metaheuristics coded is presented with the aid of flowcharts.

ALGORITHM 1. NSGA-II for Sustainable Distribution Network Design.

Input:
Population size N
Maximum iterations T_{max}
Crossover rate p_c
Mutation rate p_m
Initialize population with candidate solutions
Each solution encodes Z_p, Z_m, x_{pm} and y_{md}
Evaluate objective functions for each solution
Perform fast non-dominated sorting
Compute crowding distance
While t < T_{max}
Select parents using binary tournament selection
Generate offspring using simulated binary crossover
Apply polynomial mutation
Repair infeasible offspring solutions
Evaluate objective functions (f1, f2, f3)
Combine parent and offspring populations
Perform fast non-dominated sorting
Select best N solutions based on rank and crowding distance
End While
Return Pareto optimal solutions

ALGORITHM 2. MOPSO for Sustainable Distribution Network Design.

Input:
Swarm size N
Maximum iterations T_{max}
Inertia weight w
Acceleration coefficients c_1 and c_2
Initialize particles with decision variables Z_p, Z_m, x_{pm} and y_{md}
Initialize particle velocities
Evaluate objective functions
Store non-dominated solutions in external archive
While t< T_{max}
Select leader particle from archive
Update particle velocity
Update particle position
Repair infeasible particles
Evaluate objective functions
Update personal best solutions
Update external archive
If archive size exceeds limit
prune archive using crowding distance
End If
End While
Return archive solutions as the approximated Pareto front

7 Case study

In this section, a case study will be provided based on the operational data of a Turkish pharmaceutical distributor to verify the proposed model and the performance of the solution algorithm. The pharmaceutical distributor is a well-known supplier of generic drugs and general medical products to a significant segment of the local market.

The company's logistics are centered around Istanbul as a central hub to receive, consolidate, and dispatch drugs. Istanbul was selected as a hub because it centralizes all the transportation networks and offers both road and sea routes. Moreover, it is strategically positioned near the country's main centers of drug supply. In addition to the main distribution center, the company has other distribution centers to efficiently and effectively address regional demands.

Data was obtained from Company sources, official Government agencies, online route planners and through consultation with industry experts. To be specific, the annual demands used were from the compiled historical distribution records of important medical products. Regional unemployment rates used were from TurkStat and served as a proxy for the social sustainability component of the model (TurkStat, 2025a). The distances between facilities and demand points were calculated based on Google Maps' road network data. The environmental emission coefficients used are based on international environmental guidelines and OECD[1] reference sources (OECD, 2025). Moreover, the specific costs used to compute the setup costs of the possible regional distribution centers and workforce requirements were triangulated from a variety of reports from the sector (IEIS, 2024), regional infrastructure data (Ministry of Industry and Technology of Türkiye, 2025), and opinions from logistics and planning managers. Some company-specific operational parameters are reported in aggregated or rounded form to preserve data confidentiality. The data used was selected as operationally relevant and appropriately related to the Turkish pharmaceutical distribution network's operational context (TurkStat, 2025b).

1 Organization for Economic Co-operation and Development.

7.1 Distribution network structure and assumptions

Based on information obtained from logistics and planning managers of company, structure of drug distribution network is modeled with following assumptions:

- Network includes one central distribution center located in Istanbul, and its capacity is defined according to total national drug distribution volume (p = 1).
- Possibility of locating 20 potential local distribution centers in selected provinces of Turkey is considered (m = 1,…,20).
- Market demand is modeled as 20 main demand zones representing major consumption clusters including hospitals, chain pharmacies, and healthcare centers (d = 1,…,20). The empirical case study uses an aggregated 20-zone demand representation. The larger instances reported later are separately generated benchmark problems used only for scalability testing of the algorithms.
- Entire drug transportation process in network is carried out using standard refrigerated fleet that is strategically owned by company.
- Initial drug inventory at the beginning of the planning period is assumed to be zero in all centers, and no inventory is held at the end of the period. Inventory holding is retained in the mathematical formulation for completeness; however, under the assumptions of this case study, the associated holding cost is negligible and therefore has no meaningful impact on the final solution.

See Figure 4 for the topology of the network in the Turkish case study. The location of the central hub, the candidate regional distribution centers and the distances between them and the demand points have been determined according to the structure and the features of the region. Thus, the geographical features of the network are included in the optimization process in order to obtain more realistic solutions for the network structure and to evaluate the effects of alternative topologies. Figure 4 shows the spatial distribution of the central hub (P), candidate regional distribution centers (M), and aggregated healthcare demand zones (D) within the Turkish case setting.

To provide a clearer representation of the decision structure of the proposed model, the conceptual configuration of the pharmaceutical distribution network is illustrated in Figure 5.

In Table 7, fixed costs of establishing candidate regional distribution centers are estimated based on regional industrial land prices, availability of infrastructures, labor costs, and access to logistics in main provinces of Turkey. All costs are stated in million US dollars and they show relative differences between locations, not exact value of investment.

Table 8 shows demand zones, which represent areas of healthcare service consumption distributed across Turkey. Annual demand values are estimated based on historical distribution records of essential medical products and they reflect relative regional consumption patterns, not exact demand at patient level.

Table 9 presents regional unemployment rates, which are used as a proxy for social sustainability objective in the model. Values related to labor market indicators at provincial level for year 2025

