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Highlights

Optimizing Vaccination Facility Locations and Capacity as a Pandemic Response: A Case Study of Mashhad, Iran

- A multi-step approach to identify vaccine facility locations is introduced.
- The underlying location-allocation model covers strategic and tactical needs.
- The model combines set covering and p-center models for fair vaccine delivery.
- An enhanced bi-objective Genetic Algorithm is used to solve the model.
- The methodology is validated on a real-world case study in Mashhad, Iran.

Optimizing Vaccination Facility Locations and Capacity as a Pandemic Response: A Case Study of Mashhad, Iran

Abstract

Strategic and tactical issues must be considered when determining the location of facilities for service provision during healthcare crises. This paper introduces a systematic multi-step approach for selecting the location of immunization centers and warehouses for medical supplies during a pandemic. Initially, the relevant strategic criteria encompassing infrastructure, environmental, and socio-demographic dimensions are identified from the literature. Expert opinions are then solicited through the Best-Worst Method to assess the importance of each criterion. In the third step, a Geographic Information System is employed to identify potential locations and their strategic cost based on these criteria. Finally, a Two-Echelon Capacitated Location Allocation Problem (2E-CLAP), integrating fairness and capacity considerations, is formulated to select optimal sites based on strategic costs utilizing the principles of the classic p-center and set covering problems. The model is solved using an enhanced multi-objective Genetic Algorithm. The methodology is validated through a case study to identify the location of vaccination facilities in Mashhad, Iran. The findings underscore the capability of the proposed approach to alleviate patient congestion at vaccination centers while concurrently optimizing the strategic criteria and ensuring comprehensive coverage for all city residents.

Keywords: Healthcare facility location, Pandemic response planning, COVID19, Geographical Information System (GIS), Multi-objective Genetic Algorithm

1. Introduction

Strategic and tactical considerations are crucial in determining the location of healthcare facilities in both normal and crisis situations (Gul and Guneri, 2021; Hoadley et al., 2010; Grot, 2024). Strategic considerations focus on the long-term impacts of decisions, such as addressing socio-demographic factors to ensure equitable access to healthcare services and minimizing environmental impacts through sustainable practices. Tactical concerns address medium-term priorities like capacity planning and meeting community health needs. Sound decision-making at both strategic and tactical levels is crucial to designing resilient and flexible health systems and to ensuring the efficiency of subsequent operational decisions, including resource management, patient flow, and staff deployment. This is especially important under crisis conditions, where service efficiency, accessibility, and response speed are critical.

Several studies highlight the significance of strategic factors in healthcare facility location problems (FLPs). For instance, Ray et al. (2015) found that overlooking socio-demographic factors can lead to disparities in healthcare access, thereby delaying treatment for specific populations. Yilmaz and Ulubaş Hamurcu (2022) demonstrated that gender, household size, and population density significantly influence COVID-19 exposure, thus affecting service provision decisions. Silva et al. (2023) highlighted the importance of incorporating environmental considerations into healthcare practices to safeguard public health and the environment. The presence of a reliable infrastructure is another crucial factor when locating health facilities, as it ensures consistent access to care and supports essential operations (Luxon, 2015). For instance, good transportation networks enable patients and healthcare workers to reach facilities efficiently, while reliable electricity is vital to power medical equipment and store vaccines at safe temperatures. These considerations are particularly critical in developing countries, where transport and electricity infrastructure are often substandard and vulnerable to disruptions (Chen et al., 2019; Shishebori and Yousefi Babadi, 2015).

Key tactical considerations include patient coverage, capacity planning, and medical supply distribution. Managing patient density and overcrowding at health service centers is also essential to reduce infectious disease transmission during healthcare crises. Ensuring full coverage for all service users requires establishing health facilities that are easily accessible by all populations to increase service uptake and reduce vaccination hesitancy (Essoh et al., 2023).

However, opening many widely accessible and adequately staffed centers may increase costs as more locations demand higher investments. Effective planning requires balancing costs and accessibility while also calibrating facility capacities to avoid overcrowding and maintain service quality.

Optimal warehouse placement for critical supplies, such as vaccines, is also crucial to provide an effective and reliable service, with closer proximity between warehouses and service centers mitigating risks like delivery delays and supply exposure to spoilage. This is especially important in low and middle-income countries where logistical challenges, including urban traffic congestion, vehicle breakdowns, and security threats, further complicate delivery. The proximity of warehouses to service centers is also vital for quickly adjusting to demand fluctuations (Dey et al., 2024), as nearby warehouses can respond promptly to unexpected spikes in demand, reducing the risk of stockouts. Additionally, certain supplies, like vaccines, require refrigeration, which may not be available at vaccine centers or on the vehicles used for delivery, making quick delivery essential to avoid spoilage and maintain supply effectiveness. Overall, reducing transport distances enhances efficient and timely distribution, minimizes supply chain disruptions, and ensures more reliable access to critical supplies during emergencies (Fahrni et al., 2022).

To address these challenges, we propose a multi-step approach for selecting the location of health service centers and warehouses during health crises, which makes the following contributions to the FLP literature:

- At the strategic level, our approach advances the literature on location-selection problems by integrating Geographical Information Systems (GIS) and Multi-Attribute Decision-Making (MADM) methodologies. Building on Eastman's foundational work (Eastman, 1999), scholars like Erdin and Akbaş (2019) have used GIS-MADM to optimize commercial and residential location selection by combining spatial data with non-spatial data. Our study uses the MADM method to categorize the strategic criteria into infrastructure, environmental, and socio-demographic factors. Then, we use GIS to cluster potential service provider centers. This clustering of potential facilities adds to the GIS-MADM application in the location-selection stream as it facilitates connecting strategic-level concerns to tactical-level decisions.
- Based on the GIS outputs, we propose a Two-Echelon Capacitated Location Allocation Problem (2E-CLAP) that incorporates strategic criteria for locating service centers while ensuring comprehensive accessibility and optimizing warehouse locations for the efficient and reliable distribution of critical supplies. Specifically, a set covering model structure (SCM) (Toregas et al., 1971) ensures that each demand point is served by at least one service center within a specified distance. We also include vaccination center capacity utilization as a decision variable to reduce patient density at vaccination centers as a tool to contain transmission. For the location of warehouses, we use the p-center principle to minimize the maximum distance between warehouses and service provider centers (Hakimi, 1965). This ensures that all service centers can receive prompt (possibly daily) deliveries from the warehouses, thus addressing issues related to stock level reliability and equity in supply distribution during crises. It also ensures that subsequent operational distribution decisions can be made efficiently, relying on a robust underlying distribution network.

The resulting 2E-CLAP is a multi-objective, hierarchical model whose solution to optimality by commercial solvers is computationally impractical for real-world instances. We therefore propose an enhanced bi-objective Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to solve instances of realistic size efficiently. The proposed NSGA-II generates initial solutions using a greedy heuristic, followed by problem-specific perturbation and efficient repair-and-improvement operators to effectively explore the search space. The application of the proposed algorithm demonstrates its efficiency in generating high-quality approximations of the optimal Pareto front for 2E-CLAP instances. The proposed NSGA-II can identify near-optimal solutions in a modest computing time compared to an exact solver such as Gurobi. Finally, the proposed methodology is applied to a real case study to identify efficient facility configurations for vaccine distribution and administration during the COVID-19 outbreak in Mashhad, Iran.

This work is organized as follows. Section 2 presents a literature review on health facility location during epidemic outbreaks to identify the research gaps. Section 3 describes the multi-step approach proposed in this study, including the multi-objective model and associated solution algorithm. Section 4 introduces the COVID-19 pandemic case study in Mashhad, Iran, followed by a comprehensive investigation of the solutions obtained and a sensitivity analysis of some of the input variations. Finally, Section 5 discusses the conclusions of this study and provides suggestions for future research.

2. Literature Review

The literature on healthcare facility location is extensive, encompassing numerous studies that have been conducted to determine the optimal locations of emergency medical services, ambulances, and hospitals within healthcare systems (see, for example, the survey papers by [Ahmadi-Javid et al., 2017](#), [Güneş et al., 2019](#), and [Rezai and Davoodi, 2024](#)). Set covering ([Li et al., 2011](#); [Wei, 2016](#)) and p-center ([Çalık et al., 2019](#)) problems are two classic facility location problems that find wide applicability in emergency healthcare settings as they ensure that demand nodes can access healthcare services within an acceptable response time or distance, while also considering efficiency and fairness in service accessibility.

Given the abundance of studies on healthcare FLP, the present review only focuses on research related to facility location and resource allocation problems during infectious disease outbreaks, such as the COVID-19 pandemic. Most studies in this area have used selection cost, overall distance traveled by patients, and fatality rate as their primary objective functions, with demography being the main strategic factor. Other important objectives, such as minimizing patient congestion and other strategic criteria, such as the infrastructural and environmental criteria, seem to have been overlooked. For example, [Ren et al. \(2013\)](#) developed a multi-city Mixed-Integer Programming (MIP) model for distributing limited vaccine supplies during a smallpox outbreak. The model optimized vaccine allocation and infection control measures to minimize fatalities, demonstrating its effectiveness in a hypothetical national outbreak by considering strategic criteria such as demographics and disease propagation dynamics. [Sun et al. \(2014\)](#) focused on optimizing patient and resource allocation among hospitals during a pandemic influenza outbreak using linear optimization models that incorporated cost factors and demographics, thereby improving resource allocation by reducing travel distances and maximizing hospital accessibility. [Yarmand et al. \(2014\)](#) proposed a two-stage stochastic linear program for optimal vaccine allocation in a two-phase vaccination policy. Their model, aiming at minimizing costs while maintaining vaccination coverage, was tested for vaccine planning for seasonal influenza in North Carolina. [Büyüktaktakın et al. \(2018\)](#) presented an epidemics-logistics MIP framework for controlling the Ebola epidemic, which integrated logistics and resource allocation with varying transmission rates and population migration, proving effective in minimizing infections and deaths within a restricted budget and time frame such as during the Ebola outbreak in Guinea, Liberia, and Sierra Leone.

The recent COVID-19 pandemic has sparked a new surge of research focused on optimizing the placement of healthcare facilities, including testing sites, vaccination centers, and vaccine distribution centers.

The location of testing centers has been considered in the work by [Devi et al. \(2021\)](#), which proposed a bi-objective location-allocation MIP model for temporary testing laboratories. Their model aimed to minimize the centers' total costs and the maximum travel time from patient nodes to testing facilities. The model included considerations about capacity under-utilization but did not consider patient congestion at the testing facilities. [Ozdemir et al. \(2022\)](#) developed a MIP model for the location and routing of temporary testing centers. The model's primary objective was to maximize the total sample collection, while also considering travel distances and diminishing sample potentials over time and coverage. The model was applied to two case studies based in Seoul, Korea, and Istanbul, Turkey, during the COVID-19 pandemic. [Abdin et al. \(2023\)](#) introduced a non-linear programming model for pandemic testing and control resource allocation, aiming to minimize new infections while considering patient demographics, community vulnerability levels, and testing center characteristics. Validated with data from the COVID-19 outbreak in France, this model provided insights into optimal testing strategies and the impact of resource allocation on disease spread. [Kuvvetli \(2023\)](#) proposed a goal programming model to design a two-echelon system for test sampling. The model sought to minimize the total distance between population nodes and testing centers, the number of testing centers, and the distance between testing centers and testing laboratories. Applied to two cities in Turkey, the study highlighted the importance of effective location-allocation decisions to contain transmission.

A comprehensive review of optimization models for vaccine distribution developed during the pandemic can be found in the work of [Dey et al. \(2024\)](#), which addressed various aspects of vaccine supply chain management, including site selection, inventory management, allocation strategies, distribution logistics, and route optimization. In the following, we review some of the relevant papers that share elements with our proposed approach, highlighting trends and gaps in this research stream.

Several recent studies have focused on optimizing vaccination center location and resource allocation during pandemics. [Alhothali et al. \(2022\)](#) analyzed the distribution of COVID-19 vaccine centers in Jeddah City using different coverage models, with and without capacity requirements. The study highlighted the importance of equitable

service distribution and efficient resource utilization during pandemics. [Bertsimas et al. \(2022\)](#) developed a novel data-driven approach to optimize COVID-19 vaccine distribution in the United States. The study augmented a state-of-the-art epidemiological model to capture the effects of vaccinations and the variability in mortality rates across age groups. This predictive model was then integrated into a bilinear, nonconvex prescriptive optimization problem to identify vaccination site locations and vaccine allocation with the primary objective of minimizing the number of deaths over the planning horizon across all regions and risk classes. Secondary objectives included minimizing the number of exposed people at the end of the horizon and the distance to the vaccination sites. The proposed optimization approach applied for identifying mass vaccination sites in the United States showed the potential to increase the effectiveness of the vaccination campaign by an estimated 20%. [Dastgoshade et al. \(2022\)](#) proposed a bi-objective two-stage stochastic programming model for locating vaccine distribution centers (DC) and allocating vaccines to various social groups. The model, which included both demand and supply uncertainty, aimed at minimizing social equity, was measured using three different social equity theories, and the system total cost, including the DC opening costs, transportation resource costs, and delivery costs. A Monte Carlo procedure was used to produce plausible scenarios with demand and supply uncertainty. The model was then solved using a Sample Average Approximation (SAA) method and was applied to two provinces in Iran.

A few papers have considered more complex vaccine supply chains, including distribution and/or inventory decisions. For example, [Li et al. \(2021\)](#) proposed a multi-objective mixed-integer nonlinear programming model for locating vaccination stations, simultaneously considering average travel distance, operational cost, medical professional work schedules, and inventory aspects. The model was solved using the ϵ -constraint method and applied to a real case study based on Shenzhen city, China. [Manupati et al. \(2021\)](#) considered large scale COVID-19 vaccine cold supply chains for entire countries and proposed a mixed-integer linear programming (MILP) model to identify the location, number and capacity of cold storage facilities, together with the required inventory levels and the allocation of storage facilities to healthcare community centers. The model aimed to minimize the overall costs for the entire supply chain network, including transportation and inventory costs. The overall approach, which was applied to India as an illustrative case study, also included the use of decision trees and predictive analytics to prioritize cities and population groups to be vaccinated. [Tavana et al. \(2021\)](#) developed a mixed-integer linear programming model for equitable COVID-19 vaccine distribution in developing countries. The proposed multi-period, multi-product model identified the location of distribution centers to maximize the minimum vaccine delivery-to-demand ratio, while considering time-dependent capacity, triple refrigeration requirement, and population grouping. The model was applied to a case study in India. [Yang et al. \(2021\)](#) developed a MIP model to locate vaccine regional and district hub distribution centers to minimize the annual hub facility costs and total annual transportation costs to serve a fixed set of local clinics. The model, which also included vehicle type and replenishment frequency decisions, was solved by a disaggregation-and-merging algorithm and tested using data derived from four different countries in sub-Saharan Africa. [Tang et al. \(2022\)](#) developed a bi-objective optimization model for COVID-19 vaccination planning to minimize operational costs and travel distances. The study used a weighted-sum method and an ϵ -constraint algorithm to balance cost efficiency with accessibility, incorporating factors like setup costs, station launch costs, and inventory management. The model was tested on a real-world case study based on the vaccination program in Tongzhou District, Beijing City, China. [Chowdhury et al. \(2022\)](#) studied the relationships among economic, environmental, and social sustainability in vaccine supply chains, with a special focus on emerging economies. Specifically, they developed a multi-echelon, multi-period, multi-objective, and multi-vaccine-type MIP model to identify the optimal location of global assembly centers and local distribution centers considering three objectives: network costs, greenhouse emissions, and job opportunities. The model was solved by two different metaheuristics and applied in Bangladesh. Environmental aspects were also considered by [Abbasi et al. \(2023\)](#), who proposed a multi-objective, multi-echelon, multi-modal transport MIP to locate different types of facilities (vaccine factories, vaccine distribution centers, vaccine centers, and disposal sites). The model aimed to minimize costs, including fixed costs, variable costs, transferring costs, hygienic costs, and wasted vials costs, as well as to minimize the environmental impact of vaccine production and distribution activities. The multi-objective Gray Wolf Optimizer algorithm was utilized to solve the model, whose effectiveness was then tested on a case study in Iran.

The analysis of the literature revealed that studies that simultaneously address the location of both vaccination centers and vaccine distribution centers (or warehouses) in multi-echelon systems are scarce. Apart from rare exceptions ([Abbasi et al., 2023](#)), even studies addressing more complex vaccine supply chains considered either the location of vaccination centers ([Li et al., 2021](#); [Tang et al., 2022](#)) or the location of distribution centers ([Manupati et al., 2021](#);

Tavana et al., 2021; Yang et al., 2021; Chowdhury et al., 2022). In addition, the models proposed in these studies are mostly operational in nature and address aspects like inventory and replenishment (Li et al., 2021; Yang et al., 2021), work schedules (Li et al., 2021), and distribution vehicle types (Yang et al., 2021). Even location decisions are sometimes considered at the operational or tactical level and involve, for example, the location of cold storage equipment (Tavana et al., 2021) or opening time decisions (Tang et al., 2022) at existing facilities.

Some studies have underlined the importance of developing models to support strategic decisions at the onset of a pandemic (Manupati et al., 2021; Bertsimas et al., 2022). During a pandemic, certain strategic decisions, such as determining the locations of vaccination centers and distribution facilities, need to be made at an early stage before detailed information about the workforce, vehicles, or vaccine availability is accessible. Effective initial planning is crucial to ensure that subsequent operational decisions can be efficiently adjusted as more data becomes available. Important strategic issues related to the identification of candidate vaccine facility sites have been neglected in existing studies. Some papers focused on the location of facilities at the full country level and assumed that candidate locations are a subset of the country's cities. For example, in the case study by Bertsimas et al. (2022), 100 of the 500 most populous cities in the USA were considered as potential sites for vaccination centers, while in Abbasi et al. (2023)'s study, eight major cities in Iran were identified as candidate locations. Although these studies focus on designing vaccine supply chains at the country level, having just one mass vaccination center per city is often impractical, especially in large urban areas where millions of people require access to vaccines. Big cities typically need many centers to meet the demand and avoid overcrowding effectively. This highlights the importance of making more granular, local-level strategic decisions in addition to national-level planning.

Some papers investigated the location of vaccination centers at the city or district level (Alhothali et al., 2022; Li et al., 2021; Tang et al., 2022). However, the case studies in these papers assumed that candidate locations are existing facilities (i.e., hospitals and health centers) without considering a variety of other potential sites (e.g., community centers, sports venues, schools, shopping malls, transport hubs, temporary tents) that can be utilized as vaccination centers during large-scale vaccination campaigns. These alternative facilities can help ensure that the vaccination efforts reach a broader population efficiently, particularly in densely populated or underserved areas. Given this multitude of options, it is essential to streamline the identification of potential candidate sites by considering infrastructure, environmental, and socio-demographic factors. Effective healthcare facility operations in crises rely heavily on public infrastructure, including electricity and transportation (Arboleda et al., 2009). Environmental considerations, including closeness to waste disposal facilities, are essential in healthcare facility location planning to support sustainable waste management practices (Chauhan and Singh, 2016; Chowdhury et al., 2022). Socio-demographic insights help tailor the efforts to population characteristics, preferences, and behaviors, impacting vaccination success (Abbas et al., 2024; Wong et al., 2022). In practice, developing mathematical models that can fully incorporate infrastructure, environmental, and socio-demographic factors is difficult, without compromising the models' tractability. Embedding these aspects in the initial selection of candidate sites can significantly simplify subsequent mathematical models. To this end, we utilize a GIS-MADM approach to determine the strategic costs associated with potential vaccination sites, which are then used in the optimization model objective, ensuring the creation of a decision-making model that is both strategically informed and computationally tractable. A few studies considered the integration of GIS and MADM to evaluate the suitability of healthcare facility locations and rank different alternatives (Dell'Ovo et al., 2018; Eldemir and Onden, 2016). GIS has also supported analytical location models (Church, 2002; Bozkaya et al., 2019). However, to the best of our knowledge, there is a noticeable gap in the integrated use of GIS, MADM, and location models, which our research aims to address. By proposing a multi-step approach that combines these methods, our study offers a replicable framework for tackling complex location-selection challenges.