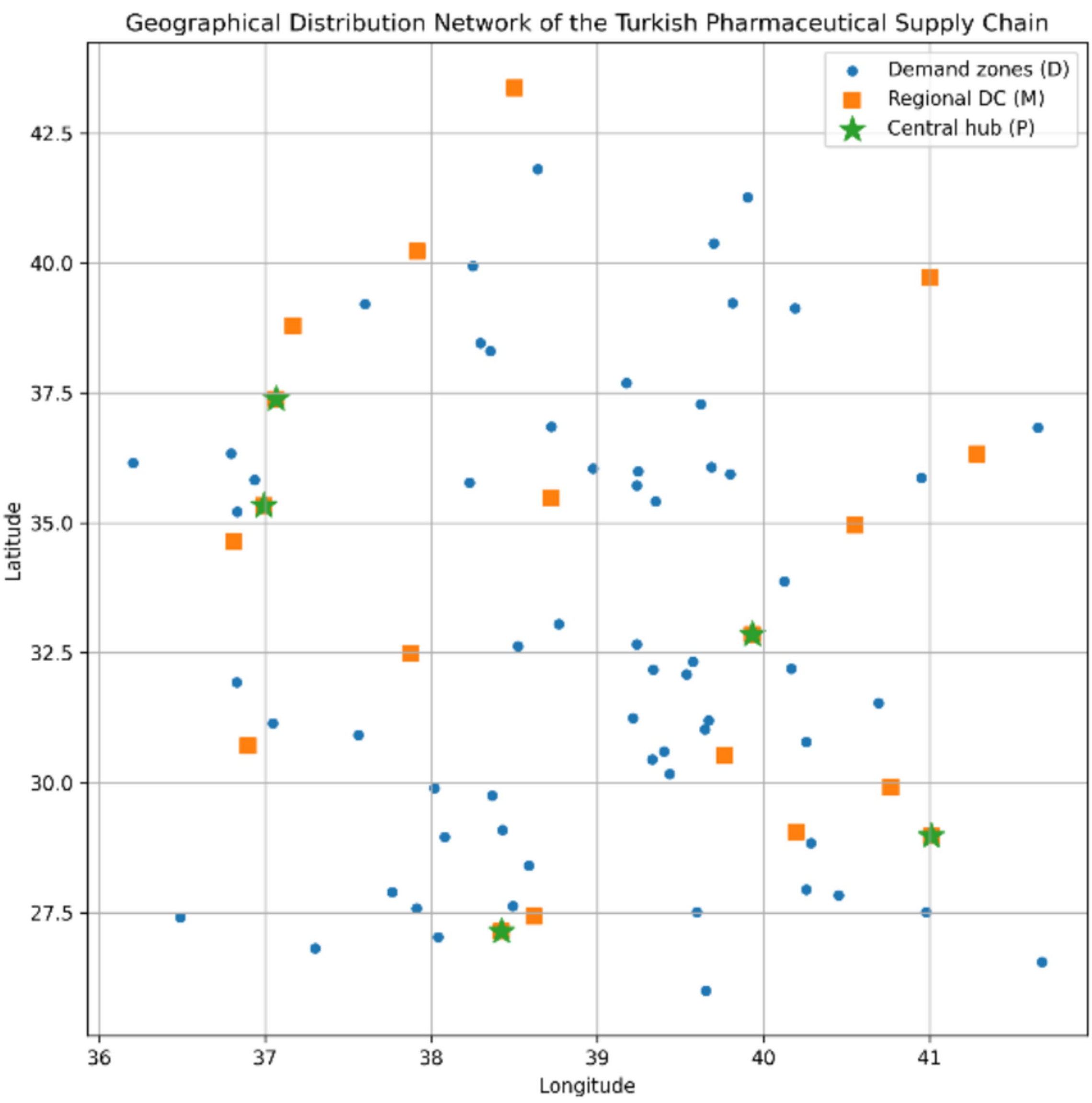

FIGURE 4
Geographical representation of the Turkish pharmaceutical distribution network used in the case study.

are reported and they are considered for prioritizing establishment of regional distribution centers in areas with relatively higher unemployment levels. Regional unemployment rates are obtained from official statistics reported by TurkStat and they are related to labor market indicators at province level for year 2025 (TurkStat, 2025a).

Table 10 shows required labor values, which indicate estimated number of full time employees needed to operate each candidate regional distribution center under standard operational conditions. These estimations are extracted from expert evaluations of warehouse capacity, handling intensity, and regional logistics practices in Turkey, and they are used to quantify social sustainability objective of model. Data used in case study are obtained from combination of official statistics, industry reports, and expert assessments. Fixed costs of establishing candidate regional distribution centers are estimated based on regional industrial land prices, availability of infrastructures, and logistics development indicators reported in national and sectoral studies. The annual demand values for the healthcare demand zones are obtained from the cumulative historical probability distribution of the medical products. The regional unemployment rates that will be used in the social sustainability dimension of the model are obtained from the provincial labor force data published by TurkStat for the year 2025. The labor needs of the regional distribution centers are obtained from the expert surveys and benchmarked with the warehouse labor practices obtained from the logistics and labor market studies. The road distances between the facilities are calculated using the Google Maps road network data. The greenhouse gas emission factors of freight transport used in the model are obtained from well-known international databases and literature such as OECD reports.

7.2 Economic, social, and demand data

Data on the fixed cost of opening local distribution centers, annual demand levels in consumption zones, provincial unemployment rates, and the number of jobs generated at each center were obtained from official sources in Turkey and from managerial estimates provided by the company. These data are presented in Tables 7–10, respectively. Table 7 reports the fixed costs of establishing local distribution centers across different provinces of Turkey, which vary

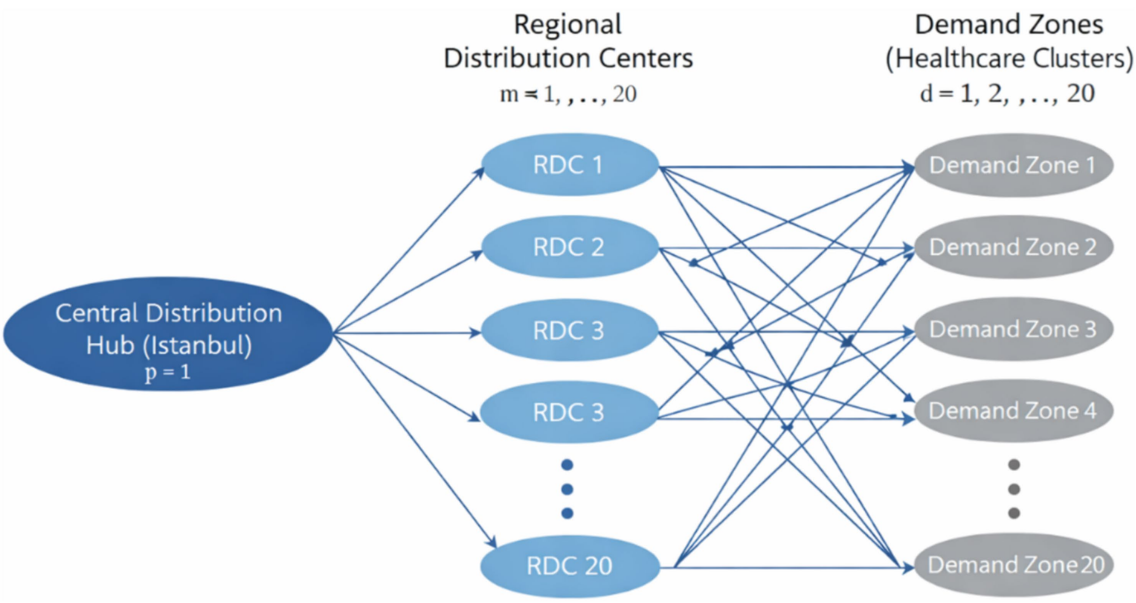

FIGURE 5
Schematic representation of the pharmaceutical distribution network, comprising a central distribution hub, multiple regional distribution centers, and aggregated demand zones.

TABLE 7 Fixed establishment costs of candidate regional distribution centers (USD million).

Regional distribution center	Fixed establishment cost (USD million)	Regional distribution center	Fixed establishment cost (USD million)
Istanbul–1	60	Istanbul–2	48
Izmir	66	Ankara	35
Bursa	15	Kocaeli	17
Antalya	27	Adana	19
Konya	16	Gaziantep	17
Mersin	4	Samsun	15
Kayseri	20	Eskisehir	11
Manisa	43	Corum	11

Source: Compiled based on sectoral reports (IEIS, 2024), regional infrastructure data (Ministry of Industry and Technology of Türkiye, 2025), and company planning assumptions for candidate regional distribution centers.

according to land cost, labor cost, and the logistics infrastructure of each region. Table 8 presents the annual demand of each pharmaceutical consumption zone based on the number of registered orders during the year. Table 9 shows the unemployment rates of the selected provinces, used in the model as a social indicator. Table 10 reports the number of personnel required to operate each local distribution center.