In addition, we propose a novel multi-echelon MILP (2E-CLAP) that simultaneously determines the strategic location of both vaccine distribution centers (warehouses) and vaccination centers, merging two classic facility location model constructs (set covering and p -center) to represent the decisions at each level. The link between p -center problems and set covering problems has been widely studied in the literature from a solution approach perspective. A few studies, starting with the seminal paper by Minieka (1970), have demonstrated how set covering solution techniques can be leveraged to solve p -center problems efficiently (Elloumi et al., 2004; Medrano, 2020). Here, we combine the two constructs into a hierarchical multi-objective model: the set covering model is used to ensure patient accessibility and fairness in the location of vaccine service centers; the p -center construct is used for the location of warehouses to ensure that periodic vaccine distribution to service centers can be performed efficiently, reliably, and fairly.

Finally, our model treats vaccine center capacity utilization as a decision variable and aims to minimize the max-

imum percentage capacity utilization at the vaccine centers using capacity management as a strategic tool to reduce patient density and contain transmission. This approach provides a simple and adaptable method for managing healthcare resources during a pandemic, directly addressing the need to control patient density at vaccination centers to mitigate the spread of infection.

3. Research Framework

This research was conducted in five steps, as illustrated in Figure 1. Initially, a literature review and interviews with experts were undertaken to identify the strategic criteria for selecting potential healthcare facility locations in a healthcare crisis like a pandemic outbreak. The resulting socio-demographic, environmental, and infrastructure strategic criteria chosen for this study are summarized in Figure 2. These criteria are considered to be strategic because they support both an efficient crisis response and long-term public health resilience. By prioritizing infrastructure readiness, environmental safety, and socio-demographic alignment, the selected locations can maintain operational efficiency, minimize ecological risks, and equitably serve high-need populations—balancing urgent needs with sustainable impact. All criteria and their subcategories are defined in Table A.1 in Appendix A.

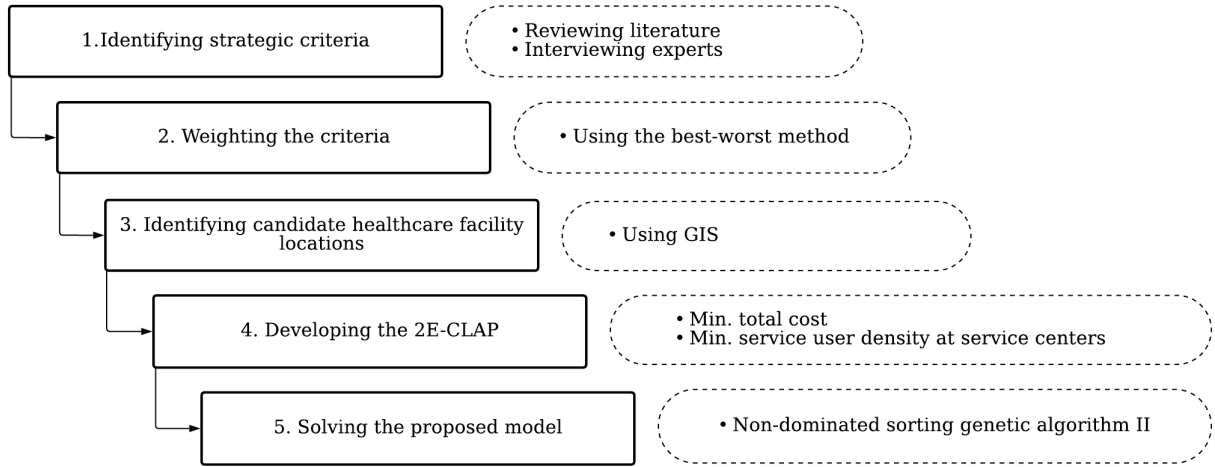


Figure 1: Research steps

In the second step, experts were invited to participate in the assessment of criteria via a Best Worst Method (Rezaei, 2015) online questionnaire. To gather expert opinions, we interviewed 26 professionals specializing in hospital location selection. The group included 23% doctors with an average of 10.5 years of experience, 46% microbiologists and immunologists with an average of 12.4 years of experience, and 31% public health experts with an average of 9.7 years of experience. Their input was used to weight the criteria presented in Figure 2.

In the third step, we used GIS to identify and prioritize potential locations for healthcare facilities. This study utilized the geographic information of Mashhad, Iran, sourced from Iranian datasets.

In the fourth step, we develop a GIS-based 2E-CLAP to select appropriate locations for healthcare facility centers during a pandemic. Finally, we employ an enhanced bi-objective Genetic Algorithm in the fifth step to solve the proposed 2E-CLAP model.

3.1. Best Worst Method

The Best Worst Method (BWM) is a pairwise comparison technique employed to calculate the relative importance of criteria in decision-making problems. It is more advantageous than other pairwise comparison-based methods, such as single vector-based methods (e.g., Swing and SMART family) and complete matrix-based methods (e.g., AHP). We used BWM because it requires fewer pairwise comparisons, resulting in a lower inconsistency rate (Rezaei, 2015). It also performs well in mitigating anchoring bias (Rezaei et al., 2024). These advantages have been demonstrated

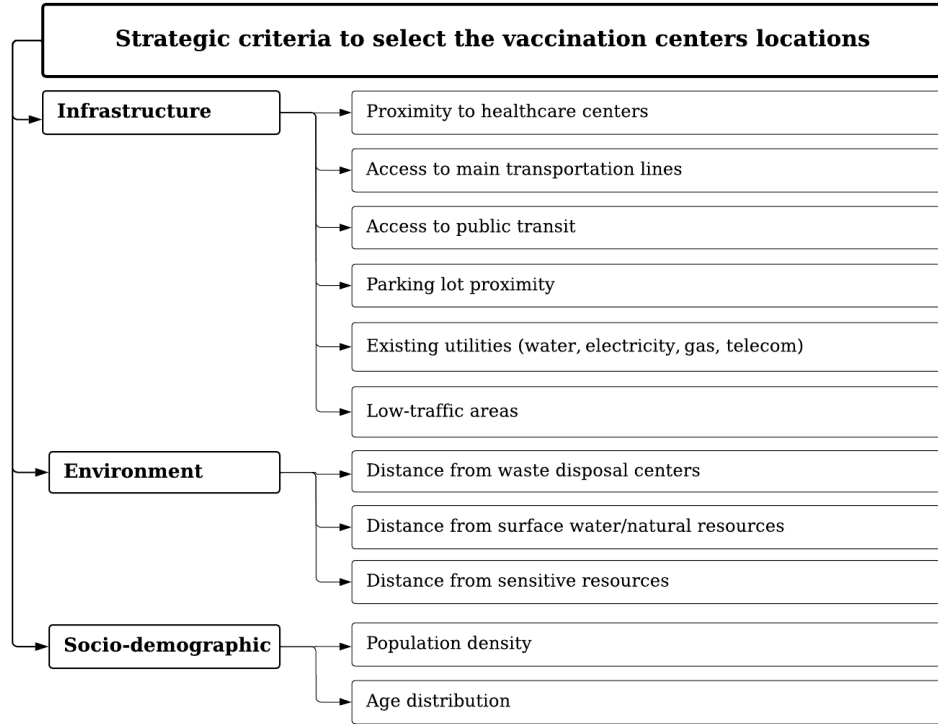


Figure 2: Strategic criteria to select candidate healthcare facility locations during a crisis.

in various decision-making scenarios, including Location Selection (Kheybari et al., 2021) and Supplier Selection (Ishizaka et al., 2022). To effectively utilize the BWM, we followed the five steps outlined in Rezaei (2015).

3.2. Geographical Information System

Geographical Information Systems (GIS) are computer systems designed to manage and analyze geographic information and support decision-making processes. The primary purpose of these systems is to support decisions based on geographical information. The process starts by identifying key criteria, such as accessibility, population density, and environmental factors when selecting healthcare facility locations. These criteria are then assigned weights using methods like the BWM. In GIS, each criterion is represented as a separate layer, and these layers are combined through spatial analysis to produce a final map that highlights the most suitable locations based on the weighted criteria. This study used ArcGIS Pro (version 3.1), a powerful platform for spatial analysis and layer integration, ensuring the methodology is transparent and reproducible. GIS was central to this study, serving as the platform for integrating the spatial and non-spatial data to support strategic healthcare facility planning. GIS was used to translate a set of weighted strategic criteria into a continuous suitability surface, a spatially informed decision-support layer that visually indicates the relative favorability of every location for a vaccine facility. This integrated surface was created by first representing each criterion as a geospatial layer, standardizing them with normalized suitability scores, and then integrating them through a weighted overlay operation in ArcGIS Pro, with each layer assigned its specific weight derived from the BWM. To extract discrete and viable candidate sites from this continuous suitability surface, the analysis employed two complementary filtering approaches. The first approach was a buffer-based method, which delineated zones of higher practical feasibility by generating areas around the key existing features such as hospitals, transport nodes, and urban infrastructure. Within these predefined zones, high-suitability regions were identified through a spatial intersection with the overarching suitability surface, ensuring that the selected sites were not only strategically aligned but also logistically deployable. The second approach utilized a regular grid sampling method to ensure that no high-suitability area was overlooked. A grid was superimposed over the entire study area, and the centroid of each cell acted as a probe to query the underlying suitability surface, systematically exploring regions

away from the existing infrastructure. These centroids were not proposed sites but a means to identify pockets of high potential. These zones were then cross-checked against feasible land-use categories, such as public buildings, empty lots, and parking areas, to generate realistic candidate locations. This two-step grid process identified 500 new sites, which, when combined with the 135 buffer-derived sites, provided a comprehensive and robust pool of 635 realistic candidate centers for evaluation.

3.3. Two-Echelon Capacitated Location Allocation Problem (2E-CLAP)

2E-CLAP can be represented on a directed graph $G = (V, A)$, where V is the set of nodes and A is the set of arcs between each pair of nodes $i, j \in V$. The set of V nodes is comprised of three subsets, $I = \{1, \dots, n\}$, $J = \{1, \dots, m\}$, and $K = \{1, \dots, p\}$, representing the demand zones (population to receive service), the candidate locations for the service centers, and the candidate locations for warehouses, respectively ($V = I \cup J \cup K$, with $v = |V| = |I| + |J| + |K| = m + n + p$). The population in zone $i \in I$ is denoted by q_i and represents the number of people in that demand zone who must receive the service throughout the planning horizon. We assume that the population of each demand zone to receive service daily is $q_i^H = \lceil q_i / H \rceil$, where H is the number of days in the time horizon. It is assumed that the demand of each zone must be entirely satisfied by one or more service centers.

In addition, each service center $j \in J$ has a fixed strategic (opening) cost S_j^c and a service capacity Q_j^c , indicating the maximum number of people who can receive service at that service center daily. Service capacity and node demand are measured based on the number of daily service users. Note that the strategic cost S_j^c associated with each service center j reflects the suitability of having a center in that location according to the strategic criteria. Namely, the cost is computed as the inverse of the strategic weight of the service centers: the higher the strategic weight of a service center calculated by GIS, the lower its strategic cost in 2E-CLAP. The distance (allocation cost) between a pair of nodes $i, j \in V$ is denoted by d_{ij} . A demand node $i \in I$ can be assigned to a service center $j \in J$ only if the distance between them, d_{ij} , is lower than or equal to a specified *coverage distance* D . This is captured through the binary parameter a_{ij} , which equals one if $d_{ij} \leq D$, zero otherwise. Each demand zone must be assigned to at least one service center within its coverage distance. A service center may cover more than one demand zone as long as its maximum capacity is not violated. Each service center $j \in J$ procures the required number of daily service units from one warehouse $k \in K$; however, a warehouse may be allocated to more than one service center. Each warehouse $k \in K$ has an opening cost S_k^w and a maximum number of deliverable service units Q_k^w , denoting the number of daily service units it can send to the service centers.

The 2E-CLAP entails six decisions: (I) Which service centers are opened (captured by the variable y_j in Table 1)? (II) How much is the capacity of each open service center utilized (decision variable C_j in Table 1)? (III) Which demand nodes are assigned to each service center (decision variable x_{ij} in Table 1)? (IV) Which warehouses are opened (denoted by decision variable v_k in Table 1)? (V) Which warehouses are allocated to the service centers (denoted by decision variable z_{jk} in Table 1)? (VI) How many service units are delivered to the service centers from the allocated warehouse (decision variable f_{jk} in Table 1)? Note that the capacity utilization C_j is a proxy for the adequate capacity needed at center j and can be used for resource planning (e.g., personnel, service unit stocks, etc.). The model has two objectives: (i) minimizing the total costs and (ii) minimizing the maximum *service user density* (decision variable z') at the vaccine centers to mitigate congestion.

The first objective function consists of three components, the first two of which are directly aligned with crisis response strategies: (a) the maximum distance (or vaccine distribution cost) between warehouses and service centers (decision variable z); (b) the strategic cost associated with service centers, derived from Geographic Information System (GIS) data; and (c) the operational costs associated with the opening of warehouses. For each service center $j \in J$, the *service user density* is defined as its percentage capacity utilization, computed by dividing its utilized capacity by its maximum capacity (mathematically C_j / Q_j^c). The 2E-CLAP's notation is summarized in Table 1. The mathematical formulation of the resulting bi-objective mixed-integer problem (2E-CLAP) is presented as follows:

$$\text{Min} \left(\frac{z}{F_1^{\max}} + \frac{\sum_{j \in J} S_j^c y_j}{F_2^{\max}} + \frac{\sum_{k \in K} S_k^w v_k}{F_3^{\max}} \right) \quad (1)$$

$$\text{Min } z' \quad (2)$$

subject to,

Table 1: 2E-CLAP Notation

Sets:	Description
V	Set of all nodes, including demand zones, candidate service centers, and candidate warehouses $V = I \cup J \cup K$
I	Set of demand zones, $ I = n$
J	Set of candidate locations for service centers, $ J = m$
K	Set of candidate locations for warehouses, $ K = p$
A	Set of arcs connecting each pair of nodes i and j ($\forall i, j \in V$)
Parameters:	
d_{ij}	Distance between each pair of nodes $i, j \in V$
S_j^c	Strategic cost of service center $j \in J$
S_k^w	Opening cost of warehouse $k \in K$
q_i	Population at node $i \in I$ to receive service during the planning horizon
q_i^H	Daily demand unit in zone $i \in I$ throughout the planning horizon H
Q_j^c	Maximum service capacity of service center $j \in J$
Q_k^w	Maximum daily deliverable vaccine units of warehouse $k \in K$
D	Coverage distance of service center
a_{ij}	=1 if $d_{ij} \leq D$ for customer $i \in I$ and service center $j \in J$; 0 otherwise.
$F_1^{max}, F_2^{max}, F_3^{max}$	Upper bounds of the elements of the first objective function.
Decision variables:	
y_j	=1 if service center $j \in J$ is utilized; 0 otherwise.
x_{ij}	=1 if demand node $i \in I$ is assigned to service center $j \in J$; 0 otherwise.
v_k	=1 if warehouse $k \in K$ is opened; 0 otherwise.
z_{jk}	=1 if warehouse $k \in K$ delivers service units (is allocated) to service center $j \in J$; 0 otherwise.
f_{jk}	Flow (quantity) of service units delivered to service center $j \in J$ from warehouse $k \in K$.
C_j	Utilized capacity of service center $j \in J$.
z	maximum distance between a demand node and the nearest service center
z'	maximum service user density

$$z \geq d_{jk} z_{jk}, \quad \forall j \in J, k \in K \quad (3)$$

$$z' \geq \frac{C_j}{Q_j^c}, \quad \forall j \in J \quad (4)$$

$$\sum_{j \in J} a_{ij} x_{ij} \geq 1, \quad \forall i \in I \quad (5)$$

$$x_{ij} \leq y_j, \quad \forall i \in I, j \in J \quad (6)$$

$$\sum_{i \in I} q_i^H x_{ij} = C_j, \quad \forall j \in J \quad (7)$$

$$C_j \leq Q_j^c, \quad \forall j \in J \quad (8)$$

$$\sum_{k \in K} z_{jk} = y_j, \quad \forall j \in J \quad (9)$$

$$f_{jk} = C_j z_{jk}, \quad \forall j \in J, k \in K \quad (10)$$

$$\sum_{j \in J} f_{jk} \leq Q_k^w, \quad \forall k \in K \quad (11)$$

$$z_{jk} \leq v_k, \quad \forall j \in J, k \in K \quad (12)$$

$$x_{ij}, y_j, z_{jk}, v_k \in \{0, 1\}, C_j, f_{jk} \in \mathbb{Z}_{\geq 0}, \quad \forall i \in I, j \in J, k \in K \quad (13)$$

In the mathematical model, the objective function (1) minimizes the total cost, including the three cost elements previously described. Each element is normalized by dividing it by its upper bound to ensure consistency in the cost units. Namely, we denote by F_1^{max} , F_2^{max} , and F_3^{max} the maximum value of each of the three objective elements. Let $d_{max} = \max_{j \in J, k \in K} d_{jk}$ be the maximum distance between any warehouse and service center pair. We then set $F_1^{max} = d_{max}$. The upper bound for the second element is $F_2^{max} = \sum_{j \in J} S_j^c$, while the upper bound for the third element is $F_3^{max} = \sum_{k \in K} S_k^w$.

The second objective function (2) minimizes the maximum service user density of the service centers. This objective function focuses on medium-term crisis management by balancing vaccine distribution across all vaccination centers, thereby reducing congestion, an essential factor in controlling healthcare crises during infectious disease outbreaks. Constraint (3) enforces z as the maximum distance between any service center j and the warehouse k to which it is assigned. Constraint (4) forces z' to be the maximum service user density. Constraint (5) ensures that each demand node must be assigned to at least one service center. Constraint (6) states that a demand node cannot be assigned to a service center unless the service center is utilized or operational. Constraint (7) ensures that the utilized capacity of a service center is equal to the total population assigned to it. Constraint (8) ensures that the utilized capacity of a service center cannot exceed its maximum service capacity. Constraint (9) ensures that exactly one warehouse must be allocated to an operational service center. Constraint (10) states that the total number of service units delivered to a service center must equal the utilized capacity of that service center. Constraint (11) indicates that the number of service units delivered by the warehouse $k \in K$ must not exceed Q_k^w . Constraint (12) indicates that a warehouse cannot be allocated to the service centers unless it is already opened. Finally, constraint (13) shows the domain of the binary and integer decision variables.

The proposed mathematical model is not linear due to constraint (10). To linearize the model, constraint (10) can be replaced by the following sets of linear constraints:

$$f_{jk} \leq M z_{jk}, \quad \forall j \in J, k \in K \quad (14)$$

$$C_j - M(1 - z_{jk}) \leq f_{jk}, \quad \forall j \in J, k \in K \quad (15)$$

$$f_{jk} \leq C_j, \quad \forall j \in J, k \in K \quad (16)$$

Constraints (14)-(15) linearize constraint (8) by using a big constant value M . Without a loss of generality, we can assume $M = Q_j^c$.

3.4. Non-Dominated Sorting Genetic Algorithm II

By removing the decisions on the utilized capacity of each service center and the decisions about the warehouse locations and warehouse-center allocations, 2E-CLAP reduces to the Capacitated Set Covering Model (CSCM), which is NP-hard (Current and Storbeck, 1988); therefore, it is proven that 2E-CLAP is an NP-hard problem. In addition, 2E-CLAP is a bi-objective problem, which adds complexity to its solution. Since large-size instances are not solvable optimally by exact solvers in a practical computing time, heuristics or metaheuristics must be designed to obtain acceptable solutions for large instances (Faramarzi-Oghani et al., 2023). This work proposes an enhanced version of the NSGA-II metaheuristic for large instances of 2E-CLAP. NSGA-II, first introduced by Deb et al. (2000), is an efficient and effective metaheuristic for solving complex multi-objective optimization problems and can provide good-quality solutions within an acceptable time (Verma et al., 2021; Babaeinesami et al., 2022). In addition, NSGA-II enables the multi-objective aspect of the problem to be addressed by generating pools of solutions and subsequently choosing non-dominated ones. The primary goals of multi-objective optimization algorithms are to identify non-dominated solutions as close as possible to the Pareto optimal solutions and to identify a diverse range of non-dominated solutions representing the entire objective space. A solution is considered non-dominated when no other solution is superior to it in all objectives, and at least one objective is preferred over another.

NSGA-II (Deb et al., 2000) is an elitist, non-dominated sorting genetic algorithm and was introduced as an alternative to NSGA (Srinivas and Deb, 1994). It provides a fast, non-dominated sorting algorithm and generates sufficiently diverse Pareto solutions, including density estimation and a crowded-comparison operator. By sorting non-dominated solutions quickly and finding a set of Pareto solutions that are appropriately diversified, NSGA-II overcomes the weakness of NSGA and other multi-objective Genetic Algorithms (Deb et al., 2002).