7.3 Transportation and logistics characteristics

Each packaging unit contains 14 medicine packs, and each carton includes 28 packs. A pallet is assumed to contain 150 cartons, while the average weight of each carton is taken as 3 kilograms. Transportation cost per kilometer includes fuel cost, driver wage, vehicle depreciation, and maintenance costs, which are estimated based on data from transportation companies active in Turkey.

For transferring medicines from central distribution center in Istanbul to local distribution centers, refrigerated trucks with capacity of 10 tons are used. Final distribution from local centers to demand zones is performed by smaller trucks with capacity of 6 tons. Geographic distances between centers are calculated using data from digital routing systems.

7.4 Environmental and social considerations

Carbon dioxide emission coefficients related to transportation fleet are extracted based on environmental standards of heavy vehicles in Turkey and international guidelines. These coefficients are considered separately in model for trucks used on central–local routes and local–demand zone routes. Also, data related to provincial unemployment rates are extracted from official statistical databases of Turkey and used as input for social objective function.

TABLE 8 Annual demand of healthcare demand zones in the Turkish case study (units per year).

Demand zone	Annual demand (units/ year)	Demand zone	Annual demand (units/ year)
Demand Zone 1	7,400	Demand Zone 11	12,910
Demand zone 2	9,020	Demand zone 12	5,355
Demand zone 3	4,817	Demand zone 13	7,641
Demand zone 4	4,775	Demand zone 14	3,910
Demand zone 5	15,328	Demand zone 15	1,152
Demand zone 6	10,480	Demand zone 16	7,794
Demand zone 7	10,140	Demand zone 17	7,284
Demand zone 8	14,052	Demand zone 18	6,484
Demand zone 9	14,397	Demand zone 19	7,734
Demand zone 10	5,822	Demand zone 20	2,510

Compiled from aggregated historical distribution records of essential medical products obtained from the focal company.

8 Computational experiments and results

8.1 Performance evaluation indices for parameter tuning

To compare and evaluate results of experiments, normalized performance indices are used in this research. These indices allow simultaneous evaluation of sustainability, solution quality, and search efficiency.

9 Number of Pareto solutions (NOS)

This index shows number of non dominated solutions extracted by algorithm and indicates ability of algorithm in covering Pareto front space.

10 Mean ideal distance (MID)

The MID index is calculated using Equation 15:

$$MID = \frac{1}{n}\sum\nolimits_{so=1}^{n}\left(\sqrt{\sum_{g=1}^{3} f_{so,g}^{2}}\right) \tag{15}$$

where $f_{so,g}$ is value of objective function g for non dominated solution *so*, and n is total number of non dominated solutions.

11 Spacing (s)

The spacing metric used to evaluate the diversity of Pareto solutions is calculated using Equation 16, Where, the auxiliary distance terms used in the spacing metric are defined in Equation 17.

$$S = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(dd_i - \bar{d}d\right)^2} \tag{16}$$

$$dd_i = \min_{k\in N_k}\sqrt{\sum_{m=1}^{3}|f_{im} - f_{km}|^2}, \bar{d}d = \frac{1}{n}\sum_{i=1}^{n} dd_i \tag{17}$$

12 Algorithm running time (time)

This index shows execution time of algorithm until stopping condition is reached and is considered as main criterion for computational efficiency.

12.1 Determination of best parameter combination

To determine optimal parameter levels, first value of relative percentage deviation (RPD) index is calculated. This index is defined as percentage difference of solution of each algorithm compared to best obtained solution. The RPD is computed according to Equation 18:

$$RPD = \frac{TC_{Alg} - TC_{best}}{TC_{best}} \times 100 \tag{18}$$

12.2 Signal to noise ratio (S/N) in Taguchi

The signal-to-noise ratio for the smaller-is-better criterion is calculated using Equation 19:

$$\frac{S}{N} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} TC_i^2\right) \tag{19}$$

where TC_i is objective function value or cost measure in experiment i, and n is total number of experiments.

12.3 Statistical comparison of performance of two algorithms

To select final suitable algorithm for solving proposed model, performance of NSGA-II and MOPSO algorithms is compared based on performance indices including MID, NOS, S, and Time. All computations, implementation, and execution of algorithms are carried out in MATLAB R2023a environment. The statistical comparison between the two algorithms is formulated using the hypotheses presented in Equation 20.

TABLE 9 Regional unemployment rates associated with candidate distribution centers in Turkey (2025).

Regional distribution center	Unemployment rate (%)	Regional distribution center	Unemployment rate (%)
Istanbul–1	13.3	Istanbul–2	13.3
Izmir	7.5	Ankara	11.8
Bursa	9.9	Kocaeli	8.0
Antalya	12.6	Adana	13.6
Konya	10.8	Gaziantep	12.8
Mersin	11.2	Samsun	11.9
Kayseri	12.5	Eskisehir	11.4
Manisa	17.4	Corum	11.4
Diyarbakir	20.3	Van	14.9

Turkish Statistical Institute (TurkStat), provincial labor force statistics for 2025 (TurkStat, 2025a).

TABLE 10 Required workforce for candidate regional distribution centers in the Turkish case study.

Regional distribution center	Required workforce (persons)	Regional distribution center	Required workforce (persons)
Istanbul–1	90	Istanbul–2	80
Izmir	30	Ankara	50
Bursa	10	Kocaeli	30
Antalya	50	Adana	50
Konya	40	Gaziantep	30
Mersin	60	Samsun	30
Kayseri	30	Eskisehir	30
Manisa	30	Corum	30
Diyarbakir	30	Van	30

Compiled from expert consultation with logistics and planning managers, warehouse capacity assessments, and regional logistics practice benchmarks used in the case study.

$$\begin{cases} H_0 : \mu_{NSGA-II}(A) = \mu_{MOPSO}(A) \\ H_1 : \mu_{NSGA-II}(A) \neq \mu_{MOPSO}(A) \end{cases} \tag{20}$$

In this framework, $\mu_{NSGA-II}(A)$ and $\mu_{MOPSO}(A)$represent mean value of performance index A for NSGA-II and MOPSO algorithms, respectively. Based on this, algorithm that shows better mean performance over set of indices is introduced as superior solution method. Since NSGA-II and MOPSO are approximate multi-objective metaheuristic algorithms, they cannot guarantee globally optimal solutions for large-scale instances of the proposed NP-hard model. Therefore, their suitability in this study is evaluated through exact MILP benchmarking on small-scale instances and through convergence and comparative performance analyses on larger instances.

12.4 Small-scale validation (MILP vs. algorithms)

To evaluate the performance and solution quality of the proposed metaheuristic algorithms, a set of 10 small-scale validation instances was generated. These instances were intentionally designed with relatively small network sizes so that the corresponding MILP formulation of the proposed model could be solved to optimality. The exact solutions were obtained using the Gurobi 10.0 MILP solver integrated within the MATLAB R2023a environment. This enables a direct comparison between the exact optimal solutions obtained from the mathematical programming model and those generated by the NSGA-II and MOPSO algorithms.

The validation instances were constructed using the same parameter ranges as those adopted in the main case study, thereby ensuring consistency between the validation experiments and the real application setting of the distribution network design problem. Since the MILP solver produces a single optimal solution for a weighted objective formulation, the economic objective $f_1$is used as the benchmark indicator for evaluating the solution quality of the metaheuristic algorithms. To measure the deviation of the metaheuristic results from the exact optimal solution, the optimality gap between the metaheuristic solution and the exact MILP solution is calculated using Equation 21:

$$Gap(\%) = \frac{f_1^{meta} - f_1^{MILP}}{f_1^{MILP}} \times 100 \tag{21}$$

.

where

- f_1^{meta}represents the economic objective value obtained by the metaheuristic algorithm, and
- f_1^{MILP} denotes the exact optimal objective value obtained by solving the MILP model using Gurobi 10.0 in MATLAB R2023a.

All reported gap values are non-negative, since the MILP solution represents the exact global optimum for each validation instance. All computational experiments were performed on a system equipped with an Intel Core i7 processor and 16 GB RAM, running MATLAB R2023a.

12.5 Analysis of results

The results presented in Table 11 indicate that both metaheuristic algorithms generate solutions extremely close to the exact MILP optimal solutions across all validation instances. The average optimality gaps are 0.25% for NSGA-II and 0.09% for MOPSO, confirming the effectiveness and reliability of the proposed solution procedures for small-scale validation instances. Furthermore, the results show that

TABLE 11 Performance comparison of the proposed metaheuristic algorithms against exact MILP solutions for small-scale validation instances.

Instance	Size (P, M, D)	MILP Optimal (f1)	NSGA-II (Best)	MOPSO (Best)	Gap NSGA-II (%)	Gap MOPSO (%)	CPU Time (s)
V1	(2, 3, 5)	1,240,500	1,240,500	1,240,500	0.00	0.00	8.4
V2	(2, 4, 8)	1,580,200	1,580,950	1,580,210	0.05	0.01	12.1
V3	(3, 5, 10)	1,920,000	1,921,800	1,920,400	0.09	0.02	16.5
V4	(3, 6, 12)	2,350,600	2,353,400	2,351,100	0.12	0.02	22.8
V5	(4, 7, 15)	2,890,000	2,895,200	2,891,500	0.18	0.05	29.4
V6	(4, 8, 18)	3,120,400	3,127,900	3,122,800	0.24	0.08	35.1
V7	(5, 9, 20)	3,560,000	3,571,400	3,564,300	0.32	0.12	41.7
V8	(5, 10, 22)	3,980,500	3,995,600	3,986,500	0.38	0.15	48.2
V9	(5, 10, 25)	4,250,000	4,269,100	4,258,500	0.45	0.20	56.9
V10	(6,12, 30)	4,680,200	4,705,900	4,692,100	0.55	0.25	69.3
Avg.					**0.25%**	**0.09%**	

MOPSO slightly outperforms NSGA-II in terms of solution quality, achieving a smaller average optimality gap. However, both algorithms consistently produce solutions very close to the optimal benchmark. These findings confirm the effectiveness, reliability, and accuracy of the proposed metaheuristic approaches for solving the multi-objective sustainable distribution network design problem, particularly for cases where exact optimization becomes computationally expensive.

12.6 Large-scale computational analysis

To further evaluate the scalability and robustness of the proposed metaheuristic algorithms, fifteen large-scale test instances (L1–L15) were generated based on the Turkish pharmaceutical distribution network dataset used in the case study. Each instance was constructed by progressively increasing the number of demand zones selected from the national distribution network of Turkey. The problem size therefore increases from medium-scale instances including 40 demand nodes to generated large-scale benchmark instances including up to 81 demand points for scalability analysis. The input parameters for these instances are derived directly from the empirical dataset used in the case study. This dataset includes the geographic coordinates of facilities, transportation distance matrices between nodes, candidate regional distribution centers, facility capacities, and regional demand data. Transportation distances are computed using road-network distance matrices based on the geographic coordinates of provinces and distribution centers. Transportation cost and emission parameters are estimated through calibrated logistics cost and emission models. When the distribution network becomes larger, the computational complexity of the exact MILP solution approaches increases exponentially because of the combinatorial characteristics of the MILP formulation. In contrast, the metaheuristic algorithms such as NSGA-II and MOPSO can maintain the computational efficiency while producing the high-quality solution. The computational results for the generated large-scale instances are summarized in Table 12.

The results show that both algorithms can solve large-scale instances of the distribution network design problem within computational times that are practical for use. As the number of demand nodes is increased, it is noted that the computational time required to execute both algorithms is increasing gradually due to the complexity of the search space. However, it is also noted that the solution time is less than eight minutes when solving the problem using the L15 instance. Moreover, it is noted that MOPSO performs better than NSGA-II in terms of objective function values. This is due to the global search capability of the particle swarm optimization mechanism. This capability allows MOPSO to explore the solution space more rapidly. In contrast, NSGA-II also performs competitively and produces a set of Pareto optimal solutions due to its crowding distance-based diversity preservation mechanism. It is noted that both algorithms are scalable and can be used to solve large-scale sustainable distribution network design problems.

12.7 Convergence analysis

The convergence of the two algorithms is analyzed by performing the convergence study for the large-scale instance, i.e., the L15 instance, of the distribution network design problem. Figure 6 shows the convergence plot of the best objective function value obtained by the two algorithms during the iterative process.

The convergence trajectories also prove that both algorithms improve the objective function value over iterations. MOPSO is seen to converge more rapidly to solutions in the early stages of both optimization algorithms. This is due to its significant exploration capability. However, NSGA-II is seen to converge a little more slowly in the beginning and then continues to improve solutions with consistent convergence. Both algorithms converge to solutions of comparable quality, which proves their suitability to tackle large-scale sustainable distribution network optimization problems.

12.8 Pareto front analysis

The Pareto fronts obtained using NSGA-II and MOPSO are shown in Figure 7.

Each point represents a non-dominated solution generated by the algorithms, reflecting the trade-off between the economic objective and the environmental objective. The results indicate that both algorithms are capable of generating useful Pareto solution sets. MOPSO tends to produce slightly better objective values in several regions of the search space and a more uniform distribution of solutions, whereas NSGA-II preserves a broader

TABLE 12 Performance comparison of NSGA-II and MOPSO for large-scale instances.