3.4.1. Enhanced NSGA-II for 2E-CLAP

The NSGA-II algorithm consists of multiple steps, including population initialization, crossover and mutation operators, non-domination sorting, crowding distance ranking, and the selection of elite solutions. To enhance the performance of the NSGA-II algorithm for solving 2E-CLAP, problem-specific repair-and-improvement operators are added to repair infeasible solutions and improve the quality of feasible solutions. The Enhanced NSGA-II algorithm for 2E-CLAP, as illustrated in Figure 3, comprises the following steps: (1) Generating an initial population of size n_p based on the encoding scheme of 2E-CLAP (Sections 3.4.2 and 3.4.3). (2) Generating an offspring population from the current (parent) population using six different mutation and one crossover moves with probabilities p_c and p_m , respectively, and a crossover point c_p (Section 3.4.4). (3) Repairing and improving all solutions in the parent and offspring populations using problem-specific repair-and-improvement operators (Section 3.4.5). (4) Sorting all repaired-and-improved solutions according to the non-domination rank to determine the non-dominated front (Section 3.4.6). (5) Ranking solutions within each front according to the crowding distance (Section 3.4.6) and (6) Selecting elite solutions from the high-ranked solutions to form the new population for the next iteration (Section 3.4.6) until the number of iterations exceeds a predetermined maximum iteration number K' (stopping criteria of the algorithm).

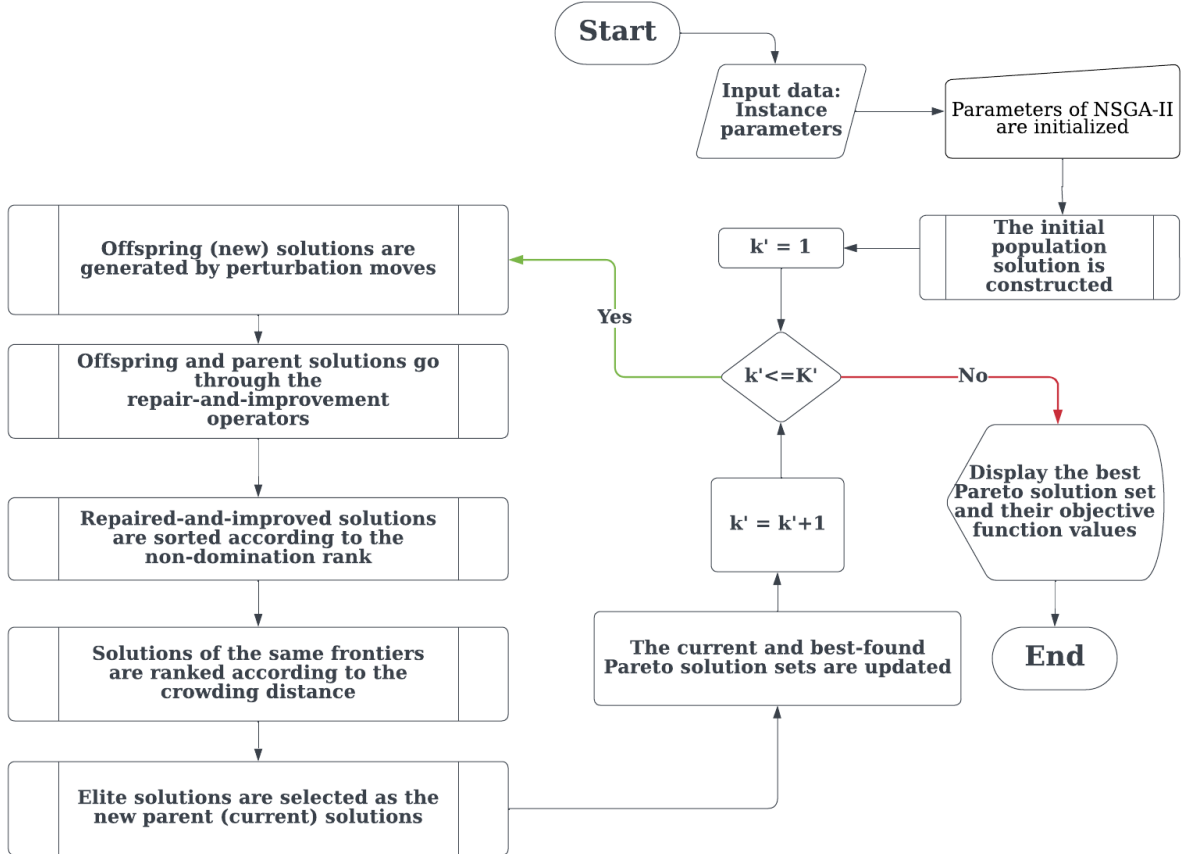


Figure 3: Flowchart of the proposed NSGA-II

3.4.2. Solution representation

In the proposed NSGA-II, an individual solution to 2E-CLAP is encoded by two chromosomes (vectors); the first chromosome, $\mathcal{A}$, has $m + n + p$ genes. The genes with index 1 to m indicate whether a service center is opened (binary values). The genes with index $m + 1$ to $m + n$ indicate the service center to which each demand point is assigned. The genes with index $m + n + 1$ to $2m + n$ denote the warehouse allocated to each service center. The second chromosome,

C , has $m + p$ genes. The genes with index 1 to m indicate the utilized capacity of each service center. The genes with index $m + 1$ to $m + p$ denote the service units delivered from each warehouse to the service centers. These two chromosomes are presented as follows:

$$\mathcal{A} = [a_1 \quad \dots \quad a_m \quad a_{m+1} \quad \dots \quad a_{m+n} \quad a_{m+n+1} \quad \dots \quad a_{2*m+n}]$$

$$C = [c_1 \quad \dots \quad c_m \quad c_{m+1} \quad \dots \quad c_{m+p}]$$

The solution representation (encoding) by NSGA-II is explained with a numerical example. In a 2E-CLAP example, two warehouses, four service centers, and twelve demand zones exist, as shown in Figure 4. We assume that each warehouse has a capacity of eight units and that all service centers can accommodate at most four service users. In the solution displayed in the figure, the first warehouse delivers the service units to the first and second service centers. The third and fourth service centers receive vaccines from the second warehouse. In the example, demand zones 1-4 are assigned to (covered by) the first service center. Demand zones 5-7, 8-9, and 10-12 are allocated to service centers 2, 3, and 4, respectively. Demand zone 4 is within the coverage range of service centers 1 and 2 and could be assigned to both; however, it will be assigned to only one center in the model. For the sake of simplicity, we assume that there is only one service user at each demand zone. Based on the covered demands, service centers 1, 2, 3, and 4 must receive at least 4, 3, 2, and 3 service units from the allocated warehouses, respectively. In the feasible solution, considering the capacities of both warehouses and service centers, the first warehouse sends four and three (a total of seven) service units to service centers 1 and 2, respectively, without violating the service capacities of the warehouse and service centers. Also, the second warehouse sends two and three service units to service centers 3 and 4, respectively. According to the solution encoding mentioned above, the solution displayed in Figure 4 is encoded by the following chromosomes (where $n = 12, m = 4, p = 2$):

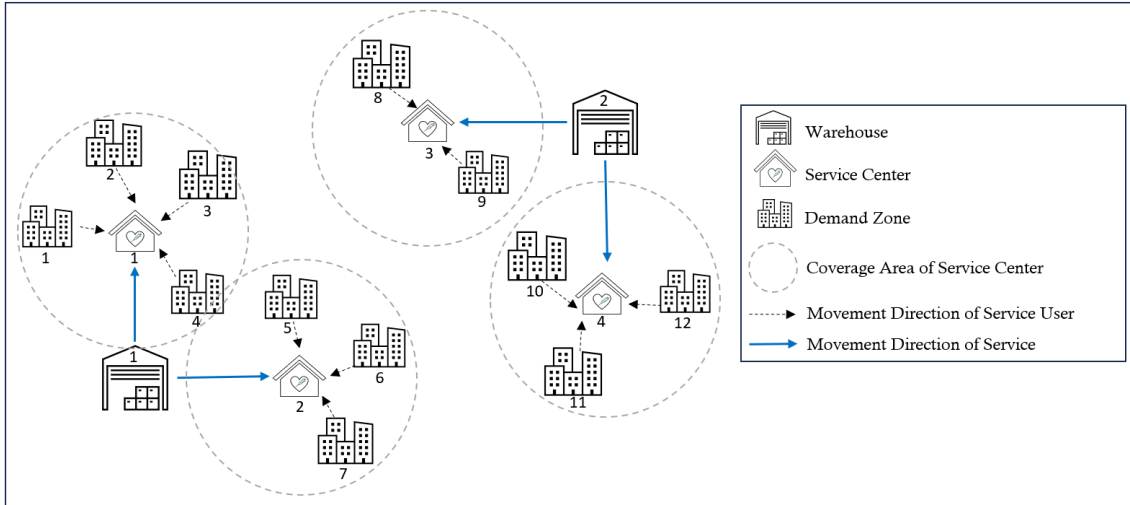


Figure 4: A schematic example for 2E-CLAP with two warehouses, four service centers, and twelve demand zones

$$\mathcal{A} = \left[\underbrace{1 \quad 1 \quad 1 \quad 1}_{\text{Service centers}} \quad \underbrace{1 \quad 1 \quad 1 \quad 1 \quad 2 \quad 2 \quad 2 \quad 3 \quad 3 \quad 4 \quad 4 \quad 4}_{\text{Covering the demand zones by service centers}} \quad \underbrace{1 \quad 1 \quad 2 \quad 2}_{\text{Allocation of service centers}} \right]$$

$$C = \left[\underbrace{4 \quad 3 \quad 2 \quad 3}_{\text{Utilized capacity of service centers}} \quad \underbrace{7 \quad 5}_{\text{Number of services delivered from each warehouse}} \right]$$

The solution in the example is feasible since it satisfies the coverage distance and the service centers' and warehouses' capacity requirements. Each open service center is assigned to precisely one warehouse, and the number of service units sent from the allocated warehouse is sufficient to satisfy all service demands allocated to that center.

3.4.3. Initial population generation

Half of the initial population is generated via the greedy approach, and the other half is generated through a random mechanism. The greedy approach sorts the center candidate locations according to their ability to cover as many demand points as possible, considering their strategic cost. Mathematically, the service centers are sorted in decreasing order of Q_j^c/S_j^c . Nearby demand nodes are then assigned to each center until the center's maximum capacity is reached, and this process is repeated for the remaining centers until the service centers cover all service users. Next, each open service center is assigned to the nearest warehouse, and the number of service units delivered from this warehouse to the service center is set as the utilized capacity. The allocation of the warehouses to the service centers is repeated until the maximum deliverable vaccine unit of the warehouses is not exceeded. In the random mechanism, each demand point is assigned to a random service center (using a uniform probability distribution) if its distance is within the coverage distance and satisfies its maximum capacity. The warehouses are then randomly assigned to the service centers while not violating the warehouse's maximum capacity.

3.4.4. Perturbation moves

For perturbing the current solutions, six mutations and one crossover move are applied: *demand_swap*, *demand_insertion_1*, *demand_insertion_2*, *center_swap*, *center_insertion_1*, *center_insertion_2*, and *crossover_demands*. At first, according to the probabilities p_m and p_c , the number of current solutions going through the mutation and crossover operators is determined. Then, $\lfloor p_c * n_p \rfloor$ solutions are chosen randomly, where $0 < p_c < 1$. If $p_c * n_p$ is an even number, the chosen solutions are divided into $\lfloor p_c * n_p \rfloor / 2$ subsets. Then, the two solutions in each subset go through the crossover operator. If $\lfloor p_c * n_p \rfloor$ is an odd number, one of the solutions is removed randomly, and a similar process is repeated. Next, $\lfloor p_m * n_p \rfloor$ solutions are selected randomly among the population for mutation. One of the six mutation moves is chosen randomly for each selected solution, and that solution is mutated according to that move. The six mutations and one crossover move are explained as follows.

The first mutation move *demand_swap* chooses two random demand zones with a uniform probability distribution and swaps their allocated service centers while satisfying the coverage range constraint. If the coverage range is violated, another two random demand zones are selected, and their allocated service centers are swapped. The second mutation move *demand_insertion_1* selects a random demand zone and allocates it to a service center (randomly chosen among the current open service centers) if the demand zone is within the coverage range of that service center. The third mutation move *demand_insertion_2* is similar to the previous one; however, it allocates the chosen demand zone to a new (not yet opened) service center if the coverage range is satisfied. The fourth mutation *center_swap* selects two random open service centers and exchanges their assigned warehouses. The fifth mutation *center_insertion_1* chooses a random open service center and allocates it to another open warehouse. The sixth mutation move *center_insertion_2* is similar to the previous move but the selected open service center is allocated to a new (not yet opened) warehouse.

The crossover move (*crossover_demands*) is only applied to the demand points of two chromosomes (solutions) by selecting a random number in the $[m + 1, m + n]$ interval (according to crossover point parameter c_p); for example, assume the number x ($m + 1 \leq x \leq m + n$) is chosen. Then, it swaps the subset of elements from $m + 1$ to x of the first chromosome with the same subset in the second chromosome. If, by this operator, a demand node is not within the coverage distance of the new service center, it is reassigned to the old service center. After these six mutations and one crossover move, the utilized capacity of each service center and the number of service units that must be sent from each warehouse to the allocated service centers are updated. These moves can render the solution infeasible because they fail to prevent the violation of service center and warehouse capacity. Repair operators are needed to restore feasibility.

3.4.5. Problem-tailored repair-and-improvement operators

We employ three repair and four problem-tailored improvement operators to restore feasibility and improve the solutions. The repair operators are applied consecutively. The first repair operator, *repair_center_capacity*, identifies service centers with a capacity exceeding the maximum service capacity. Next, one of the demand zones assigned to the infeasible service center is randomly selected and reassigned to another open service center within the coverage radius that has sufficient service capacity. If no open service center is found, the demand zone is covered by opening a new service center. This procedure is repeated until no infeasible service center remains. The second repair operator *assign-new-centers* identifies the service centers that have been newly opened as a result of the previous operator.

Then, it assigns these new service centers to new warehouses. The third repair operator *repair_warehouse_capacity* is similar to the first repair operator but for the infeasible warehouses. It identifies the infeasible warehouse whose maximum daily vaccine delivery capacity is exceeded. Then, one of its allocated service centers is randomly chosen and re-allocated to another open warehouse with spare delivery capacity. If no open warehouse is found, it is assigned to a new warehouse. This process is repeated for all infeasible warehouses until a feasible solution is found.

After applying the repair operators, each solution in the population is improved by randomly selecting one of the four improvement operators. The first improvement operator, *imp_demand_allocation*, reduces the maximum service user density by identifying the service center with the highest service user density among all service centers. One of its demand zones is selected randomly. The demand zone is allocated to a new service center if the following three conditions are satisfied: (i) the demand zone is within the coverage radius of the new service center; (ii) the newly allocated service center must not become infeasible concerning service capacity; and (iii) the service user density at the new allocated service center is less than the previous maximum service user density. This operator functions according to a first-improvement strategy: the algorithm goes to the next step when this operator improves the second objective function for the first time. Additionally, this operator selects the new service center from among the open and closed centers.

The second improvement operator *center_closing* improves the first objective function by removing (closing) a service center according to a first-improvement strategy. It identifies a service center with demand zones that can be reassigned to another nearby open service center, ensuring the service capacity of the newly allocated centers is met. The third improvement operator *warehouse_closing* is similar to the previous operator. It reduces warehouse opening costs by closing warehouses whose assigned service centers can be allocated to other open warehouses without violating their delivery capacity. Finally, the fourth improvement operator *imp_center_allocation* improves the first element of the first objective function by reducing the maximum distance between a warehouse and its allocated service centers, represented as the variable z in the objective function (1). It finds the warehouse and its allocated service center, whose distance from each other is the maximum among all distances. Next, it allocates this service center to another warehouse if the following conditions are satisfied: (i) the newly allocated warehouse does not become infeasible with respect to its delivery capacity, and (ii) the distance between the service center and its newly allocated warehouse is less than the previous maximum distance. Notably, the first improvement operator may lead to opening more service centers. After that, we apply the repair operator *assign-new-centers* to determine the warehouses for the newly opened service centers.

We present the following example to illustrate the improvement operator *imp_center_allocation* and demonstrate that a service center with a higher strategic cost that is closer to the warehouse may be preferred over another with a lower strategic cost that is farther from the warehouse. This example could help interpret the algorithm's results.

Example 3.1. Consider a simple 2E-CLAP instance with one warehouse, two candidate service centers (with similar service capacity), and one demand zone. The demand zone is within the coverage range of both service centers, and they can cover that demand zone based on maximum service capacity (i.e., $Q_j^c = Q_{j'}^c \geq q_i$). In the current solution for the simple sample instance, service center j is selected to serve demand zone i , and warehouse w delivers the service units to this center j , as shown in Figure 5. The total cost and patient density of this current solution are $Z = d_{jk}/F_1^{max} + S_j^c/F_2^{max} + S_k^w/F_3^{max}$ and q_i/Q_j^c where $F_1^{max} = \max\{d_{jk}, d_{j'k}\}$, $F_2^{max} = S_j^c + S_{j'}^c$, and $F_3^{max} = S_k^w$. In a better solution, service center j' serves demand zone i if $Z' - Z < 0$ where Z' is the new solution's total cost and $Z' = d_{j'k}/F_1^{max} + S_{j'}^c/F_2^{max} + S_k^w/F_3^{max}$. Since $Q_j^c = Q_{j'}^c$, the patient density for the current and new solutions are the same. $Z' - Z$ can be computed as follows:

$$\begin{aligned} Z' - Z &= d_{j'k}/F_1^{max} + S_{j'}^c/F_2^{max} + S_k^w/F_3^{max} - d_{jk}/F_1^{max} - S_j^c/F_2^{max} - S_k^w/F_3^{max} \\ &= d_{j'k}/F_1^{max} + S_{j'}^c/F_2^{max} - d_{jk}/F_1^{max} - S_j^c/F_2^{max} \\ &= (d_{j'k} - d_{jk})/F_1^{max} - (S_j^c - S_{j'}^c)/F_2^{max} \end{aligned}$$

If $(d_{j'k} - d_{jk})/F_1^{max} < (S_j^c - S_{j'}^c)/F_2^{max}$, then $Z' < Z$ and the new solution outperforms the current solution. This shows that a high-strategic-cost vaccination center closer to the warehouse may be selected instead of a low-strategic-cost center farther from the warehouse (and vice versa), depending on which option reduces the total cost the most.

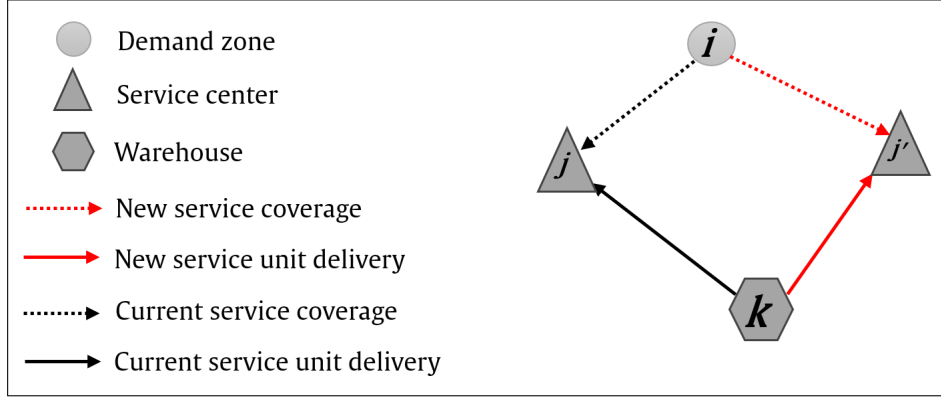


Figure 5: A simple example for 2E-CLAP

3.4.6. Solutions sorting, ranking and selection

After employing the repair-and-improvement operators, the objective function values of the parent and offspring solutions are calculated. Based on these values, the parent and offspring solutions are divided into different fronts (layers), where solutions in the first front are non-dominated by any other solution, solutions in the second front are dominated only by solutions in the first front, and so on. In other words, the solutions in the first front get the highest non-domination rank. After dividing the parent and offspring solutions into fronts with different non-domination ranks, the solutions in each front are compared with those in the same front and sorted based on crowding distance. This paper calculates the crowding distance similar to the study by [Deb et al. \(2000\)](#). The crowding distance measures the density of solutions in a particular region of the objective space. Solutions with higher crowding distances are preferred. Then, a new population with size n_p is created by selecting the parent and offspring solutions based on non-dominated fronts and crowding distances. Solutions from less crowded regions and higher non-dominated fronts are given preference. This new population is saved, and the algorithm is terminated when the stopping criterion is reached (the number of iterations reaches its maximum, K').