Instance	Size (P, M, D)	NSGA-II Best f1	MOPSO Best f1	NSGA-II Time (s)	MOPSO Time (s)
L1	(5, 15, 40)	5,420,000	5,395,000	112	105
L2	(5, 16, 42)	5,780,000	5,750,000	120	110
L3	(5, 17, 45)	6,150,000	6,110,000	138	125
L4	(5, 18, 48)	6,780,000	6,740,000	150	135
L5	(5, 19, 50)	7,280,000	7,245,000	165	148
L6	(5, 20, 52)	7,640,000	7,600,000	175	158
L7	(5, 20, 55)	8,150,000	8,110,000	190	170
L8	(5, 20, 58)	8,520,000	8,480,000	205	185
L9	(5, 20, 60)	8,950,000	8,910,000	210	192
L10	(5, 20, 65)	9,520,000	9,480,000	235	210
L11	(5, 20, 68)	9,850,000	9,810,000	250	225
L12	(5, 20, 70)	10,120,000	10,085,000	265	235
L13	(5, 20, 73)	10,820,000	10,770,000	300	260
L14	(5, 20, 77)	11,640,000	11,580,000	360	310
L15[2]	(5, 20, 81)	12,450,000	12,380,000	450	380

[2]Instance L15 represents the largest generated benchmark instance used for scalability analysis, including 81 demand points.

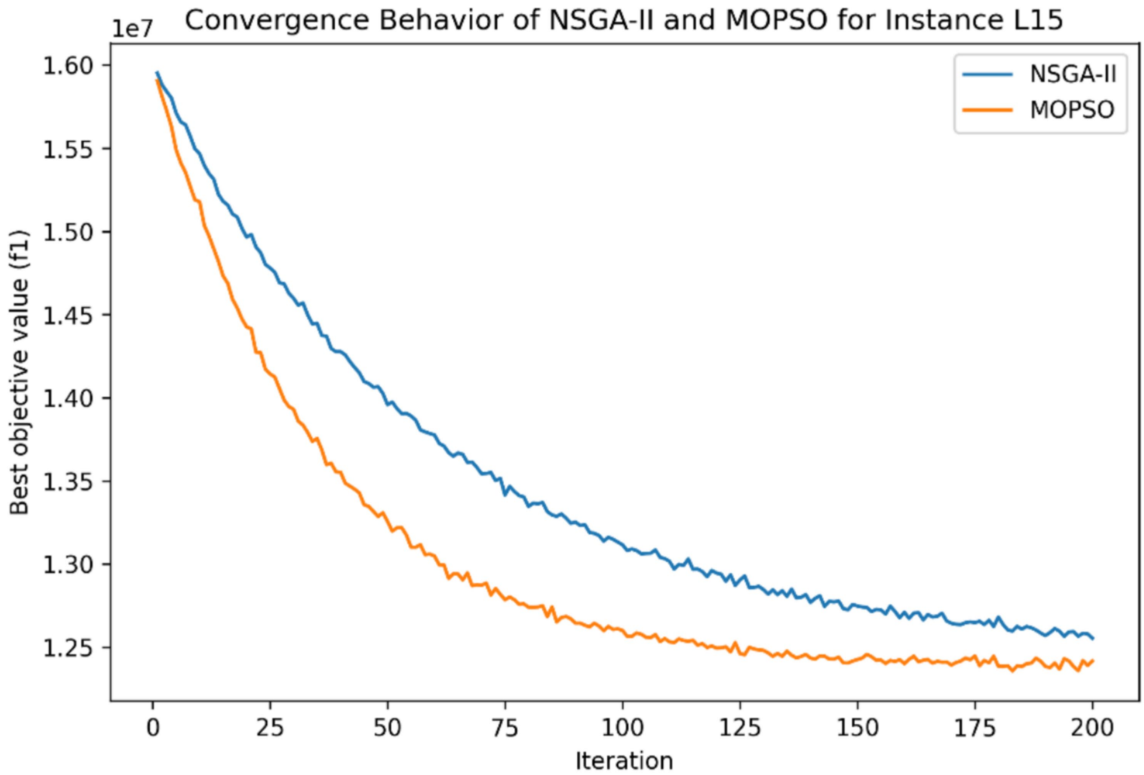

FIGURE 6
Convergence behavior of NSGA-II and MOPSO for the largest instance (L15) of the Turkish pharmaceutical distribution network.

spread of alternatives along the Pareto front due to its crowding-distance mechanism. This broader spread may provide decision makers with additional trade-off choices, although the statistical comparison later shows no significant difference between the two algorithms in terms of the number of non-dominated solutions.

13 Discussion

By inserting case study data related to essential medical product distribution network in Turkey, proposed model for network design and flow allocation is executed. Network structure includes one main distribution center located in Istanbul, a set of candidate regional

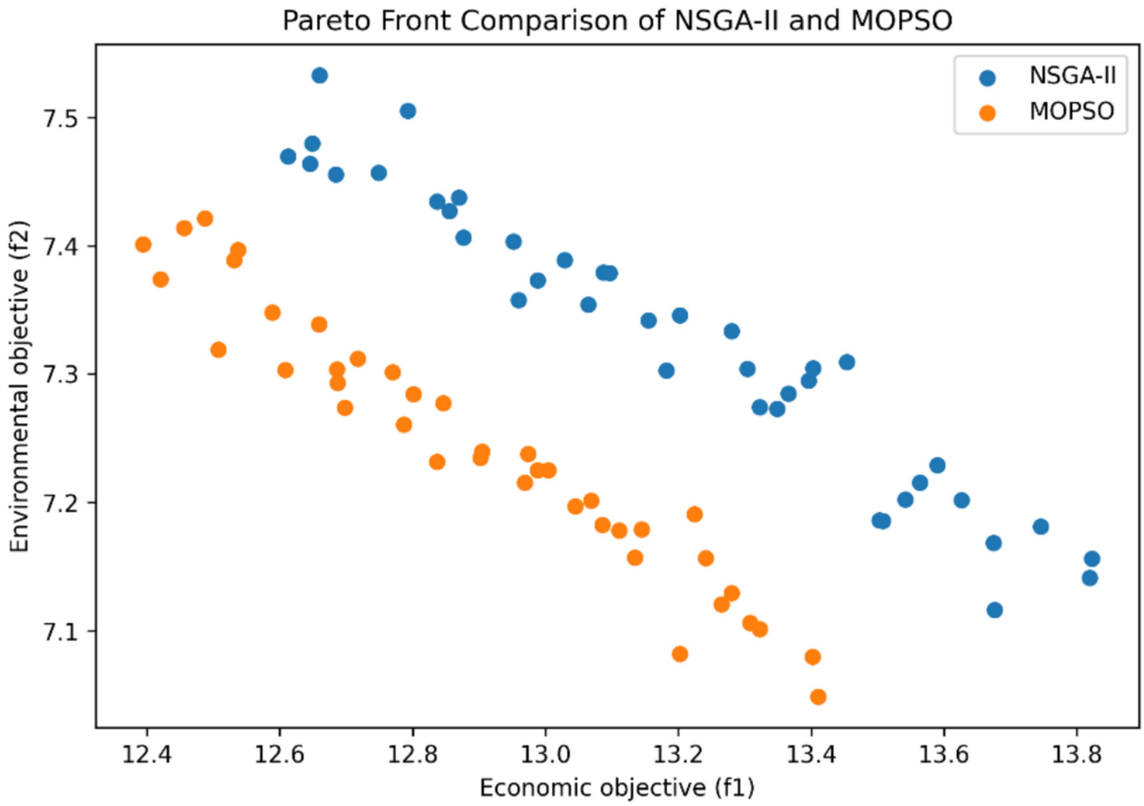

FIGURE 7
Pareto front comparison of NSGA-II and MOPSO for the sustainable pharmaceutical distribution network design problem.

distribution centers, and several healthcare demand zones, which are represented by indices $p \in \{1,\ldots,P\}$ `$m \in \{1,\ldots,M\}$ `$d \in \{1,\ldots,D\}$, respectively. Decisions related to opening distribution centers are modeled through binary variables Y_p and Z_m, and flow of medical products from main center to regional centers and then to demand zones is expressed by continuous variables X_{pm} and X_{md}. Annual demand of each zone is considered by parameter D_d, and capacity constraints of centers are included in model constraints through Cap_p and Cap_m.