4. Results and Discussion

In this section, the applicability of the proposed framework is demonstrated in a real case study based on the city of Mashhad, Iran, to design an efficient vaccine distribution network during the COVID-19 pandemic. The case study is briefly introduced in Section 4.1, which also describes how the strategic costs that influence the selection of candidate vaccination center locations were identified using the BWM method and GIS. Detailed information about the actual data and assumptions made to set up the 2E-CLAP model is also provided. In Section 4.2, the real case study data is used to generate realistic problem instances of various sizes to test the performance of the NSGA-II algorithm. The instances are solved via an exact method, and the proposed NSGA-II is used to compare the obtained optimal and near-optimal Pareto solutions. Section 4.3 analyzes the solutions of the case study in various scenarios obtained by varying some of the problem parameters, such as the planning horizon, the coverage distance, the maximum service capacity of the service centers, and the maximum number of deliverable vaccine units that the warehouses can hold. **Finally, Section 4.4 presents a detailed comparison between the proposed NSGA-II approach and the real-world vaccination center configurations, highlighting cost savings and improvements across multiple operational scenarios.**

All experiments were performed on a Core i7 1.60 GHz laptop with 16 GB RAM. Gurobi implemented and solved the mathematical model in the Python environment. The proposed metaheuristic was also coded in Python. To obtain the optimal (exact) Pareto solutions, the ϵ -constraint method was applied, a technique used in multi-objective optimization for generating the Pareto set ([Deb et al., 2016](#); [Davoodi, 2019](#); [Govindan et al., 2023](#)). In the ϵ -constraint method applied to a multi-objective minimization problem, one of the objectives (e.g., the first) is minimized. In contrast, the remaining objectives are moved to the constraints with an upper bound ϵ . Namely, the problem becomes $Min. f_1(X)$, s.t., $f_2(X) \leq \epsilon_2, f_3(X) \leq \epsilon_3, \dots, f_o(X) \leq \epsilon_o, X \in \mathcal{S}$, where $f_1(X), \dots, f_o(X)$ are the objective functions of the original problem, X is the vector of the decision variables, and $\mathcal{S}$ is the region of feasible solutions. In our case,

the objective function (1) was minimized subject to constraints (3)-(9), (11)-(16) and $z' \leq \epsilon_2$. By varying the ϵ_2 levels, a sequence of constrained single-objective problems is solved, generating a set of potential Pareto optimal solutions. The traditional ϵ -constraint method with fixed increments selects ϵ_2 values at regular intervals, which may result in an incomplete Pareto front by missing intermediate non-dominated solutions due to the non-uniform shape of the trade-off surface. To overcome this limitation, we applied the recursive bisection search method (Dehghan and Ong, 2013) to determine the different ϵ_2 values.

Algorithm 1 outlines a recursive ϵ -constraint method for generating all supported non-dominated solutions in a bi-objective optimization problem. The algorithm begins by identifying the two extreme solutions: one that minimizes the first objective f_1 and another that minimizes the second objective f_2 , both without constraints imposed on the other. These two points define the boundaries of the Pareto front. The core procedure, RecursiveSearch, performs a bisection search over the ϵ_2 values of f_2 . Each recursive step solves the ϵ -constrained problem by minimizing f_1 while restricting f_2 to be less than or equal to the midpoint ϵ_2 . If a new non-dominated solution is found, it is added to the solution set, and the search continues recursively on both sub-intervals. The recursion stops when the difference in f_2 values between points becomes smaller than a user-defined tolerance τ (which was chosen as 0.0001 in our case). Unlike uniform ϵ steps that may skip critical points on the Pareto front, this adaptive strategy ensures that no supported non-dominated solution is missed. In the experiments, the execution time of the Gurobi solver in the recursive ϵ -constraint method was limited to one hour (3600 seconds).

Algorithm 1 Recursive ϵ -Constraint Method

Require: Function solve_epsilon_constraint(ϵ), Tolerance τ

Ensure: Set of non-dominated solutions solutions

- 1: solutions $\leftarrow \emptyset$
 - 2: Solve $\min f_1(x)$ without constraint on f_2 ; let $(f_1^L, f_2^L) \leftarrow \text{result}$
 - 3: solutions.append(f_1^L, f_2^L)
 - 4: Solve $\min f_2(x)$ without constraint on f_1 ; let $(f_1^H, f_2^H) \leftarrow \text{result}$
 - 5: solutions.append(f_1^H, f_2^H)
 - 6: **call** RecursiveSearch($f_2^L, f_1^L, f_2^H, f_1^H$, solutions, τ)
 - 7: **return** solutions sorted by f_2
-

Algorithm 2 RecursiveSearch($f_2^a, f_1^a, f_2^b, f_1^b$, solutions, τ)

- 1: $\epsilon \leftarrow \frac{f_2^a + f_2^b}{2}$
 - 2: $(f_1^m, f_2^m) \leftarrow \text{solve_epsilon_constraint}(\epsilon)$
 - 3: **if** $(f_1^m, f_2^m) \notin \text{solutions}$ **then**
 - 4: solutions.append(f_1^m, f_2^m)
 - 5: **if** $|f_2^m - f_2^a| > \tau$ **then**
 - 6: **call** RecursiveSearch($f_2^a, f_1^a, f_2^m, f_1^m$, solutions, τ)
 - 7: **end if**
 - 8: **if** $|f_2^m - f_2^b| > \tau$ **then**
 - 9: **call** RecursiveSearch($f_2^m, f_1^m, f_2^b, f_1^b$, solutions, τ)
 - 10: **end if**
 - 11: **end if**
-

4.1. Case study description

To test the validity of our proposed methodology and to illustrate its practical applicability, we utilize the COVID-19 pandemic as a healthcare crisis in Mashhad, Iran. Mashhad, the second largest and second most populous city in Iran, was among the most vulnerable cities during the first wave of the pandemic in Iran (Hazzbavi et al., 2021), making it a relevant case to test our proposed methodological validity in terms of context. Mashhad's socio-demographic characteristics, such as its diverse and densely populated urban areas, make it a suitable testing ground for studying

the impact of demographic factors on vaccination strategies. The city's population density and distribution enable targeted vaccination efforts, ensuring equitable access to vaccination services across different community segments (Chavehpour et al., 2019; Sharifi et al., 2021). Mashhad has a population of approximately 3.4 million people, distributed across 64 demand zones, as displayed in Figure 6. Public health guidelines recommend that at least 70% of the population of a city or region must be vaccinated for 'herd immunity' (Ning et al., 2022); therefore, for our study, we consider that 70% of Mashhad's population needs to be vaccinated during the planning horizon.

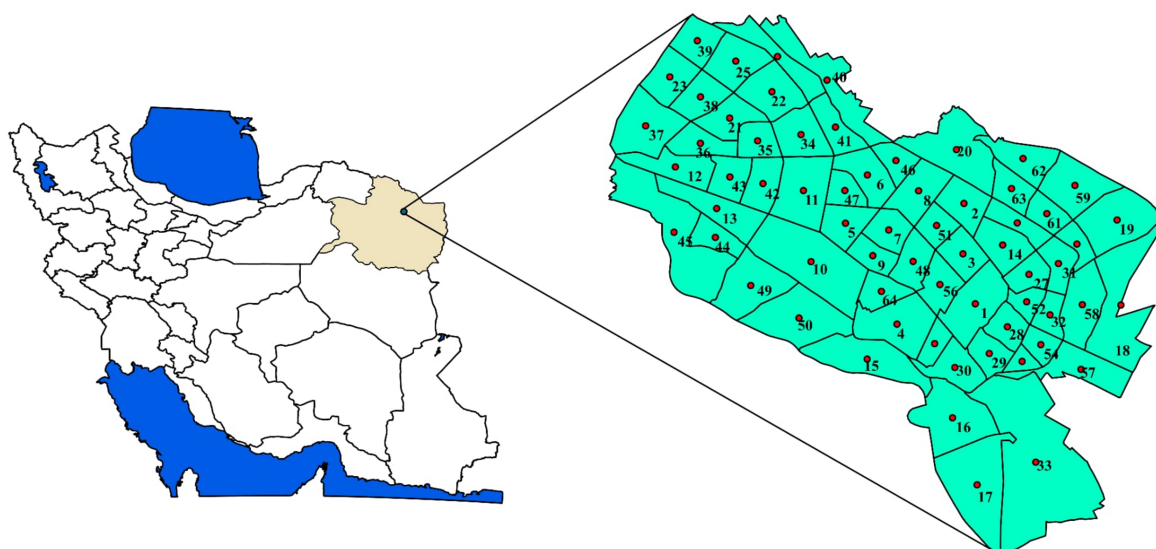


Figure 6: City of Mashhad, Iran, partitioned into 64 demand zones

4.1.1. Identification of strategic costs

The BWM method was employed in this research to calculate the weight of the criteria. As presented in Table 2, according to the experts' opinion, population density and age distribution substantially influence the selection of the vaccination center candidate locations. In contrast, distance from sensitive resources and traffic have the most modest effects. During a pandemic outbreak, population density is a critical factor in determining the number of individuals that need to be vaccinated in a given area, as areas with greater population densities tend to have higher rates of disease transmission. Subsequently, these necessitate more vaccination centers to serve the patients (people who need to be vaccinated). Population density can also influence the size and layout of vaccination centers as a greater population requires more space and resources. Age distribution is another critical criterion that should be considered to ensure that the most vulnerable members of society can access the vaccinations they need. By identifying areas with a higher risk for infection, resources can be targeted to those most in need, such as the elderly or immunocompromised individuals. Age distributions help to ensure that the vaccinations are used as efficiently and effectively as possible. The detailed measure of each criterion is explained in Table B.1 of Appendix B.

Subsequently, we classified the criteria into five levels (5=very good, 4=good, 3=average, 2=poor, and 1=very poor) based on the opinion of experts (Table B.1). The weight of the criteria and their classification were considered inputs for the GIS. The GIS process involves standardizing each of the 10 strategic criteria layers to a common suitability scale (e.g., 0-100) and then multiplying each layer by its assigned weight to reflect its relative importance. These weighted layers are summed cell-by-cell to generate a continuous suitability score surface. This surface is then classified into five distinct categories using a method like Natural Breaks (Slocum et al., 2022) to optimize grouping, thereby producing a clear and actionable suitability map. As presented in Figure 7, the utilization of GIS on the maps of criteria compiled by the Mashhad Planning Organization revealed that the 635 potential temporary sites could be categorized into five distinct classes, designated A to E. To determine the final priority of these classes, a representative landmark site was selected from each cluster. Experts were then asked to perform pairwise comparisons of these representative sites using the BWM procedure. After aggregating their opinions using the arithmetic mean,

Table 2: Weight of criteria in the candidate location selection process

Criteria	Weights
Population (p) density	0.196
Age distribution (y)	0.144
Distance (d) to the healthcare centers for immediate side effects	0.096
Distance from waste disposal centers	0.077
Distance to the main transportation lines	0.065
Distance to public transportation	0.064
Distance to the nearest parking lot	0.061
Distance from sensitive natural resources	0.060
Distance from surface water	0.055
Existing infrastructure (water, electricity, gas, and telephone)	0.050
Distance from sensitive resources	0.043
Traffic	0.144

strategic coefficients (weights) for Classes A to E were set to 0.36, 0.28, 0.20, 0.12, and 0.04, respectively. It is worth mentioning that these 635 sites are the result of applying strategic criteria as a filter within the GIS analysis. If different strategic criteria had been used or if the experts had assigned different weights to these criteria, the number of resulting areas would have been different.

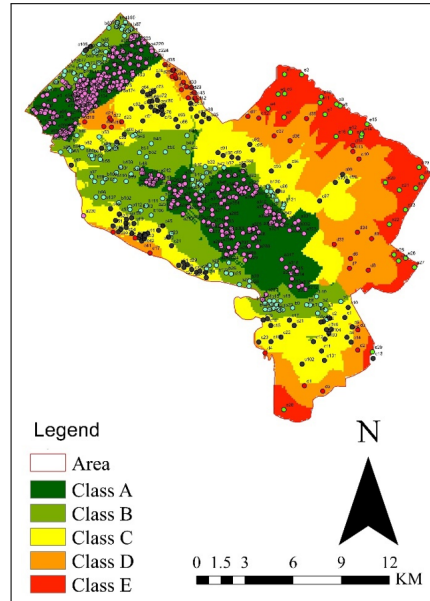


Figure 7: Candidate vaccination locations identified by GIS.

4.1.2. Input settings

In all experiments run on the case study-related instances, we use the following values for the problem parameters, except for the tests reported in Section 4.3 where some parameters are varied for the analysis. We consider 635 candidate locations for vaccination centers found by GIS ($|J| = 635$); these candidate vaccination centers may be located inside a healthcare service provider like clinics or hospitals or be installed temporarily on an empty site like tents. Also, 50 of these 635 vaccination centers from different regions (25, 10, 8, 5, and 2 locations from regions A to E, respectively) are considered candidate locations for vaccine warehouses ($|K| = 50$). The coverage distance of the vaccination centers was set as 10 kilometers or $D = 10$. In Iran, healthcare policymakers of the Ministry of

Health, especially in severely affected provinces like Mashhad (the focus of our case study), suggested a two-month planning horizon, i.e., $H = 60$ days. Accordingly, the population of each demand zone $i \in I$ (q_i) in Mashhad is divided by 60 to distribute the patients into daily time intervals. The vaccination centers' utilized capacity and patient density are obtained according to daily planning. Generally, we assume that the population of each demand zone to be vaccinated daily in Mashhad city is $q_i^H = \lceil q_i/H \rceil$. Section 4.3 analyzes the impact of various planning horizons ($H = 45, 60, 75, 90, 105$ days) on the objective function value and distribution of the opened vaccination centers and vaccine warehouses.

For the sake of simplicity, in all experiments, we assume that vaccination centers and vaccine warehouses are homogeneous in terms of capacity, i.e., $Q_j^c = Q^c, \forall j \in J$, and $Q_k^w = Q^w, \forall k \in K$. Consultations with key stakeholders highlighted the need for vaccine warehouses to have sufficient buffer capacity to ensure daily deliveries to vaccine centers despite supply chain disruptions. This is according to the best practices suggested by the WHO and the CDC (UNICEF-WHO, 2021; Centers for Disease Control and Prevention, 2021; National Academies of Sciences, Engineering, and Medicine and National Academy of Medicine, 2022). In our experiments, we assume that a vaccination center can accommodate 4,000 vaccines daily ($Q^c = 4,000$), and we set the maximum number of daily deliverable vaccine units of a warehouse at twice this number, i.e., $Q^w = 2 \times Q^c = 8,000$. The strategic cost for each vaccination center equals the inverse of the strategic coefficients of that center's location. For example, the strategic cost of a class 'A' center equals $1/0.36 = 2.78$, the inverse of the strategic coefficient of class 'A' sites. In the case study, the main focus is on identifying the number of opened warehouses. We set the opening cost of vaccine warehouses equal to one ($S^w = 1$). We also assume that the selected vaccination centers and vaccine warehouses are opened at the beginning of the planning horizon and remain unchanged until the end of the planning horizon (single-period planning).

4.2. Performance evaluation of NSGA-II

To evaluate the performance of the proposed NSGA-II and compare it with the exact solutions returned by the ϵ -constraint method, eight various-sized instances were generated with combinations of $|I| = \{30, 40, 50, 60\}$, $|J| = \{90, 150\}$ and $|K| = 50$. These sizes for the generated instances were chosen for two reasons. The first reason was to create small to medium cases of sufficient variety. The second reason was that by running the ϵ -constraint method on preliminary tests, we noticed that the exact (optimal) Pareto solutions, considering an execution time limit of one hour, could only be obtained for instances with 30 to 60 demand zones, 90 to 150 candidate vaccination center sites and 50 candidate warehouse sites. For larger problems, for example, with $|I| = 64$, $|J| = 300$, $|K| = 50$, and $\epsilon_2 = 0.70$, the optimality gaps of Gurobi were 36.71%, 27.63%, 25.99%, and 18.93% when the execution time reached 3600, 7200, 10800, and 86400 seconds, respectively. For the actual size of the case study (as explained in Section 4.1.2), Gurobi's optimality gaps were 70.11%, 55.72%, 37.49%, and 22.58% when the execution time reached 3600, 7200, 10800, and 86400 seconds, respectively. The chosen sizes allowed us to compare the NSGA-II solutions for small and medium instances with the proven optimal solutions generated by Gurobi.

The first instance, named *1-I30-J90-K50*, was generated by choosing the first 30 out of 64 demand zones in the case study data and randomly selecting 90 out of 635 vaccination centers with different strategic costs. All other instances of different sizes were generated similarly (see Table C.1 in Appendix C for more details). In each instance name, the first number denotes the index of the instance, and the numbers after the I , J , and K are the instance's size. We used these small and medium instances (instances with an index of one to eight) to tune the NSGA-II parameters (see Appendix E for full explanation) and evaluate the performance of the proposed NSGA-II by comparing its results with the exact solutions of the ϵ -constraint method.

The comparison of solutions for small instances with $|J| = 90$ is presented in Figure 8. The average execution time of Gurobi to obtain each solution of the Pareto set with a zero optimality gap was 198.03 seconds. Figures 8a-8b compare the Pareto set obtained by the NSGA-II algorithm with the optimal Pareto set for the instances *1-I30-J90-K50* and *2-I40-J90-K50*. The NSGA-II algorithm's solutions are closely aligned with the optimal Pareto front, indicating its accuracy and efficiency in finding near-optimal solutions for these instances. In Figures 8c-8d, the comparison is made for *3-I50-J90-K50* and *4-I60-J90-K50*. The pattern of NSGA-II's solutions remains close to the optimal Pareto front, demonstrating the algorithm's capability to maintain accuracy as the problem size increases.

The comparison of the proposed NSGA-II and the ϵ -constraint method for medium instances (when $|J| = 150$) is shown in Figure F.1 in Appendix F. The Gurobi average running time for solving these instances to optimality was 2384.55 seconds. Figures F.1a-F.1d collectively demonstrate the NSGA-II algorithm's strengths in approximating the optimal Pareto front for medium-sized instances.

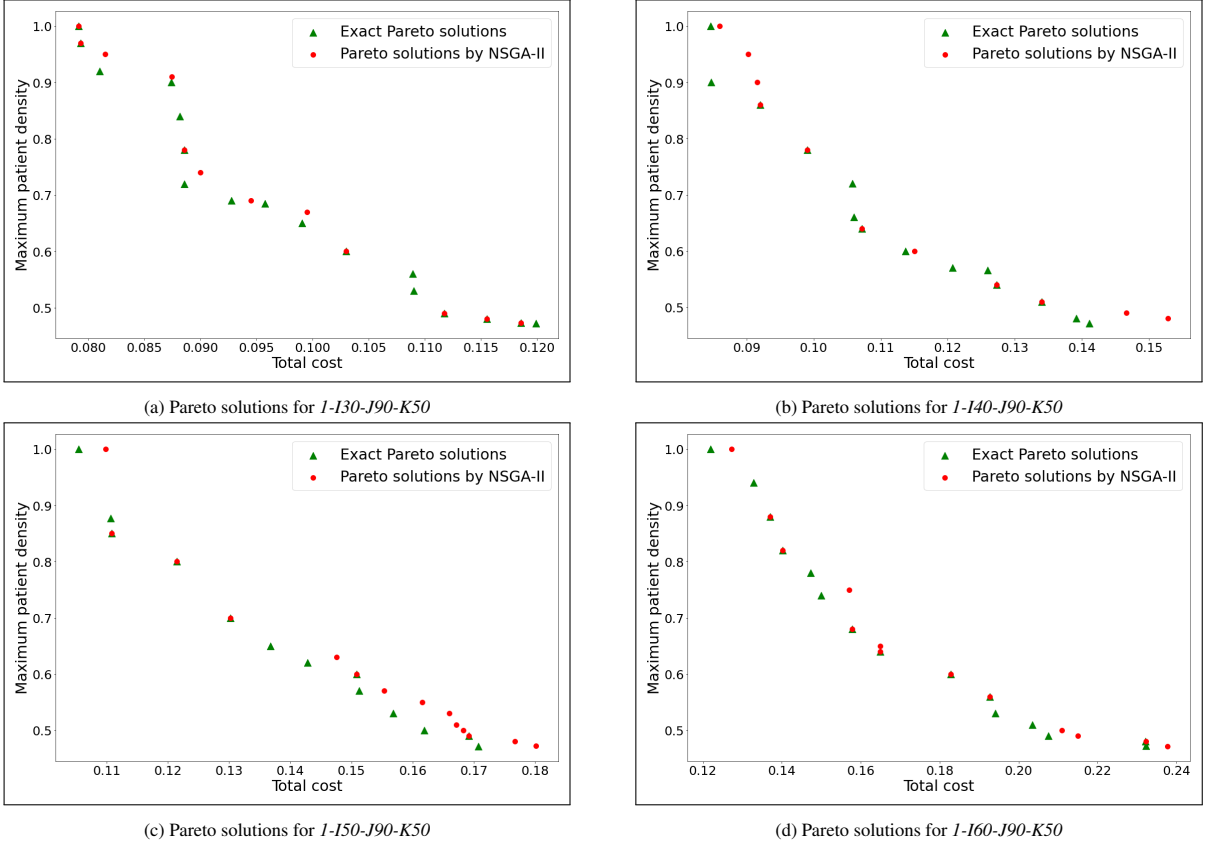


Figure 8: Pareto front obtained with NSGA-II compared to the optimal Pareto front for various instances with $|J| = 90$ (the x-axis and y-axis represent dimensionless values because both denominator and numerator of three elements of (1) and constraint (4) have the same unit)

We evaluated the performance of the proposed NSGA-II based on seven indicators commonly employed in the literature to assess multi-objective optimization methods. Specifically, we used the following: (i) Generational Distance (GD) (Van Veldhuizen, 1999): This measures the average Euclidean distance between the solutions in the Pareto front obtained by the algorithm and the exact Pareto front. A smaller GD indicates that the solutions are closer to the exact Pareto front. (ii) Inverted Generational Distance (IGD) (Coello and Cortés, 2005): Similar to GD, it measures the average distance from the exact Pareto front to the obtained Pareto front. A smaller IGD indicates that the obtained Pareto front is close to the exact Pareto front and well-distributed. (iii) Epsilon Indicator (ϵ): This measures the minimum factor by which the Pareto front obtained by an algorithm needs to be translated in the objective space to dominate the exact Pareto front completely. A smaller ϵ value indicates a better quality Pareto front. (iv) Spacing (SP) (Riquelme et al., 2015): This measures the uniformity of the distribution of solutions in the Pareto front. It is the standard deviation of the distances between neighboring solutions. A smaller spacing value indicates a more uniform distribution. (v) Completeness (Xu et al., 2023): It measures how many of the exact Pareto solutions are also found in the Pareto solution set by the NSGA-II. (vi) Inferiority (Xu et al., 2023): It measures the proportion of solutions found by the NSGA-II that are dominated by at least one solution in the exact Pareto set. (vii) Maximum Gap (Xu et al., 2023): For the exact Pareto solutions not found by the NSGA-II, it calculates the maximum percentage gap between these solutions and their closest counterpart in the NSGA-II with respect to both objectives.

Table 3 presents the values of the performance indicators used to assess the NSGA-II compared to the exact Pareto solutions. This table shows that the proposed NSGA-II algorithm has a robust performance across various instances when evaluated against the exact Pareto solutions. For GD and IGD, values approaching zero are ideal. In our results, the GD and IGD averages are low, at 0.0102 and 0.0107, respectively, implying that the solutions generated by NSGA-II are very close to the exact Pareto front, confirming the accuracy and proximity of the solutions. The

completeness and inferiority metrics indicate that NSGA-II can identify about 40% of the optimal Pareto solutions on average and misses about 55% of them. Despite this, the distance metrics previously discussed demonstrate that the NSGA-II solutions provide a good approximation of the optimal ones. The Epsilon indicator (ϵ) averages 0.5208, which shows that the solutions are well-distributed and not significantly dominated by the exact Pareto front. This means that the NSGA-II algorithm maintains a balanced distribution of solutions across the objective space. The SP average of 0.0298 indicates a uniform solution distribution, validating the algorithm's capability to provide evenly spread-out solutions across the Pareto front. The average percentage maximum gap is about 7% and 5% for the two objectives, respectively, indicating the good level of closeness of the NSGA-II solutions to the missed Pareto optimal solutions. The GD, IGD, ϵ , SP, completeness, inferiority, and maximum gap formulas used in this work are presented in [Appendix D](#).

Table 3: Performance indicators to evaluate the proposed NSGA-II

Instance	GD	IGD	ϵ	SP	Completeness	Inferiority	Maximum gap (%)
1-130-J90-K50	0.0056	0.0124	0.5280	0.0383	0.4118	0.4167	(7.93,7.55)
2-140-J90-K50	0.0078	0.0124	0.5288	0.0344	0.3571	0.5455	(8.32,8.33)
3-150-J90-K50	0.0062	0.0072	0.5288	0.0409	0.3846	0.6429	(7.90,3.08)
4-160-J90-K50	0.0040	0.0110	0.5278	0.0316	0.4000	0.3846	(6.63,6.38)
5-130-J150-K50	0.0219	0.0153	0.5200	0.0195	0.3000	0.6923	(15.01,4.00)
6-140-J150-K50	0.0082	0.0063	0.5270	0.0219	0.4615	0.5714	(2.15,5.00)
7-150-J150-K50	0.0124	0.0096	0.4780	0.0228	0.3846	0.5385	(7.03,3.33)
8-160-J150-K50	0.0154	0.0115	0.5280	0.0287	0.4545	0.6429	(4.73,5.26)
Average	0.0102	0.0107	0.5208	0.0298	0.3943	0.5543	(7.46,5.37)

4.3. Case study solution analysis

In this section, we report the results obtained by NSGA-II for the case study with an actual size, i.e., $|I| = 64$, $|J| = 635$, and $|K| = 50$ (a large instance). We first display the Pareto set of solutions and the trade-off between the total cost (first objective function) and the maximum patient density (second objective function). Next, we analyze the sensitivity of the solutions to variations in some of the inputs. Since the location of the candidate vaccination centers, vaccine warehouse, and demand points were obtained by GIS, the *Haversine* formula is used to calculate the distances in kilometers. In the following, we refer to the case study with the actual size and $D = 10$, $Q^c = 4000$, $Q^w = 8000$, $H = 60$ as the *Baseline scenario*. Figure 9 presents the Pareto and dominated solutions (408 solutions in total) for the *Baseline scenario* generated by NSGA-II with $n_p = 50$, $p_c = 0.5$, $p_m = 0.2$, $c_p = 0.3$. This parameter setting was obtained through the parameter tuning explained in [Appendix E](#). Overall, 17 non-dominated solutions with various costs and maximum patient densities were obtained. In addition, Figure 10 provides the trade-off between the normalized (to a range between 0 and 1) total cost and the maximum patient density of the vaccination centers. The red and blue lines in Figure 10 correspond to the normalized patient density and normalized total cost, respectively.

As expected, Figure 10 shows that the maximum patient density at the vaccination centers is lower when the total cost is higher, and vice versa. For instance, Solution '1' provides the minimum total cost but the highest possible value for patient density. Consultations with stakeholders revealed that up to 70% patient density is acceptable at the vaccination centers. So, we set $\epsilon_2 = 0.70$ and solve the problem with a single objective function (minimizing the total cost) while setting an upper bound ϵ_2 on the patient density at the vaccination centers. The selected vaccination centers, vaccine warehouses, and covered demand zones for the *Baseline scenario* with $\epsilon_2 = 0.70$ for Mashhad city are given in Table 4. This table shows the associated regions of the opened vaccination centers ('A' to 'E' as illustrated in Figure 7). For example, a vaccine warehouse with index 106 is opened and sends 631, 2799, 2474, and 1655 vaccines to four vaccination centers (42, 89, 109, and 130, respectively), all located in region class 'A.' The amount of vaccine flow a vaccination center receives equals its utilized capacity. The sum of the vaccine flows from each warehouse is less than its maximum deliverable vaccine units. Each open vaccination center covers the demand zones listed in the last column of the table. All vaccine warehouses, vaccination centers, and covered demand zones can be observed in Table 4. In the *Baseline scenario* with $\epsilon_2 = 0.70$, the maximum distance between a selected vaccine warehouse and an open vaccination center (the p-center objective function) is 2.20 km with six warehouses opened. The total and

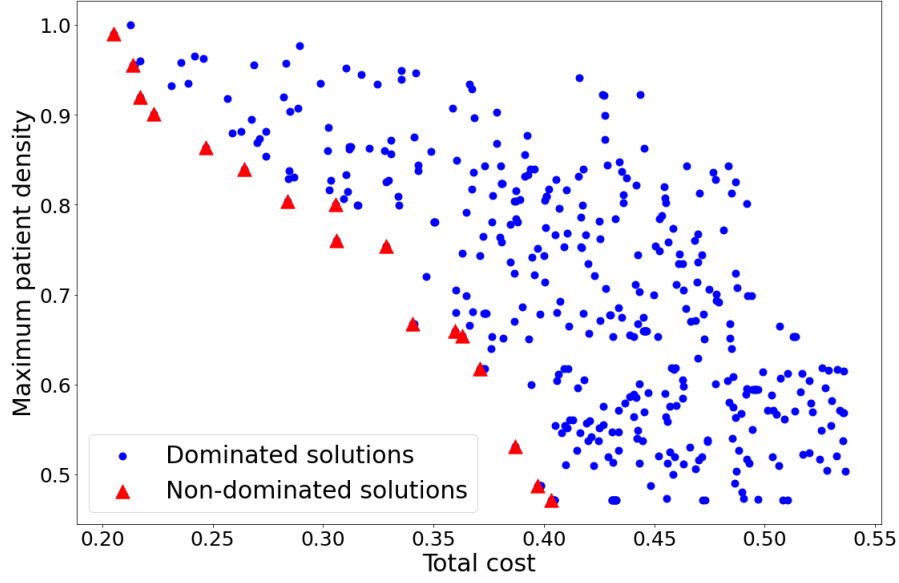


Figure 9: Dominated and non-dominated (Pareto) solutions of the *Baseline scenario* by NSGA-II (the x-axis and y-axis represent dimensionless values because both denominator and numerator of three elements of (1) and constraint (4) have the same unit)

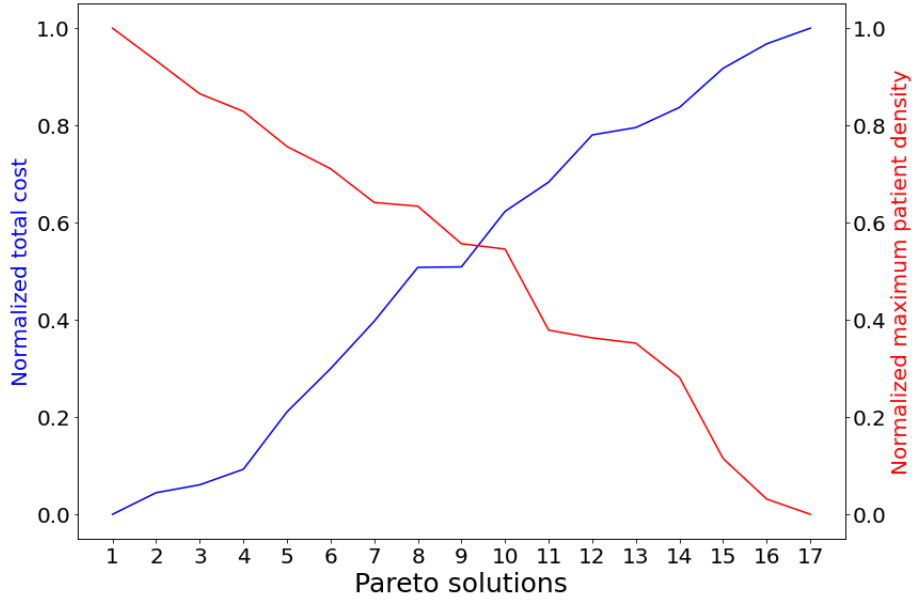


Figure 10: Trade-off between the strategic cost and maximum patient density in Pareto solutions of the *Baseline scenario*

strategic costs of vaccination centers were 0.218 and 56.35 (20 vaccination centers were selected: 19 from region ‘A’ and one from region ‘B’), respectively. The minimum and maximum patient densities for this solution are 15.78% and 69.98%, respectively, for vaccination centers 42 and 89. It can be observed that the model selects the vaccination centers mostly from region ‘A’ (associated with the lowest strategic cost).

In Tables 5 and 6, we present the results of the two extreme Pareto front solutions associated with minimum and maximum patient densities ($\epsilon_2 = 0.48$ and 1.00, respectively) for the *baseline scenario*. When $\epsilon_2 = 1.00$, the total and strategic costs are 0.205 and 37.70, lower than in the case with $\epsilon_2 = 0.70$ (i.e., 0.218 and 56.35). The reason for this is

Table 4: Opened vaccination centers and vaccine warehouses with assigned customers for the *Baseline scenario* with $\epsilon_2 = 0.70$

Warehouse index	Vaccine flow	Vaccination center index	Center region	Covered demand zones
106	631	42	A	42
	2799	89	A	11,24,36,38,41
	2474	109	A	10,44,45,50
	1655	130	A	12,43,49
293	1966	266	A	27,55,61
	2401	278	A	2,14,32
	1777	288	A	57,63
	861	343	A	33,52
295	2777	289	A	31,58
	2446	307	A	17,19
	2715	316	A	18,59
335	2439	265	A	1,3,28,54
	2241	271	A	16,30,62
	2458	273	A	29,53,56
533	1717	155	A	35,46
	2563	191	A	6,7,40,64
	1623	212	A	20,51,
597	2703	114	A	13,22,34,37,39
	1998	193	A	5,9,21,47
	2621	410	B	4,8,15,23,48

Total cost: 0.218, z : 2.20, strategic cost of centers: 56.35, opening cost of warehouses: 6, number of opened centers: 20

that fewer vaccination centers can be selected to cover the demand zones with a higher maximum patient density (e.g., 100%). For $\epsilon_2 = 1.00$, the p-center objective function value (z) equals 2.02 km (less than in the case with $\epsilon_2 = 0.70$), while the same number of vaccine warehouses are selected. However, the minimum and maximum patient densities are 31.38% and 99.42%, respectively. When $\epsilon_2 = 0.48$, seven warehouses are chosen against the five warehouses opened when $\epsilon_2 = 0.70$, and the p-center objective function value is 6.20 km, higher than the z value for the cases with $\epsilon_2 = 0.70$ and 1.00. Also, more vaccination centers are opened (i.e., 30) compared to the previous cases, and the strategic cost of vaccination centers is higher (the upper bound on the patient density effectively impacts the selection and number of vaccination centers). By forcing the maximum patient density to be smaller, more vaccination centers are needed to cover the demand zones, resulting in high total and strategic costs, and choosing centers from different regions (e.g., 10 from region class ‘A,’ 10 from region class ‘B,’ and 10 from region class ‘C’). The minimum and maximum patient density for this case are 0.18% and 47.13%, respectively. As observed, with a higher maximum patient density, the vaccination centers are selected close to the open vaccine warehouses, while their location is mainly from region class ‘A.’

Table 5: Opened vaccination centers and vaccine warehouses with assigned customers for the *Baseline scenario* with $\epsilon_2 = 1.00$

Warehouse index	Vaccine flow	Vaccination center index	Center region	Covered demand zones
101	3634	113	A	11,21,38,41,43,45
291	2657	278	A	25,26,32,61,63
	1225	288	A	53
	3960	358	A	17,55,57,58,62
295	2107	214	A	30,32,47,54,60
	2250	291	A	31,33,54,
	3624	315	A	15,18,19
335	3920	395	B	14,16,20,27,39,52
	3975	402	B	1,2,3,28,56
533	3977	206	A	6,8,48,49
	3585	209	A	4,10,23,44,51,64
597	3815	137	A	5,9,12,13,35,40
	3907	157	A	7,22,24,34,37,46,50

Total cost: 0.205, z : 2.02, strategic cost of centers: 37.70, opening cost of warehouses: 6, number of opened centers: 13

In the remainder of this section, some of the parameters of the *baseline scenario* are changed to analyze the sensitivity of the solutions to input variations. As shown in Table 7, 16 scenarios are generated. Scenarios 1-4 are

Table 6: Opened vaccination centers and vaccine warehouses with assigned customers for the *Baseline scenario* with $\epsilon_2 = 0.48$

Warehouse index	Vaccine flow	Vaccination center index	Center region	Covered demand zones
66	449	422	B	5
	1884	430	B	10,40
	1847	445	B	12,35,36,43
	1665	545	C	20
	1751	549	C	2
274	1877	321	A	19,32
	949	349	A	14
	1789	487	C	31,61
291	1807	341	A	62,63
	1827	488	C	29,58
	1676	559	C	1,33,53
	1885	563	C	18
293	1879	215	A	16,59
	1848	276	A	48,57
	1178	333	A	30,64
	61	350	A	15
	810	470	B	50,56
335	1496	344	A	27,54,60
	1305	346	A	17,21
	622	502	C	28
	1414	503	C	26,52
509	1805	416	B	37,41,45,47
	1805	448	B	9,11
	1813	513	C	4,8
533	7	49	A	25,39
	1731	420	B	7,46
	1756	429	B	13,23,49
	1577	431	B	6,22,38
	1070	446	B	24,34
	797	496	C	51

Total cost: 0.400, z : 6.20, strategic cost of centers: 113.49, opening cost of warehouses: 7, number of opened centers: 30

solved to analyze the effect of the vaccination centers' coverage radius (D). In scenarios 5-8 and 9-12, the impacts of the service capacity of the vaccination centers (Q^c) and the maximum deliverable vaccine units of the vaccine warehouses (Q^w) are analyzed. Finally, the effect of changing the planning horizon (H) is addressed in scenarios 13-16. For each set of scenarios, we report the impact of the associated parameter change on the objective functions to offer policymakers a range of possible outcomes for evaluation. In all scenarios, we assume that $\epsilon_2 = 0.70$ to obtain a single solution instead of a Pareto set.

4.3.1. Impact of the vaccination center's coverage distance (Scenarios 1-4)

In scenarios 1-4, the maximum coverage distance D is modified to take on four values: 2, 4, 6, and 8 kilometers, respectively. The results for these scenarios are reported in Table 8, which shows the impact of D on the total cost, the cost component z , the strategic cost of vaccination centers and the opening cost of warehouses, and the minimum and maximum patient density. In this table, as well as in Tables 9-11, T_{Sc} , N_c , and N_w represent the strategic cost of the selected vaccination centers, the number of chosen vaccination centers, and the number of opened vaccine warehouses, respectively. Figure 11 visualizes each solution related to different values of D on the Mashhad map. Table 8 and Figure 11 reveal some distinct patterns when examining the impact of varying the coverage range (D) of vaccination centers on costs and patient density. As expected, the total cost decreases as D increases (for example, compare Figure 11a with Figure 11b). The value of the objective function component z typically decreases with increasing values of D (see column 3 in Table 8). The reason for this is that vaccination centers can be selected closer to vaccine warehouses, allowing for a higher coverage distance while still covering all demand zones. Also, the strategic cost of vaccination centers decreases with higher values of D since the model can select vaccination centers with lower strategic costs while still covering the demand zones. The number of warehouses is not affected by changes in D . In conclusion, the patterns in Table 8 and Figure 11 suggest that increasing the coverage distance of vaccination centers reduces the total cost, z , and strategic cost because the vaccination centers can be located nearer to the warehouses in low-strategic-cost

Table 7: Scenarios generated to analyze the impact of problem input variations

Scenario	D (km)	Q^c (# patients)	Q^w (# vaccines)	H (days)
1	2	4000	8000	60
2	4	4000	8000	60
3	6	4000	8000	60
4	8	4000	8000	60
5	10	5000	8000	60
6	10	6000	8000	60
7	10	7000	8000	60
8	10	8000	8000	60
9	10	4000	10000	60
10	10	4000	12000	60
11	10	4000	14000	60
12	10	4000	16000	60
13	10	4000	8000	45
14	10	4000	8000	75
15	10	4000	8000	90
16	10	4000	8000	105

regions while still covering all demand zones.