In economic dimension, fixed costs of opening main and regional centers are included in objective function by parameters $F_p and\ F_m$, and transportation costs between different levels of network are represented by $c_{pm} and\ c_{md}$. Also, holding costs per unit of product at distribution centers are considered through parameters $H_p and\ H_m$. To cover environmental dimension, carbon emission coefficients caused by road transportation between main and regional centers and also between regional centers and demand zones are included in model by $e_{pm} and\ e_{md}$, respectively. Finally, social sustainability dimension is incorporated in model using regional coefficients $\omega_p and$ ω_m, which represent labor market conditions at location of centers, and employment parameters $J_p and\ J_m$, in a way that location decisions also consider areas with higher social priority.

To extract a representative and managerially interpretable solution, the multi-objective model was first converted into a single-objective form using the weighted-sum approach. Based on the opinions of experts in the field of medical product distribution in Turkey, the weights of the economic, environmental, and social objectives were set to 0.70, 0.17, and 0.13, respectively, in order to reflect decision-maker preferences in the final objective function. These weights were determined according to expert judgment with the aim of representing the practical priorities of healthcare distribution planning in Turkey. The resulting single-objective MILP model was solved exactly using Gurobi 10.0 in the MATLAB R2023a environment, and the corresponding optimal solution was used as the benchmark for further analysis. Considering problem size and increasing computational complexity in large scales, NSGA-II and MOPSO metaheuristic algorithms are used to efficiently solve multi objective model. To improve quality of Pareto front and obtain more stable solutions, control parameters of these algorithms are tuned before final execution. Parameter tuning process is performed using Taguchi design of experiments and L9 orthogonal array, so that effect of different parameter levels can be evaluated with limited number of experiments. Then, the performance of the algorithms is compared based on standard multi-objective indicators including NOS, MID, spacing metric (S), and execution time. Also, to quantitatively compare the quality of the obtained solutions, RPD from the best observed solution is reported as an additional measure. The performance of the parameter combinations was evaluated using the metrics reported in Table 13.

Based on values of mean response and S/N that are calculated in Taguchi experiment design framework, optimal levels of control parameters for each algorithm are determined separately. According to results shown in Figures 8a,b, in NSGA-II algorithm, level one for first and second parameters and level three for third parameter is selected as optimal combination.

In similar way, results related to MOPSO algorithm that are shown in Figures 9a,b show that level one for first and second parameters and level two for third parameter give best performance in terms of average performance indicators and stability of response.

For comparing the performance of the two algorithms in solving the sustainable distribution network design model for essential

TABLE 13 Performance metrics used for parameter tuning.

NSGA-II					MOPSO				
Exp.	NOS	Time (s)	MID	S	Exp.	NOS	Time (s)	MID	S
1	18	35.69	1.97945	660.15333029	1	25	16.09	1.73693	678.2967938
2	20	70.99	1.94865	463.74724549	2	37	36.58	1.72347	636.5019999
3	19	107.59	1.98119	697.64323010	3	21	41.70	1.51737	503.8350562
4	23	124.14	1.96667	555.21311105	4	15	23.48	1.25675	492.62911042
5	21	25.89	1.98043	377.78945626	5	24	48.22	1.19217	511.29893649
6	22	375.32	2.00107	550.38424008	6	21	76.93	1.72156	766.20801950
7	23	270.94	2.05257	793.66213580	7	33	48.32	1.54795	938.40250238
8	23	556.01	1.99272	754.70856364	8	25	89.16	1.72114	753.3394370
9	27	803.11	1.04515	674.87957058	9	30	137.87	1.20456	446.46848787

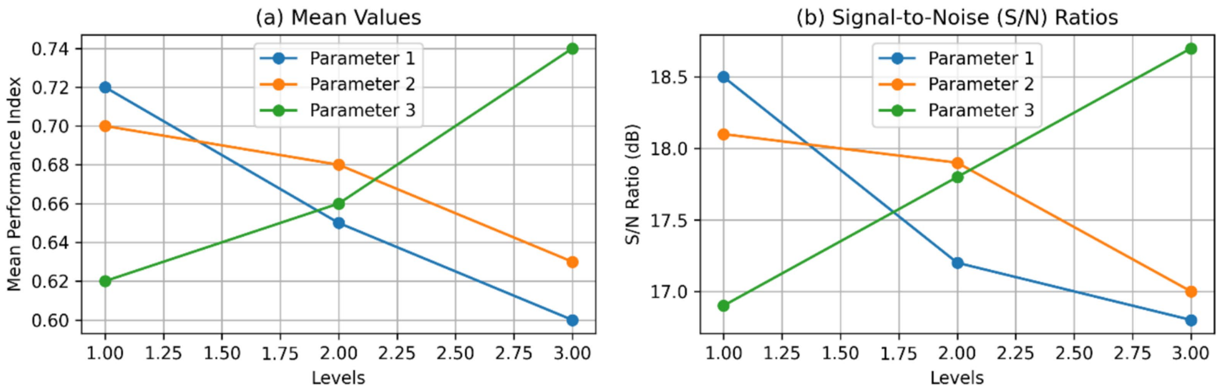

FIGURE 8
Main effects plots of the NSGA-II algorithm parameters: **(a)** Mean values of performance indices; **(b)** Signal-to-noise (S/N) ratios.