Table 8: Analyzing the impact of changing the coverage range of vaccination centers

D (km)	Total cost	z	T_{Sc}	N_c	N_w	Min. patient density	Max. patient density
2	0.305	3.518	165.71	24	6	0.02	0.67
4	0.237	2.644	67.14	20	6	0.13	0.69
6	0.229	2.436	66.35	20	6	0.31	0.70
8	0.229	2.436	66.35	20	6	0.31	0.70
10*	0.218	2.200	65.35	20	6	0.16	0.70

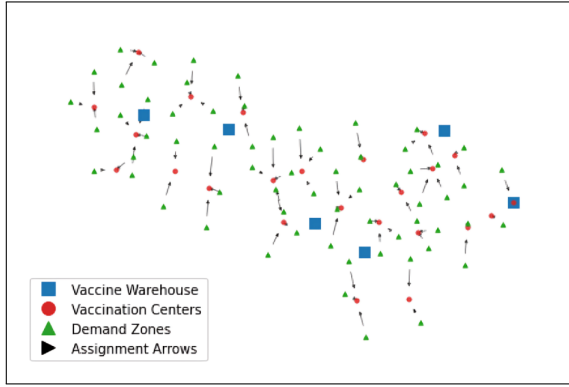
*This row represents the *baseline scenario*

4.3.2. Impact of the vaccination center's service capacity (Scenarios 5-8)

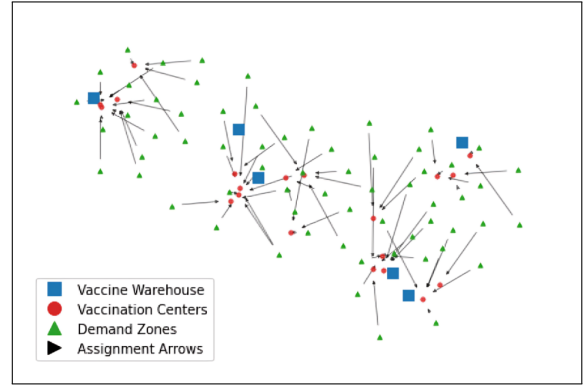
In scenarios 5-8, four different values for the maximum service capacity of vaccination centers, Q^c , are considered (namely 5000, 6000, 7000, and 8000 daily patients). The results for these scenarios and the *baseline scenario* are displayed in Table 9. It can be noted that when Q^c increases from 5000 to 8000 daily patients, the total cost decreases. Specifically, the strategic cost for vaccination centers T_{Sc} decreases, while the number of vaccine warehouses and the p-center objective function z remain the same. As the maximum service capacity increases, fewer vaccination centers are required, as reflected by the reduced number of vaccination centers (from 20 to 16). Compared to the changes in the coverage distance D in Table 8, the maximum patient density decreases with higher Q^c and never reaches the maximum allowed density (e.g., 70%).

4.3.3. Impact of the warehouses' maximum number of deliverable vaccine units (Scenarios 9-12)

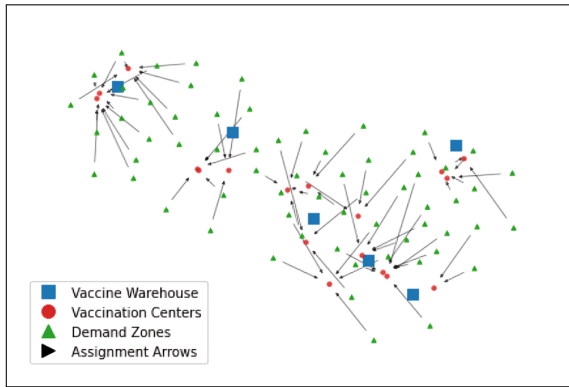
In scenarios 9-12, the warehouses' maximum number of deliverable vaccine units, Q^w , is adjusted to four different values: 10000, 12000, 14000, and 16000 vaccines daily, respectively. Table 10 is provided to analyze and visualize the impact of changing Q^w in these scenarios. Consistent with expectations, changing Q^w affects the number of open warehouses, which decreases for increasing values of Q^w . These, in turn, affect the overall total cost. Variations of Q^w do not directly impact the strategic cost of vaccination centers and their number and z . Opening fewer warehouses reduces the total cost despite increasing z and T_{Sc} .



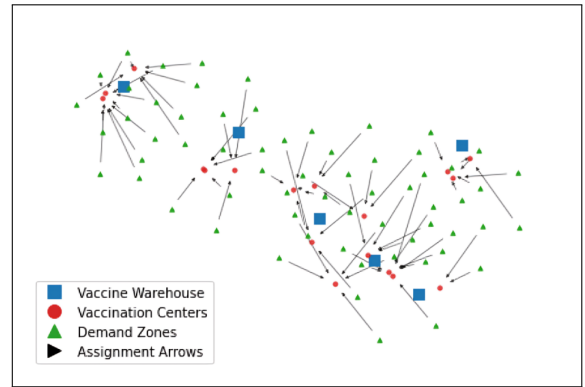
(a) Solution to scenario 1 with $D = 2$ km and total cost of 0.305



(b) Solution to scenario 2 with $D = 4$ km and total cost of 0.237



(c) Solution to scenario 3 with $D = 6$ km and total cost of 0.229



(d) Solution to scenario 4 with $D = 8$ km and total cost of 0.229

Figure 11: Impact of changing the coverage range of vaccination centers on total cost

Table 9: Analyzing the impact of changing the service capacity of vaccination centers

Q^c (patients)	Total cost	z	T_{S^c}	N_c	N_w	Min. patient density	Max. patient density
4000*	0.218	2.200	56.35	20	6	0.16	0.70
5000	0.176	1.111	47.22	17	6	0.26	0.66
6000	0.176	1.111	47.22	17	6	0.22	0.55
7000	0.175	1.111	44.44	16	6	0.20	0.47
8000	0.175	1.111	44.44	16	6	0.17	0.42

*This row represents the *baseline scenario*

Table 10: Analyzing the impact of changing the warehouses' maximum number of deliverable vaccine units

Q^w (patients)	Total cost	z	T_{S^c}	N_c	N_w	Min. patient density	Max. patient density
8000*	0.218	2.200	56.35	20	6	0.16	0.70
10000	0.189	2.070	47.22	17	5	0.38	0.69
12000	0.174	2.111	55.55	20	4	0.10	0.70
14000	0.145	1.284	53.57	19	4	0.14	0.70
16000	0.136	1.717	45.24	16	3	0.58	0.69

*This row represents the *baseline scenario*

4.3.4. Impact of the planning horizon (Scenarios 13-16)

In scenarios 13-16, we consider different durations for the planning horizon (H), ranging from 45 to 105 days. The impact of varying planning horizon duration H is shown in Table 11. As H increases, the total cost decreases due to a reduction in the p-center objective function z , the strategic cost of vaccination centers T_{Sc} , and the number of warehouses N_w . The reason for this is that, with a longer planning horizon, the number of patients vaccinated each day decreases, resulting in fewer vaccination centers and warehouses. Unlike previous parameters, H directly impacts all three elements of the total cost, including z and strategic and opening costs. Despite the cost savings, a longer planning horizon to vaccinate people and fewer vaccine centers may cause delays in preventing the disease from spreading through the city, delaying overall immunity, and potentially prolonging the pandemic.

Table 11: Analyzing the impact of changing the planning horizon

H (days)	Total cost	z	T_{Sc}	N_c	N_w	Min. patient density	Max. patient density
45	0.370	5.049	90.87	25	8	0.35	0.70
60*	0.218	2.200	56.35	20	6	0.16	0.70
75	0.182	1.840	47.89	17	5	0.23	0.70
90	0.168	1.600	33.33	12	5	0.42	0.69
105	0.139	1.392	28.57	10	4	0.35	0.69

*This row represents the *Baseline scenario*

4.4. Comparison of model results for identified sites with real-world configuration

During the COVID-19 period, based on the guidelines of the Ministry of Health and Medical Education of Iran, vaccination sites were established in clinics and hospitals. Using information obtained from Google Maps, we identified 38 such locations across five administrative regions, which were the sites used for vaccination during COVID-19. We referred to these 38 candidate locations as *real-world configurations*. It should be noted that we do not claim these represent all vaccination sites in the city. Rather, they are the locations that could be identified through Google Maps and official reports as being actively used for vaccinations during the COVID-19 period. These included 10 candidate centers from Region A, 7 from Region B, 12 from Region C, 6 from Region D, and 3 from Region E. We solved both real-world configurations (38 candidate locations) and identified sites (635 candidate locations, as described in Section 4.1) with the proposed methodology. For fair comparison, we selected a Pareto solution for which the ϵ_2 parameter in the model was set to 0.70. To ensure a fair comparison, the same values for coverage distance (D), service center capacity (Q^c), time horizon (H), and warehouse capacity (Q^w) were used for both approaches.

Figure 12 compares the *total cost* of the solutions produced by the model for identified sites with those obtained under the real-world configuration. Across all parameter variations, the results for identified sites achieve a notable cost reduction ranging between 46% and 64%, with an average improvement of approximately 52%. The largest cost reduction is observed in scenarios with $Q^w = 16000$, where the model reduces the total cost by over 64.8% compared to the real-world case. These savings reflect the model's ability to select centers and warehouses that minimize the combined strategic and operational cost structure while satisfying all coverage constraints. In addition, Figure 13 focuses on the *strategic cost* of vaccination centers (T_{Sc}). Here, the model results for identified sites consistently yield substantial reductions, with improvements of 20% to 62% depending on the scenario compared to the real-world configuration. The largest relative improvements are again seen in cases with small coverage distances, where strategic selection becomes critical. On average, the model solutions for identified sites reduce T_{Sc} by approximately 34%, demonstrating the model's ability to identify more strategically advantageous locations, i.e., centers with lower GIS-based strategic costs, without compromising demand coverage. Note that in these experiments, we did not report results for $D = 2$ km since there was no feasible solution to the real-world setup.

Figure 14 shows the *number of vaccination centers* (N_c) chosen under each scenario. The solution returned by the method for identified sites typically selects 5%–23% fewer centers than the real-world configuration while still covering all demand zones within the allowed distance with an average improvement of 11.2%. For example, in the $D = 4$ km scenario, the real-world setup utilizes 26 centers, whereas the method's solution for identified sites requires only 20, resulting in a 23.1% reduction. More pronounced efficiency gains are observed in high-capacity scenarios, where fewer but optimally located centers suffice. Figure 15 compares the *number of warehouses* (N_w)

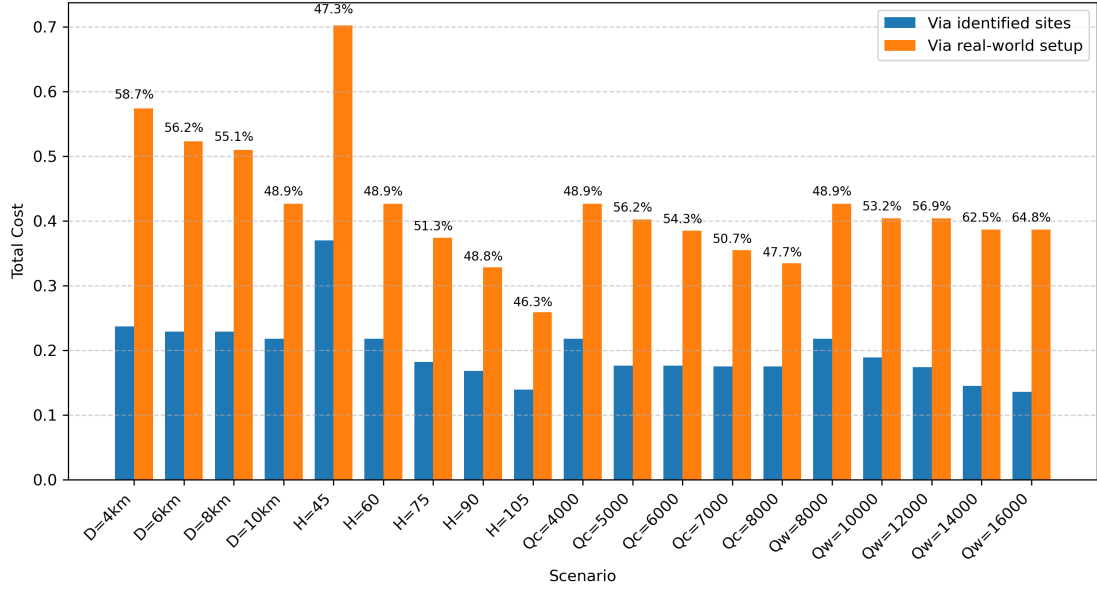


Figure 12: Comparison of total cost between the proposed method's results for identified sites and real-world configuration across different parameter settings.

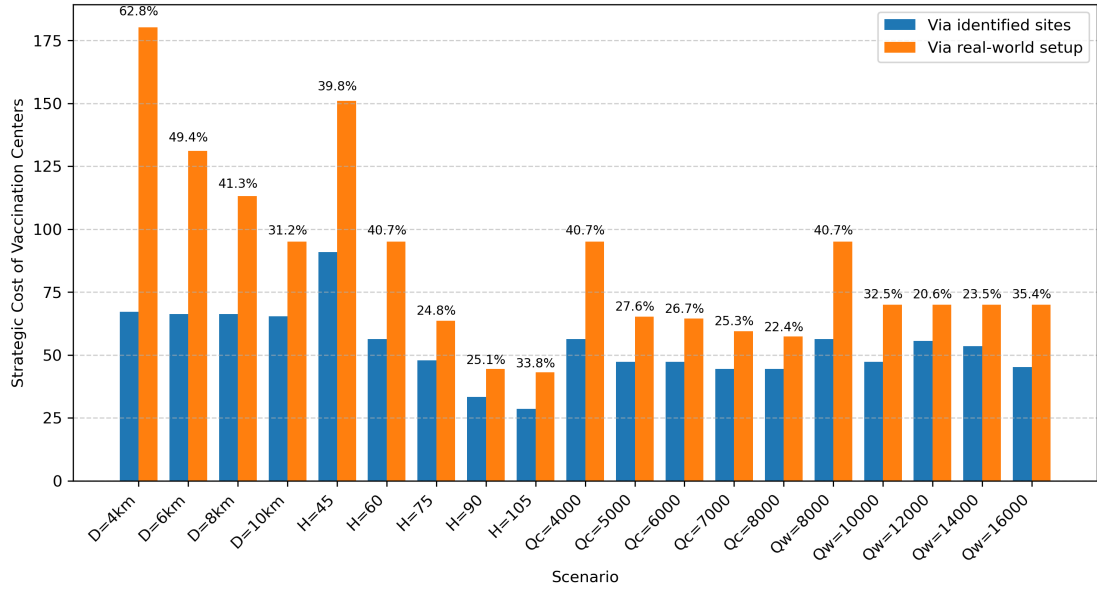


Figure 13: Comparison of the strategic cost of selected vaccination centers (T_{Sc}) between the proposed method's results for identified sites and real-world configuration across different parameter settings.

required. The solution by the method for identified sites matches or reduces the number of warehouses in nearly all cases, achieving reductions of up to 40%. In scenarios with large warehouse capacities ($Q^w \geq 10,000$), the model frequently consolidates supply into fewer warehouses without violating capacity or coverage constraints, thus reducing infrastructure and operational complexity.

Figure 16 compares the maximum distance z between any warehouse and the service center it supplies, based on

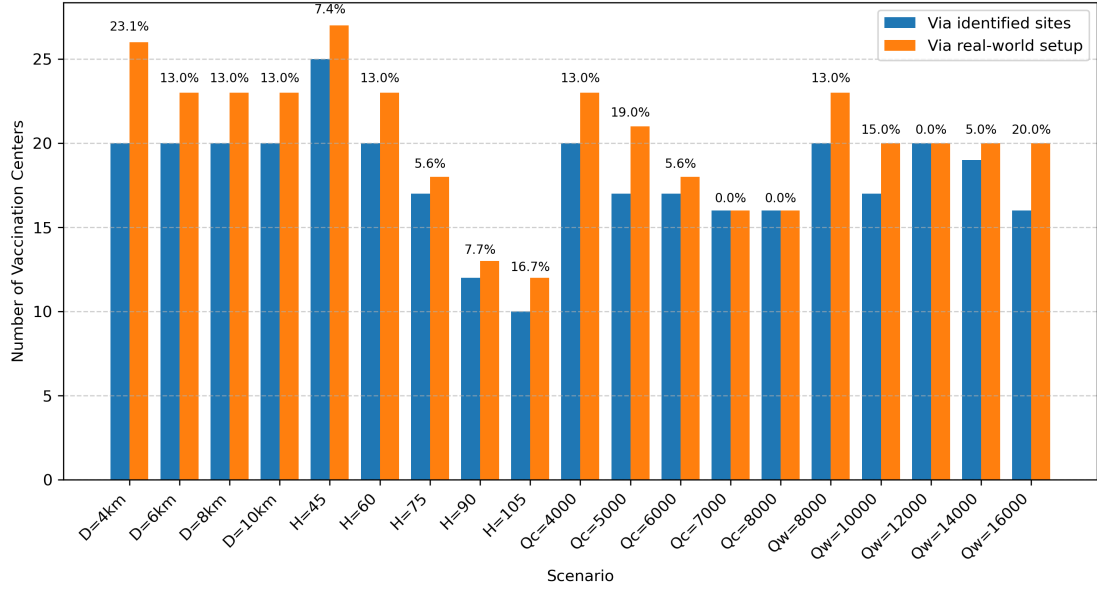


Figure 14: Comparison of the number of vaccination centers (N_c) between the proposed method's results for identified sites and real-world configuration across different parameter settings.

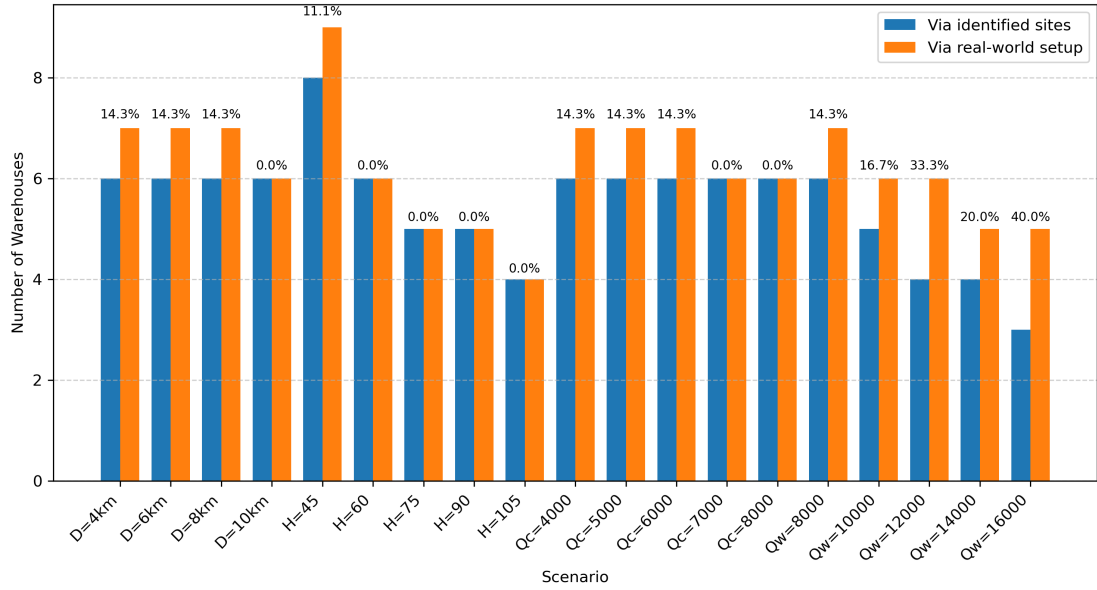


Figure 15: Comparison of the number of warehouses (N_w) between the proposed method's results for identified sites and real-world configuration across different parameter settings.

the method's results for identified sites and the real-world configuration, across all scenarios. The results for identified sites consistently outperform the real-world setup, reducing z in nearly every scenario. The percentage improvement ranges from approximately 0.5% to over 55%, with an average reduction of about 26% across all tested parameter settings. These improvements are especially pronounced in scenarios with $Q^c \geq 5000$, where the model achieves a 55% reduction in z by optimizing both the placement of vaccination centers and the allocation of warehouses. In

$H = 75$ and $H = 90$, the improvement exceeds 35%, indicating that the proposed method is particularly effective at planning for extended operational periods. Scenarios with higher warehouse capacities (Q^w) also benefit from the method's result for identified sites. However, the relative improvement in z is somewhat smaller due to the inherently greater flexibility these capacities provide. Even in these cases, however, the model still delivers shorter maximum distances compared to the real-world setup, which translates into lower transportation times, reduced fuel consumption, and faster delivery of critical supplies. By shortening the longest supply routes, the proposed approach not only lowers operational costs but also increases the network's resilience and responsiveness in a crisis. This is critical in real-world public health emergencies where rapid and reliable supply delivery can directly impact the effectiveness of vaccination campaigns.

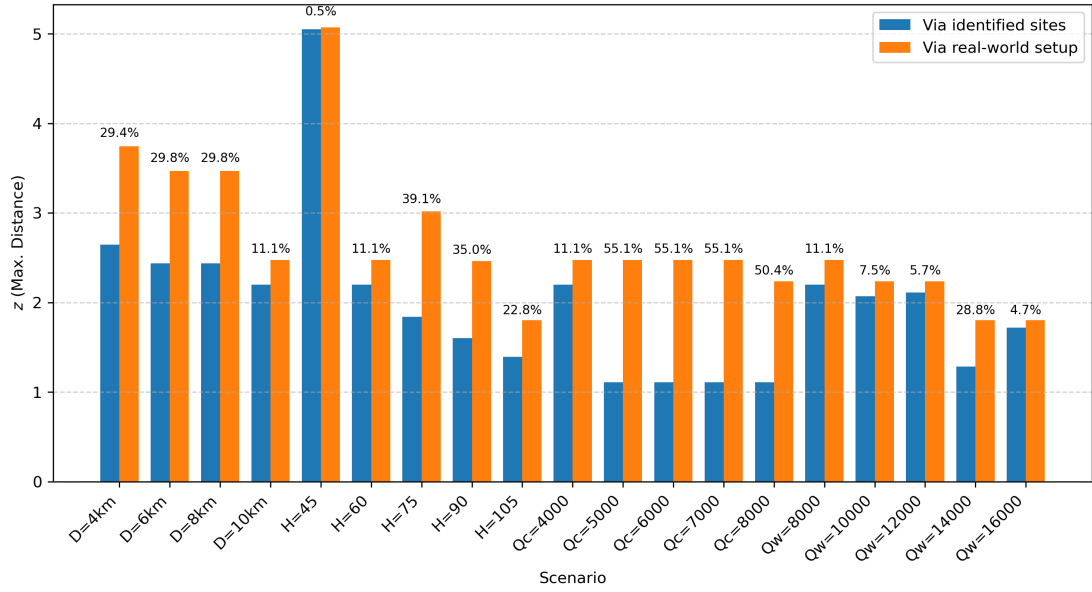


Figure 16: Comparison of the maximum warehouse-to-center distance z between the proposed method's results for identified sites and real-world configuration across different parameter settings.

Overall, the results returned by the method for identified sites (635 candidate locations) produce solutions that significantly outperform the real-world configuration (38 candidate locations) across all evaluated metrics. On average, the method's solution for identified sites improves total cost by 52%, reduces the strategic cost by 34%, decreases the number of vaccination centers by 11%, lowers the number of warehouses by 12%, and decreases the z by 26%. These improvements are achieved while respecting all capacity, coverage, and operational constraints, and without compromising service accessibility. In practical terms, such improvements mean that during real-world vaccination campaigns, authorities could provide the same level of service at nearly half the total cost and simplify logistics by operating fewer facilities, increasing both efficiency and resilience in public health emergency responses.

5. Conclusion and Future Research Directions

This study presents a multi-step approach for selecting locations for vaccination centers and vaccine warehouses as part of a pandemic response strategy. While many studies in the literature assume the existence of a set of potential candidate sites without detailing how these sites are identified, we propose a comprehensive methodological framework that also supports identifying candidate locations using strategic criteria from the literature and expert interviews. Specifically, the Best-Worst Method is first used to prioritize infrastructure, environmental, and socio-demographic criteria, which are then incorporated within GIS to build a set of candidate locations with associated strategic costs. In the following step, the Two-Echelon Capacitated Location Allocation Problem (2E-CLAP) is solved to identify the optimal locations for both vaccine warehouses and service centers while considering several planning aspects

including strategic costs, patient accessibility, facility crowding, and vaccine distribution reliability. High-quality solutions to 2E-CLAP are found through a Non-Dominated Sorting Genetic Algorithm II whose efficiency is validated on randomly generated instances and a real case study based on the city of Mashhad in Iran.

The application of the proposed multi-step approach offers important managerial insights for optimizing healthcare facility location during crises. By integrating strategic considerations such as socio-demographics, infrastructure, and environmental factors with tactical decisions like capacity utilization planning and vaccine allocation, this framework provides a robust foundation for equitable and efficient service delivery. For healthcare managers, the ability to identify suitable facility locations for vaccination using GIS-based analysis, combined with the fairness and coverage guarantees of the 2E-CLAP model, ensures that critical public health objectives such as accessibility and congestion management are achieved under constrained resources.

Our results can inform decision-makers during healthcare crises like the COVID-19 pandemic and provide them with a scientific tool to evaluate the trade-off solutions that balance strategic costs, accessibility, and virus transmission. For example, the managerial insights derived from the model application include the following:

- Lengthening the planning horizon improves the cost and resource distribution, minimizing the number of needed centers and warehouses. While extending the duration can mitigate logistical challenges, it is crucial to balance this against the urgency of vaccinating people to reduce virus transmission and achieve herd immunity.
- Choosing solutions that keep the patient density at vaccination centers within an acceptable threshold avoids overcrowding and reduces transmission risks, while still ensuring high quality with respect to strategic costs, accessibility, and distribution efficiency.
- The service capacity and coverage radius of vaccination centers play a significant role in determining the location and number of selected centers and warehouses. Stakeholders must consider the trade-offs between logistical costs and service accessibility, which ultimately affect vaccine uptake.
- Across all scenarios, the method's results for identified sites (635 candidate locations) consistently dominate the real-world configuration (with 38 candidate locations). On average, the results for identified sites reduce the *total cost* by approximately 52% and lower the *strategic cost of selected centers* by roughly 34%. It also shortens the *maximum warehouse-center distance z* by about 26% on average, while using 11% fewer vaccination centers and 12% fewer warehouses on average. Practically, this translates to materially lower spending, simpler infrastructure, and shorter supply chains, key advantages for rapid and resilient vaccination operations in a real-world configuration.

This study has limitations that future research could address. Notably, the model does not fully capture the uncertain and dynamic demand fluctuations that are critical during healthcare crises. Future work could enhance this framework by integrating models that explicitly account for fluctuating demand patterns, improving the responsiveness to rapidly changing conditions. Incorporating epidemiological models within the multi-step framework could further strengthen decision-making by considering disease transmission dynamics, vaccination thresholds, and behavioral factors such as vaccine hesitancy. Additionally, integrating this strategic framework with operational models such as inventory management, real-time logistics, and workforce scheduling could enhance its applicability across different phases of the pandemic response. Integrating uncertain elements, epidemiological aspects, and operational decisions would undoubtedly increase the complexity of the resulting models, requiring the development of more sophisticated algorithms for the solution of complex multi-objective stochastic and/or robust optimization models. Finally, this model is designed for urban environments with a developed infrastructure and high population density. Future research should explore adaptations for rural or less-developed areas where logistical constraints, equity concerns, and cost considerations present distinct challenges.

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Conflict of interest

The authors have no conflicts of interest to disclose.

Data Availability Statement

Data, models, and codes are available upon request.

References

- Abbas, H.W., Sajid, Z., Dao, U., 2024. Assessing the impact of risk factors on vaccination uptake policy decisions using a Bayesian Network (BN) approach. *Systems* 12, 167.
- Abbasi, S., Zahmatkesh, S., Bokhari, A., Hajiaghaei-Keshteli, M., 2023. Designing a vaccine supply chain network considering environmental aspects. *Journal of Cleaner Production* 417, 137935.
- Abdin, A.F., Fang, Y.P., Caunhye, A., Alem, D., Barros, A., Zio, E., 2023. An optimization model for planning testing and control strategies to limit the spread of a pandemic—the case of COVID-19. *European Journal of Operational Research* 304, 308–324.
- Ahmadi-Javid, A., Seyed, P., Syam, S.S., 2017. A survey of healthcare facility location. *Computers & Operations Research* 79, 223–263.
- Alhothali, A., Alwated, B., Faisal, K., Alshammari, S., Alotaibi, R., Alghanmi, N., Bamasag, O., Bin Yamin, M., 2022. Location-allocation model to improve the distribution of COVID-19 vaccine centers in Jeddah city, Saudi Arabia. *International Journal of Environmental Research and Public Health* 19, 8755.
- Arboleda, C.A., Abraham, D.M., Richard, J.P.P., Lubitz, R., 2009. Vulnerability assessment of health care facilities during disaster events. *Journal of Infrastructure Systems* 15, 149–161.
- Babaeinesami, A., Tohidi, H., Ghasemi, P., Goodarzian, F., Tirkolaee, E.B., 2022. A closed-loop supply chain configuration considering environmental impacts: a self-adaptive NSGA-II algorithm. *Applied Intelligence* 52, 13478–13496.
- Bertsimas, D., Digalakis Jr, V., Jacquillat, A., Li, M.L., Previero, A., 2022. Where to locate COVID-19 mass vaccination facilities? *Naval Research Logistics (NRL)* 69, 179–200.
- Bozkaya, B., Bruno, G., Giannikos, I., 2019. *Location and Geographic Information Systems*. Springer International Publishing, Cham. pp. 559–590.
- Büyüktaktın, İ.E., des Bordes, E., Kızı, E.Y., 2018. A new epidemics–logistics model: Insights into controlling the ebola virus disease in west africa. *European Journal of Operational Research* 265, 1046–1063.
- Çalik, H., Labbé, M., Yaman, H., 2019. *P-Center Problems*. Springer International Publishing. pp. 51–65.
- Centers for Disease Control and Prevention, 2021. Vaccine storage and handling resources. URL: <https://www.cdc.gov/vaccines/hcp/admin/storage/index.html>. Accessed: 04-12-2024.
- Chauhan, A., Singh, A., 2016. A hybrid multi-criteria decision making method approach for selecting a sustainable location of healthcare waste disposal facility. *Journal of Cleaner Production* 139, 1001–1010.
- Chavehpoor, Y., Rashidian, A., Woldemichael, A., Takian, A., 2019. Inequality in geographical distribution of hospitals and hospital beds in densely populated metropolitan cities of Iran. *BMC Health Services Research* 19, 1–8.
- Chen, Y.J., Chindarkar, N., Xiao, Y., 2019. Effect of reliable electricity on health facilities, health information, and child and maternal health services utilization: evidence from rural gujarat, India. *Journal of Health, Population and Nutrition* 38, 1–16.
- Chowdhury, N.R., Ahmed, M., Mahmud, P., Paul, S.K., Liza, S.A., 2022. Modeling a sustainable vaccine supply chain for a healthcare system. *Journal of Cleaner Production* 370, 133423.
- Church, R.L., 2002. Geographical Information Systems and location science. *Computers & Operations Research* 29, 541–562. Location Analysis.
- Coello, C.A.C., Cortés, N.C., 2005. Solving multiobjective optimization problems using an artificial immune system. *Genetic Programming and Evolvable Machines* 6, 163–190.
- Current, J.R., Storbeck, J.E., 1988. Capacitated covering models. *Environment and Planning B: Planning and Design* 15, 153–163.
- Dastgoshade, S., Shafiee, M., Klibi, W., Shishebori, D., 2022. Social equity-based distribution networks design for the COVID-19 vaccine. *International Journal of Production Economics* 250, 108684.
- Davoodi, M., 2019. k-Balanced Center Location problem: A new multi-objective facility location problem. *Computers & Operations Research* 105, 68–84.
- Deb, K., 2011. Multi-objective optimisation using evolutionary algorithms: an introduction, in: *Multi-objective evolutionary optimisation for product design and manufacturing*. Springer, pp. 3–34.
- Deb, K., Agrawal, S., Pratap, A., Meyarivan, T., 2000. A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II, in: *International conference on parallel problem solving from nature*, Springer. pp. 849–858.
- Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation* 6, 182–197.
- Deb, K., Sindhya, K., Hakanen, J., 2016. Multi-objective optimization, in: *Decision sciences*. CRC Press, pp. 161–200.
- Dehghan, M., Ong, C.J., 2013. Computations of mode-dependent dwell times for discrete-time switching system. *Automatica* 49, 1804–1808.

- Dell'Ovo, M., Capolongo, S., Oppio, A., 2018. Combining spatial analysis with mcda for the siting of healthcare facilities. *Land use policy* 76, 634–644.
- Devi, Y., Patra, S., Singh, S.P., 2021. A location-allocation model for influenza pandemic outbreaks: A case study in India. *Operations Management Research*, 1–16.
- Dey, S., Kurbanzade, A.K., Gel, E.S., Mihaljevic, J., Mehrotra, S., 2024. Optimization modeling for pandemic vaccine supply chain management: A review and future research opportunities. *Naval Research Logistics (NRL)*.
- Eastman, J.R., 1999. Multi-criteria evaluation and GIS. *Geographical Information Systems* 1, 493–502.
- Eldemir, F., Onden, I., 2016. Geographical information systems and multicriteria decisions integration approach for hospital location selection. *International Journal of Information Technology and Decision Making* 15, 975 – 997.
- Elloumi, S., Labbé, M., Pochet, Y., 2004. A new formulation and resolution method for the p-center problem. *INFORMS Journal on Computing* 16, 84–94.
- Erdin, C., Akbaş, H.E., 2019. A comparative analysis of fuzzy topsis and geographic information systems (GIS) for the location selection of shopping malls: a case study from Turkey. *Sustainability* 11, 3837.
- Essoh, T.A., Adeyanju, G.C., Adamu, A.A., Tall, H., Aplogan, A., Tabu, C., 2023. Exploring the factors contributing to low vaccination uptake for nationally recommended routine childhood and adolescent vaccines in Kenya. *BMC Public Health* 23, 912.
- Fahrni, M.L., Ismail, I.A.N., Refi, D.M., Almeman, A., Yaakob, N.C., Saman, K.M., Mansor, N.F., Noordin, N., Babar, Z.U.D., 2022. Management of COVID-19 vaccines cold chain logistics: a scoping review. *Journal of Pharmaceutical Policy and Practice* 15, 16.
- Faramarzi-Oghani, S., Dolati Neghabadi, P., Talbi, E.G., Tavakkoli-Moghaddam, R., 2023. Meta-heuristics for sustainable supply chain management: A review. *International Journal of Production Research* 61, 1979–2009.
- Govindan, K., Salehian, F., Kian, H., Hosseini, S.T., Mina, H., 2023. A location-inventory-routing problem to design a circular closed-loop supply chain network with carbon tax policy for achieving circular economy: An augmented epsilon-constraint approach. *International Journal of Production Economics* 257, 108771.
- Grot, M., 2024. Decision support framework for tactical emergency medical service location planning. *Omega* 125, 103036.
- Gul, M., Guneri, A.F., 2021. Hospital location selection: A systematic literature review on methodologies and applications. *Mathematical Problems in Engineering* 2021, 6682958.
- Güneş, E.D., Melo, T., Nickel, S., 2019. Location problems in healthcare. *Location Science*, 657–686.
- Hakimi, S.L., 1965. Optimum distribution of switching centers in a communication network and some related graph theoretic problems. *Operations Research* 13, 462–475.
- Hazbavi, Z., Mostafazadeh, R., Alaei, N., Azizi, E., 2021. Spatial and temporal analysis of the COVID-19 incidence pattern in Iran. *Environmental Science and Pollution Research* 28, 13605–13615.
- Hoadley, E.D., Jorgensen, B., Masters, C., Tuma, N., Wulff, S., et al., 2010. Strategic facilities planning: A focus on health care. *Journal of Service Science (JSS)* 3.
- Ishizaka, A., Khan, S.A., Kheybari, S., Zaman, S.I., 2022. Supplier selection in closed loop pharma supply chain: A novel BWM–GAIA framework. *Annals of Operations Research*, 1–24.
- Kheybari, S., Ishizaka, A., Salamirad, A., 2021. A new hybrid risk-averse best-worst method and portfolio optimization to select temporary hospital locations for COVID-19 patients. *Journal of the Operational Research Society*, 1–18.
- Kuvvetli, Y., 2023. A goal programming model for two-stage COVID19 test sampling centers location-allocation problem. *Central European Journal of Operations Research* 31, 1–20.
- Li, X., Pan, Y., Jiang, S., Huang, Q., Chen, Z., Zhang, M., Zhang, Z., 2021. Locate vaccination stations considering travel distance, operational cost, and work schedule. *Omega* 101, 102236.
- Li, X., Zhao, Z., Zhu, X., Wyatt, T., 2011. Covering models and optimization techniques for emergency response facility location and planning: a review. *Mathematical Methods of Operations Research* 74, 281–310.
- Luxon, L., 2015. Infrastructure - the key to healthcare improvement. *Future Healthcare Journal* 2, 4–7.
- Manupati, V.K., Schoenherr, T., Subramanian, N., Ramkumar, M., Soni, B., Panigrahi, S., 2021. A multi-echelon dynamic cold chain for managing vaccine distribution. *Transportation Research Part E: Logistics and Transportation Review* 156, 102542.
- Medrano, F.A., 2020. The complete vertex p-center problem. *EURO Journal on Computational Optimization* 8, 327–343.
- Minieka, E., 1970. The m-center problem. *Siam Review* 12, 138–139.
- Moradi, N., Boroujeni, N.M., 2024. Prize-collecting electric vehicle routing model for parcel delivery problem. *Expert Systems with Applications*, 125183.
- Moradi, N., Sadati, İ., Çatay, B., 2023. Last mile delivery routing problem using autonomous electric vehicles. *Computers & Industrial Engineering* 184, 109552.
- National Academies of Sciences, Engineering, and Medicine and National Academy of Medicine, 2022. Globally Resilient Supply Chains for Seasonal and Pandemic Influenza Vaccines. The National Academies Press. URL: <https://nap.nationalacademies.org/catalog/26285/globally-resilient-supply-chains-for-seasonal-and-pandemic-influenza-vaccines>, doi:10.17226/26285. Accessed: 04-12-2024.
- Ning, C., Wang, H., Wu, J., Chen, Q., Pei, H., Gao, H., 2022. The COVID-19 vaccination and vaccine inequity worldwide: an empirical study based on global data. *International Journal of Environmental Research and Public Health* 19, 5267.
- Ozdemir, I., Dursunoglu, C.F., Kara, B.Y., Dora, M., 2022. Logistics of temporary testing centers for coronavirus disease. *Transportation Research Part C: Emerging Technologies* 145, 103954.
- Ray, K.N., Chari, A.V., Engberg, J., Bertolet, M., Mehrotra, A., 2015. Disparities in time spent seeking medical care in the United States. *JAMA Internal Medicine* 175, 1983–1986.
- Ren, Y., Ordóñez, F., Wu, S., 2013. Optimal resource allocation response to a smallpox outbreak. *Computers & Industrial Engineering* 66, 325–337.
- Rezaei, J., 2015. Best-worst multi-criteria decision-making method. *Omega* 53, 49–57.
- Rezaei, J., Arab, A., Mehregan, M., 2024. Analyzing anchoring bias in attribute weight elicitation of smart, swing, and best-worst method. *International Transactions in Operational Research* 31, 918–948.