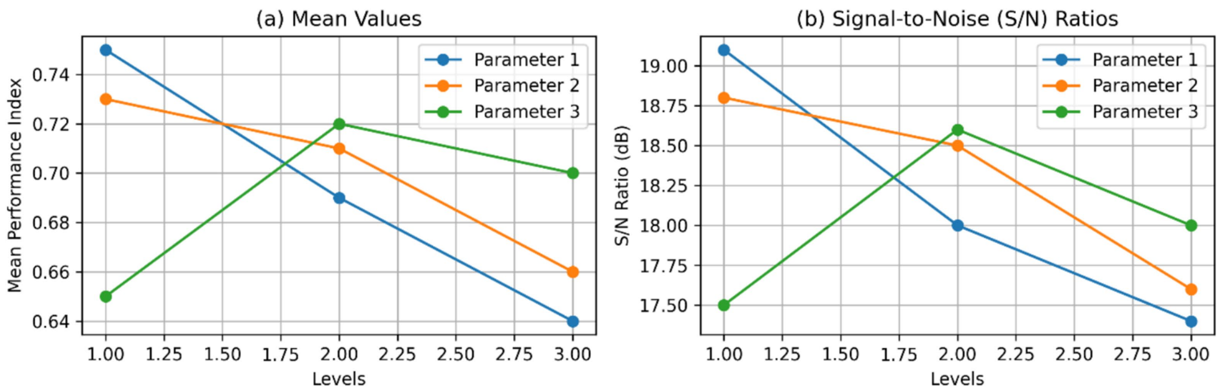

FIGURE 9
Main effects plots of the MOPSO algorithm parameters: **(a)** Mean values of performance indices; **(b)** signal-to-noise (S/N) ratios.

medical products, NSGA-II and MOPSO were each run 30 times under the extracted optimal settings. The performance indicators obtained from each run were calculated and statistically analyzed using SPSS version 20. The mean values of the performance indicators were compared between the two algorithms using independent-samples t-tests at the 95% confidence level. The results of the statistical comparison are presented in Table 14. Based on these results, MOPSO shows better overall performance than NSGA-II in terms of mean ideal distance, spacing, and computational time. In particular, MOPSO achieves faster convergence, a more uniform distribution of Pareto solutions, and a lower MID value. However, no statistically significant difference is observed between the two algorithms in terms of

TABLE 14 Statistical comparison results of NSGA-II and MOPSO algorithms.

No.	Performance indicator	Statistical test	Algorithm	Mean value	Significance level (95%)	Superior algorithm
1	MID	*t*-test	NSGA-II	2.0737E+05	0.000	MOPSO
			MOPSO	1.6500E+05		
2	NOS	*t*-test	NSGA-II	19.9667	0.299	No significant difference
			MOPSO	23.3333		
3	Spacing Metric (S)	*t*-test	NSGA-II	7.0440E+05	0.000	MOPSO
			MOPSO	4.2596E+05		
4	Computational time (Time)	*t*-test	NSGA-II	35.4809	0.000	MOPSO
			MOPSO	15.4012		

the number of non-dominated solutions. These findings indicate that MOPSO is the more efficient solution method for the proposed national-scale sustainable distribution network design problem, while NSGA-II still provides a broader spread of alternative Pareto solutions.

The designed model for selection and configuration of sustainable distribution network in this study was implemented using MOPSO algorithm. After applying optimal tuning of algorithm parameters, a set of non dominated solutions is obtained which is shown in Figure 10. Points marked in this figure represent optimal and selectable options in objective space. This set of solutions makes possible choosing final solution based on preferences of decision makers.

The output of distribution network design model includes selection of local distribution centers, amount of product flow sent from upstream centers to intermediate centers, and also allocation level of flow from intermediate centers to demand points. The distribution flow patterns obtained from the optimization results are illustrated in Figure 11.

The results show that MOPSO performs better than NSGA-II in terms of MID, uniformity of Pareto solution distribution, and computational time. However, no meaningful difference is observed between the two algorithms with respect to the number of non-dominated solutions. These findings confirm the higher computational efficiency of MOPSO for solving the distribution network design problem at large scales.

Based on these results, it can be concluded that MOPSO algorithm, by creating suitable balance between solution quality, result stability and computational cost, is more suitable option for solving proposed sustainable distribution network design model in this research.

Table 15 compares the best solution obtained by MOPSO with the benchmark solution derived from the weighted sum method in terms of the economic, environmental, and social objective values.

As shown in Table 15, the comparison between the best MOPSO solution and the weighted sum benchmark reveals a clear trade-off among the three sustainability objectives. The MOPSO solution achieves better values for the economic and environmental objectives, indicating lower total system cost and reduced environmental impact. However, the weighted sum solution performs better in terms of the social objective. Therefore, Table 15 should not be interpreted as evidence of absolute superiority of one method over the other; rather, it demonstrates that different solution methods may favor different sustainability dimensions depending on the decision-making priorities.

So far, large part of studies done in medical product supply chain area have mainly focused on topics like performance evaluation, supplier selection, or managerial type analysis, and less attention is given to design of distribution network structure and location–flow decisions at operational scale. Especially in many of these works, sustainability dimensions are considered only in limited or single way, and simultaneous interaction between economic, environmental, and social objectives is not much studied. Also, use of multi objective optimization models together with advanced metaheuristic algorithms for solving real large scale problems is still facing research gap.

In this study, a multi-objective planning model for sustainable distribution network design is developed for the national essential medical product distribution network of Turkey, with Istanbul functioning as the primary central hub. This model considers three main sustainability dimensions, including economic costs, environmental impacts from transportation, and social considerations related to employment and fair access, in an integrated way inside decision structure.

Due to NP-hard nature of distribution network design problem and increasing computational complexity in real dimensions, solving model by classical exact methods is not possible, therefore multi objective metaheuristic algorithms NSGA-II and MOPSO are selected as main solution tools. Obtained results show that these algorithms have high ability in extracting quality Pareto fronts, keeping diversity of solutions, and reaching efficient solutions in reasonable computation time. In this way, proposed framework can be used as practical decision support tool for sustainable distribution planning of medical products in real and large scale conditions.

To further interpret the network structure, the annual shipment allocation from the central distribution hub to candidate local distribution centers is examined. Figure 11 shows the annual outbound flow of essential medical products from the central hub to each candidate local distribution center in the Turkish case study. It can be observed that the shipment volume has non-uniform distribution among the centers, and there are considerable differences among the candidate centers. The heterogeneity in this case arises from the diverse nature of the demands imposed upon the centers by the regions in which they are located, the location of the centers relative to these demands, and the constraints imposed by center capacity.

The results show that there are some candidate local distribution centers that are handling a larger portion of the hub's outbound shipments and are more important in the network, while others are