- Rezai, H.Z., Davoodi, A., 2024. Healthcare facility location, in: *Decision Making in Healthcare Systems*. Springer, pp. 129–150.
- Riquelme, N., Von Lücken, C., Baran, B., 2015. Performance metrics in multi-objective optimization, in: *2015 Latin American computing conference (CLEI)*, IEEE. pp. 1–11.
- Sharifi, T., Hosseini, S.E., Mohammadpour, S., Javan-Noughabi, J., Ebrahimipour, H., Hooshmand, E., 2021. Quality assessment of services provided by health centers in Mashhad, Iran: Servqual versus healthqual scales. *BMC Health Services Research* 21, 397.
- Shishebori, D., Yousefi Babadi, A., 2015. Robust and reliable medical services network design under uncertain environment and system disruptions. *Transportation Research Part E: Logistics and Transportation Review* 77, 268–288.
- Silva, A.R.M.V.e., Iwata, B.d.F., dos Santos, M.d.S.F., Neto, J.M.M., 2023. Impacts and regulations of healthcare solid waste management during the COVID-19 pandemic: A systematic review. *Sustainability* 15, 14462.
- Slocum, T.A., McMaster, R.B., Kessler, F.C., Howard, H.H., 2022. *Thematic cartography and geovisualization*. CRC Press.
- Srinivas, N., Deb, K., 1994. Multiobjective optimization using nondominated sorting in genetic algorithms. *Evolutionary Computation* 2, 221–248.
- Sun, L., DePuy, G.W., Evans, G.W., 2014. Multi-objective optimization models for patient allocation during a pandemic influenza outbreak. *Computers & Operations Research* 51, 350–359.
- Tang, L., Li, Y., Bai, D., Liu, T., Coelho, L.C., 2022. Bi-objective optimization for a multi-period COVID-19 vaccination planning problem. *Omega* 110, 102617.
- Tavana, M., Govindan, K., Nasr, A.K., Heidary, M.S., Mina, H., 2021. A mathematical programming approach for equitable COVID-19 vaccine distribution in developing countries. *Annals of Operations Research*.
- Toregas, C., Swain, R., ReVelle, C., Bergman, L., 1971. The location of emergency service facilities. *Operations Research* 19, 1363–1373.
- UNICEF-WHO, 2021. Covax ultra-low temperature freezers boost vaccine storage capacity to nine million. UNICEF URL: <https://www.unicef.org/press-releases/covax-ultra-low-temperature-freezers-boost-vaccine-storage-capacity-nine-million>. Accessed: 04-12-2024.
- Van Veldhuizen, D.A., 1999. Multiobjective evolutionary algorithms: classifications, analyses, and new innovations. *Air Force Institute of Technology*.
- Verma, S., Pant, M., Snasel, V., 2021. A comprehensive review on NSGA-II for multi-objective combinatorial optimization problems. *IEEE Access* 9, 57757–57791.
- Wei, R., 2016. Coverage location models: alternatives, approximation, and uncertainty. *International Regional Science Review* 39, 48–76.
- Wong, C.L., Leung, A.W., Chung, O.M.H., Chien, W.T., 2022. Factors influencing COVID-19 vaccination uptake among community members in Hong Kong: a cross-sectional online survey. *BMJ Open* 12, e058416.
- Xu, J., Murray, A.T., Church, R.L., Wei, R., 2023. Service allocation equity in location coverage analytics. *European Journal of Operational Research* 305, 21–37.
- Yang, Y., Bidkhor, H., Rajgopal, J., 2021. Optimizing vaccine distribution networks in low and middle-income countries. *Omega* 99, 102197.
- Yarmand, H., Ivy, J.S., Denton, B., Lloyd, A.L., 2014. Optimal two-phase vaccine allocation to geographically different regions under uncertainty. *European Journal of Operational Research* 233, 208–219.
- Yilmaz, M., Ulubaş Hamurcu, A., 2022. Relationships between socio-demographic structure and spatio-temporal distribution patterns of COVID-19 cases in Istanbul, Turkey. *International Journal of Urban Sciences* 26, 557–581.

Appendix A. Strategic criteria clarifications

Appendix B. Weight of criteria and distance-geographical area selection level

Based on expert assessments, we categorized the criteria into five tiers, with a score equal to 5 denoting ‘very good’, 4 for ‘good’, 3 for ‘average’, 2 for ‘poor’, and 1 for ‘very poor’ (see Table B.1). The GIS considered both the criteria weighting and their categorization as inputs.

Table B.1: Weight of criteria and distance-geographical area selection level

Criteria	Weight	Measurement	Score
Population (p) density	0.196	11458≤p ≤17186	1
		7639≤ p ≤11457	2
		3820≤ p ≤7638	3
		1910≤ p≤3819	4
		0≤ p≤1909	5
Age distribution (y)	0.144	y> 65	5
		65≥ y >60	4
		60≥ y >50	3
		50≥ y >40	2
		40 ≥y	1
Continued on next page			

Table B.1 – Continued from previous page

Criteria	Weight	Measurement	Score
Distance (d) to the laboratory	0.096	d<250m	5
		250m≤d<500m	4
		500m≤d<800m	3
		800m ≤d<1.5km	2
		d≥1.5km	1
Distance from waste disposal centers	0.077	d<200m	5
		200m≤d<700m	4
		700m≤d<900m	3
		900m ≤d<1.2km	2
		d≥1.2km	1
Distance to the main transportation lines	0.065	d<250m	5
		250m≤d<500m	4
		500m≤d<800m	3
		800m≤d<1.2km	2
		d≥1.2km	1
Distance to public transportation	0.064	d<400m	5
		400m≤d<800m	4
		800m≤d<1.5km	3
		1.5km ≤d<2km	2
		d≥2km	1
Distance to the nearest parking lot	0.061	d<500m	5
		500m≤d<1km	4
		1km≤d<1.5km	3
		1.5km ≤d<2km	2
		d≥2km	1
Distance from sensitive natural resources	0.060	d>3km	5
		2km<d≤3km	4
		1km<d≤2km	3
		500m<d≤1km	2
		d≤500m	1
Distance from surface water	0.055	d>3km	5
		3km≥d>2km	4
		2km≥d>1km	3
		1km≥d>500m	2
		d≤500m	1
Existing infrastructure (water, electricity, gas, and telephone)	0.050	d<0.6km	5
		0.6km≤d<1.5km	4
		1.5km≤d<2km	3
		2km≤d<2.5km	2
		d≥2.5km	1
Distance from sensitive resources	0.043	d≥3km	5
		2km≤d<3km	4
		1km≤d<2km	3
		500m≤d<1km	2
		d<500m	1
Traffic	0.144	11458≤p ≤17186	5
		7639≤ p ≤11457	4
		3820≤ p ≤7638	3
Continued on next page			

Table B.1 – Continued from previous page

Criteria	Weight	Measurement	Score
		$1910 \leq p \leq 3819$	2
		$0 \leq p \leq 1909$	1
* The analysis of the distance from sensitive resources and traffic was conducted by taking into account the experts' opinions on the measurement of the distance from sensitive natural resources and population density, respectively.			

Appendix C. Generated small and medium instances based on the case study data

The generated small and medium instances with 30 to 60 demand zones, 90 to 150 vaccination centers, and 50 vaccine warehouses are presented in Table C.1 with their size. These instances are solved by the ϵ -constraint method and NSGA-II to compare their performance. Notably, for larger instances ($|I| > 60$ and $|J| > 150$), the Gurobi could not obtain the optimal solution within the set time limit.

Appendix D. Formulas of comparison metrics

This section presents the metrics formula for comparing the proposed NSGA-II and Gurobi over small and medium instances. To calculate Generational Distance (GD), the goal is to measure how close the solutions obtained by NSGA-II are to the exact Pareto front (Gurobi solutions in this case). The GD's formula is given in Eq. D.1:

$$IGD = \frac{1}{|S|} \sum_{\mathbf{x} \in S} \min_{\mathbf{x}^* \in P^*} \|\mathbf{x} - \mathbf{x}^*\| \quad (D.1)$$

S is the set of solutions generated by NSGA-II. P^* is the set of solutions Gurobi generates (the exact Pareto front). $\mathbf{x}$ and $\mathbf{x}^*$ are the NSGA-II and Gurobi solutions, respectively. Also, $\|\cdot\|$ denotes the distance metric (Euclidean in this work). This formula calculates the Euclidean distance between each solution in the NSGA-II set and the closest solution in the Gurobi set and then averages these distances.

The Inverted Generational Distance (IGD) is a metric used to evaluate the quality of a set of solutions in multi-objective optimization. It measures how well a set of solutions approximates the exact Pareto front. The formula for IGD is given by Eq. D.2:

$$IGD = \frac{1}{|P^*|} \sum_{\mathbf{x}^* \in P^*} \min_{\mathbf{x} \in S} \|\mathbf{x} - \mathbf{x}^*\| \quad (D.2)$$

Note that GD measures the distance of the solutions obtained to the exact Pareto front, focusing on how close the solutions are to the Pareto front. IGD measures how well the obtained solutions cover the exact Pareto front, focusing on how well the solutions are approximated and how well they are covered.

The Epsilon Indicator (ϵ) is used to evaluate the quality of a set of solutions in multi-objective optimization by measuring the extent to which a solution set approximates the exact Pareto front, considering the worst-case scenario. It measures the smallest value of ϵ for which all points in the exact Pareto front are approximated within ϵ by at least one solution from the obtained set S . The formula for the Epsilon Indicator is given by Eq. D.3:

$$\epsilon = \min \{ \epsilon \mid \forall \mathbf{x}^* \in P^*, \exists \mathbf{x} \in S \text{ such that } \mathbf{x} \geq \mathbf{x}^* - \epsilon \mathbf{e} \} \quad (D.3)$$

where $\mathbf{e}$ is a vector with all components equal to 1 (unit vector). Also, $\geq$ denotes the component-wise greater-than-or-equal-to relationship.

The Spacing (SP) metric is used to evaluate the diversity of a set of solutions in multi-objective optimization. It measures how evenly the solutions are distributed along the Pareto front. The formula for SP is given by Eq. D.4:

$$SP = \sqrt{\frac{1}{|S|} \sum_{i=1}^{|S|} (d_i - \bar{d})^2} \quad (D.4)$$

Table A.1: Strategic criteria and their clarifications

Criteria	Clarifications
Proximity to healthcare centers	Ensures immediate medical support for rare adverse vaccine reactions (e.g., anaphylaxis).
Access to main transportation lines	Enables efficient vaccine supply delivery and reduces logistical delays.
Access to public transit	Ensures equitable access for populations without private vehicles.
Parking lot proximity	Accommodates high-volume traffic from staff, volunteers, and recipients.
Existing utilities (water, electricity, gas, telecom)	Avoids costly infrastructure delays; critical for cold storage (vaccine stability) and operations.
Low-traffic areas	Low-traffic areas minimize congestion for faster throughput and emergency vehicle access. We assume areas with more population density have more traffic.
Distance from waste disposal centers	Closeness to waste disposal centers are desirable to support sustainable disposal management.
Distance from surface water/natural resources	Prevents accidental pollution from medical waste (e.g., syringes, vials). Urban sites require water access but avoid ecologically sensitive zones.
Population density	Prioritizes high-demand areas.
Age distribution	Focuses on vulnerable groups (e.g., elderly).
Distance from sensitive resources	Prevents proximity to livestock/wildlife to avoid zoonotic transmission of vaccine-derived viruses (e.g., oral polio vaccine risks).

Table C.1: Features of generated small and medium instances based on the case study

Instance name	Index	I	J	K
1-I30-J90-K50	1	30	90	50
2-I40-J90-K50	2	40	90	50
3-I50-J90-K50	3	50	90	50
4-I60-J90-K50	4	60	90	50
5-I30-J150-K50	5	30	150	50
6-I40-J150-K50	6	40	150	50
7-I50-J150-K50	7	50	150	50
8-I60-J150-K50	8	60	150	50

where d_i is the Euclidean distance of the i -th solution to its nearest neighbor in the set S and $\bar{d} = \frac{1}{|S|} \sum_{i=1}^{|S|} d_i$ is the average distance between neighboring solutions in the set S . A lower SP value indicates that the solutions are more uniformly distributed along the Pareto front, meaning better diversity.

The completeness calculates the number of exact Pareto solutions in the NSGA-II's solution set. Its formula is given by Eq. (D.5):

$$\text{Completeness} = \frac{|Q^*|}{|P|} \quad (\text{D.5})$$

where P is the exact Pareto set, and Q is the NSGA-II's solution set (mapped into the objective space). The $Q^* = P \cap Q$ is the overlap between the two sets of P and Q .

The inferiority measures the ratio of the NSGA-II's solutions dominated by at least one solution in the exact Pareto set. It is found by Eq. (D.6):

$$\text{Inferiority} = \frac{|Q'|}{|Q|} \quad (\text{D.6})$$

where Q' is the set of solutions in Q that are dominated by at least one in P .

Finally, the maximum gap calculates the maximum percentage gap between the exact Pareto solutions not found by the NSGA-II and their closest counterpart in the NSGA-II regarding both objectives. It is calculated by Gap_1 and Gap_2 given by Eqs. (D.7) and (D.8):

$$Gap_1\% = \max_{t \in P-Q} \frac{|Z_1^t - Z_1^{t'}|}{Z_1^t} \times 100 \quad (D.7)$$

$$Gap_2\% = \max_{t \in P-Q} \frac{|Z_2^t - Z_2^{t'}|}{Z_2^t + \epsilon'} \times 100 \quad (D.8)$$

where Z_1^t and Z_2^t are the first and second objectives of the exact Pareto solutions. t' is the closest solution to t from the set of solutions by NSGA-II. ϵ' is a very small number to avoid division by zero.

Appendix E. Parameter tuning of the proposed NSGA-II

To fine-tune the NSGA-II parameters (n_p , p_c , p_m , c_p , and K'), a similar approach to that described by Moradi et al. (2023); Moradi and Boroujeni (2024) was employed. Each parameter was assigned five distinct values, as detailed in Table E.1, to maintain execution times under 100 seconds while ensuring sufficient variability for analysis. During tuning, one parameter was adjusted while the others were kept constant. Eight small and medium generated instances (see Table C.1) were selected for the tuning process. As a comparison criterion among the different parameter values, the Gap_Ave , similar to $Best_Sol$ (Deb, 2011), was chosen. To calculate the Gap_Ave , the objective function values of the optimal Pareto sets obtained by ϵ -constraint (denoted by P_ϵ^1 and P_ϵ^2 for the first and second objective functions) and the objective function values of the near-optimal Pareto sets obtained by NSGA-II (denoted by P_{nsga}^1 and P_{nsga}^2 for the first and second objective functions) were normalized by dividing each solution by their maximum value (Sets NP_ϵ^1 , NP_ϵ^2 , NP_{nsga}^1 , and NP_{nsga}^2 are the normalized objective function values). Then, the average of these normalized objective function values for the optimal Pareto set (ANP_ϵ^1 and ANP_ϵ^2 for the first and second objective functions) and near-optimal Pareto set (ANP_{nsga}^1 and ANP_{nsga}^2 for the first and second objective functions) were calculated. Finally, the gap between the weighted sum of averages of the objective function values in the optimal Pareto set ($0.5 * ANP_\epsilon^1 + 0.5 * ANP_\epsilon^2$) and the weighted sum of averages of the objective function values in the near-optimal Pareto set ($0.5 * ANP_{nsga}^1 + 0.5 * ANP_{nsga}^2$) was considered as the comparison criteria, i.e., Gap_Ave . The NSGA-II parameter value resulting in the smallest Gap_Ave was deemed appropriate. Initially, n_p was tuned across its five values, with the other parameters fixed at their initial values. The value that minimized the Gap_Ave was selected for T_{max} . This procedure was then repeated for the remaining parameters. The optimized parameter values of the NSGA-II are as follows: $n_p = 50$, $p_c = 0.5$, $p_m = 0.3$, $c_p = 0.3$, and $K' = 100$, as shown in Table E.2. The values in parentheses represent the value of criteria Gap_Ave . The optimal parameter values are highlighted in bold. If two parameter values were identical in Gap_Ave , the one with the shorter execution time was preferred.

Table E.1: The candidate values for NSGA-II parameters

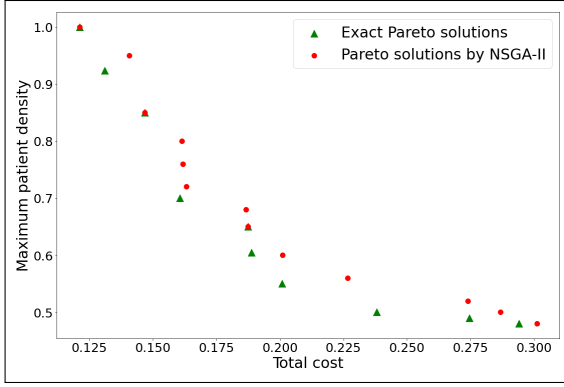
Parameters	Candidate values
n_p	{10, 20, 30, 40, 50}
p_c	{0.1, 0.3, 0.5, 0.7, 0.9}
p_m	{0.1, 0.3, 0.5, 0.7, 0.9}
c_p	{0.1, 0.3, 0.5, 0.7, 0.9}
K'	{10, 50, 100, 200, 300}

Appendix F. Performance evaluation of the proposed NSGA-II for medium instances

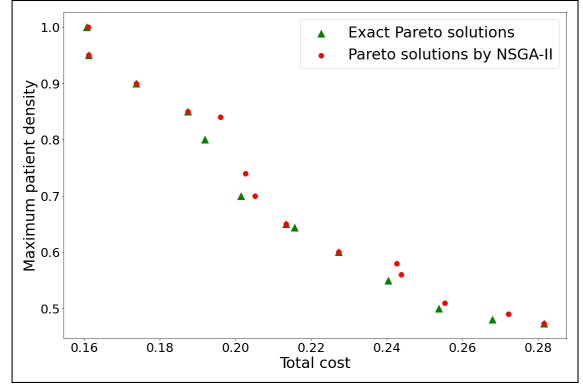
The comparison of the proposed NSGA-II and the ϵ -constraint method for medium instances is presented in Figures F.1a-F.1d for 5-I30-J150-K50, 6-I40-J150-K50, 7-I50-J150-K50, and 8-I60-J150-K50, respectively. The Gurobi average running time for these instances was 2384.55 seconds, achieving an optimality gap of zero.

Table E.2: Parameter tuning of the NSGA-II

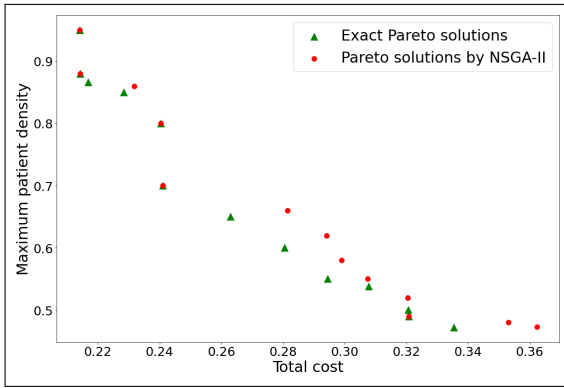
Parameters	Values				
n_p	10 (16.11)	20 (15.36)	30 (15.01)	40 (14.77)	50 (14.61)
p_c	0.1 (14.61)	0.3 (14.52)	0.5 (11.28)	0.7 (11.38)	0.9 (14.54)
p_m	0.1 (11.28)	0.3 (8.09)	0.5 (8.87)	0.7 (10.02)	0.9 (10.97)
c_p	0.1 (8.09)	0.3 (7.71)	0.5 (7.90)	0.7 (8.05)	0.9 (8.84)
K'	10 (7.71)	50 (5.49)	100 (4.37)	200 (4.37)	300 (4.37)



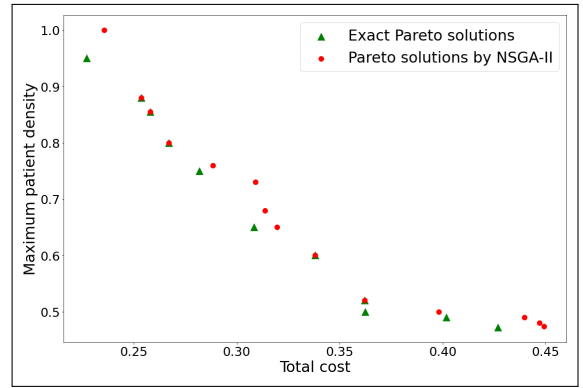
(a) Pareto solutions for 5-I30-J150-K50



(b) Pareto solutions for 6-I40-J150-K50



(c) Pareto solutions for 7-I50-J150-K50



(d) Pareto solutions for 8-I60-J150-K50

Figure F.1: Pareto set obtained by NSGA-II compared to optimal Pareto set for various instances when $|J| = 150$ (the x-axis and y-axis represent dimensionless values because both denominator and numerator of three elements of (1) and constraint (4) have the same unit)