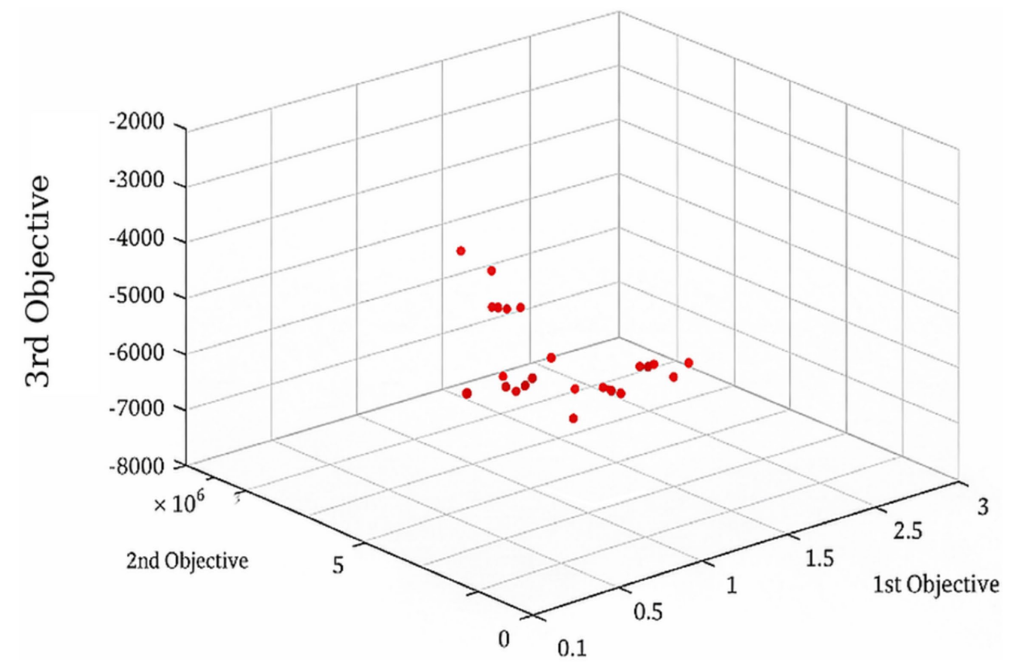

FIGURE 10
Three-dimensional Pareto front obtained using the MOPSO algorithm, illustrating the trade-offs among the objective functions.

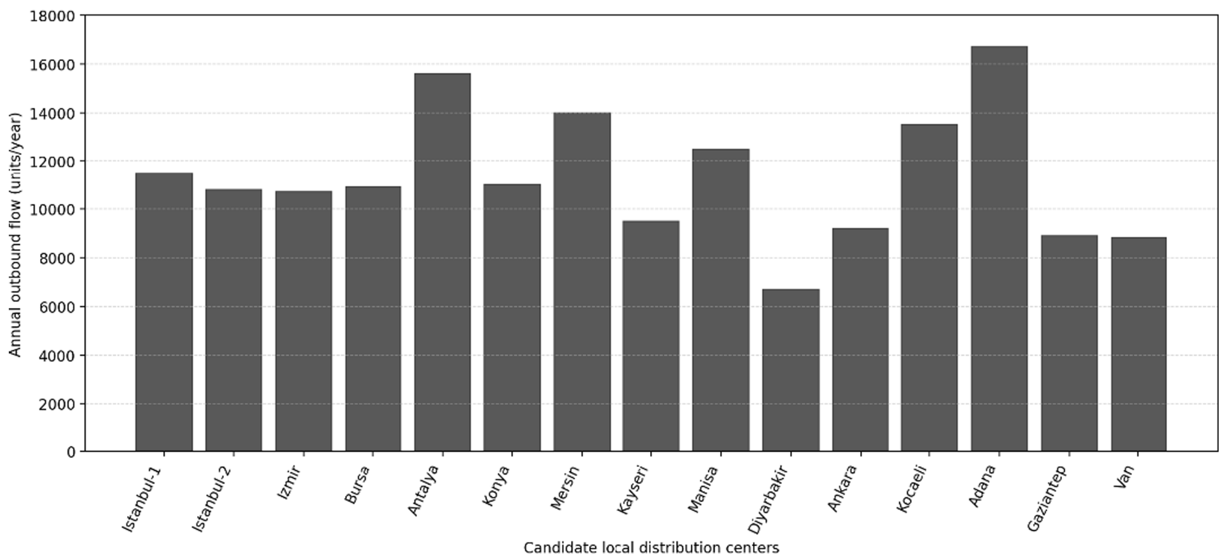

FIGURE 11
Annual outbound flow from the central distribution hub to each candidate local distribution center in the Turkey case study.

auxiliary centers with fewer assigned volumes. This allocation pattern is a direct outcome of the integrated location–flow decisions of the model and demonstrates the ability of the proposed framework to adapt the upstream distribution structure to real demand conditions and operational constraints.

14 Conclusion

Distribution networks of essential medical products, as one of critical parts of health system, need designs that can cover economic efficiency, environmental concerns, and social effects at same time. In this research, by focusing on the Turkish healthcare distribution context, a multi objective optimization model for design of essential medical product distribution network is developed, which considers strategic decisions of distribution center location and tactical decisions of product flow allocation in an integrated way.

Numerical and comparative results obtained from solving the model, as reported in Tables 11, 12, 14, 15, indicate that the proposed network structure is able to improve the economic, environmental, and social performance of the system simultaneously. The analysis of the objective function values shows that the optimal selection of local

TABLE 15 Comparison of the best solutions obtained by MOPSO and the weighted sum method.

Algorithm	Economic objective value (f_1) (USD)	Environmental objective value (f_2)	Social objective value (f_3)
Weighted Sum Method	302,900,000,000	8,856,100	10,029
MOPSO	155,200,000,000	5,540,000	6,569

distribution centers and the allocation of product flows between these centers and demand zones play a decisive role in reducing total system cost, lowering transportation-related environmental impacts, and improving social indicators associated with regional distribution. These findings confirm that jointly considering the three dimensions of sustainability can lead to more balanced network-level decisions than approaches based on a single performance dimension.

Because of the computational complexity of the model and the NP-hard nature of the network design problem, two multi-objective metaheuristic algorithms, NSGA-II and MOPSO, were used to generate sets of non-dominated solutions. Their performance was evaluated using standard quantitative indicators, namely NOS, MID, spacing metric (S), and running time. The results show that both algorithms are able to produce valid and acceptable Pareto fronts. However, MOPSO outperforms NSGA-II in most cases, as confirmed by the lower value of MID, a more uniform distribution of points on the Pareto front, and lower computational time required to run the algorithm. Conversely, no significant differences between the two metaheuristics were found in terms of NOS. This implies that MOPSO is a more efficient approach to solve the suggested model, while NSGA-II is also effective in maintaining a wide range of alternative Pareto front solutions.

Parameter tuning of algorithms using the Taguchi method for the design of experiments has traditionally been of pivotal importance for performance improvement. More particularly, the identification of the right parameter levels results in the improvement of the quality of the solution and the reduction of the variability in the performance of the algorithm for multiple runs. The results have shown that the combination of the design of experiments and the metaheuristic algorithms can be an effective solution for solving complex distribution network problems involving multiple objectives.

From a practical point of view, the findings of this study quantitatively prove that the proposed model is an efficient decision support tool for managing essential medical product supply chain operations. The ability of the model to assess quantitatively the effects of decisions on costs, environmental performance, and social performance simultaneously makes it applicable to decision situations under practical conditions, especially for countries like Turkey that experience geographical diversity and disparities in healthcare services.

Finally, while in this study we considered certain parameters deterministic and used a single-period planning horizon, future studies can be extended to multiple period, multiple product, and uncertain models. Moreover, a quantitative assessment of the model's performance over various types of networks and comparison with other advanced multiple objective algorithms would add more strength to the study.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

MS: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. KY: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. SD: Data curation, Formal analysis, Investigation, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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