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Enhancing COVID-19 vaccination and medication distribution routing strategies in rural regions of Morocco: A comparative metaheuristics analysis

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ABSTRACT

The optimization of the vaccination campaign and medication distribution in rural regions of Morocco conducted by the Ministry of Health can be significantly improved by employing metaheuristic algorithms in conjunction with a tour planning system. This research proposes the utilization of six metaheuristic algorithms: genetic algorithm, rat swarm optimization, whale optimization, spotted hyena optimizer, penguins search optimization, and particle swarm optimization, to determine the most efficient routes for equipped trucks carrying vaccines and medications. These algorithms consider critical field constraints, such as operating hours of vaccination centers, vaccine availability, and distances between centers while minimizing the overall journey duration. In addition, a comprehensive tour planning system is integrated into the optimization framework accounting for transportation costs such as fuel expenses and truck maintenance costs. By incorporating these factors, the Ministry of Health aims to achieve the maximum efficiency while minimizing the financial burden associated with the vaccination campaign in rural areas. The integration of metaheuristics and the tour planning system presents a robust and data-driven solution for the Ministry of Health to enhance the effectiveness of their vaccination and medication distribution campaigns in rural regions of Morocco. This approach not only minimizes costs but also improves overall efficiency by ensuring timely access to vaccines and medications for the rural population. The findings of this research contribute to the growing body of knowledge in the field of healthcare logistics optimization and provide valuable insights for policymakers and practitioners involved in similar campaigns worldwide.

1. Introduction

Efficient vaccine distribution is not only a logistical challenge but a vital component of public health, impacting the well-being of entire populations, especially those residing in remote and underserved regions. Optimizing vaccine distribution is of paramount importance, particularly in rural areas of Morocco, where improving vaccination coverage holds the potential to significantly transform healthcare

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delivery and public health outcomes [1–4]

To comprehend the issue fully, it is imperative to examine quantitative data regarding the current state of vaccination in Morocco. While the national vaccination coverage rate stands at 79%, an accomplishment worth noting, it falls short of the ambitious 95% target set by the Moroccan Ministry of Health and the World Health Organization (WHO) [5]. This gap underscores the pressing need for more efficient vaccine distribution strategies.

However, the challenges of vaccine distribution extend beyond merely increasing immunization rates. They encompass minimizing expenses, reducing travel time, and optimizing routes to efficiently deliver vaccines to their intended recipients. These challenges are amplified by the vast distances between healthcare facilities, often situated in remote and challenging-to-reach locations. Traditional route planning methods struggle to cope with the complexities of varying operating hours, vaccination storage requirements, and the conditions of different healthcare centers, necessitating the use of more advanced optimization techniques.

One of the central challenges in optimizing vaccine distribution is determining the most efficient routes for trucks carrying vaccines and medications to various healthcare centers in rural areas. This problem necessitates finding routes that minimize travel distances and times while considering the unique constraints associated with each healthcare center, including operating hours, vaccine availability, and storage requirements. The optimization of routes is pivotal for reducing fuel costs, minimizing journey duration, and enhancing overall distribution efficiency.

Achieving high vaccination coverage in rural areas is a critical public health objective. However, disparities in vaccination rates between rural and urban regions pose a significant concern. This research addresses the problem of low vaccination coverage in rural areas and seeks to optimize distribution strategies to increase coverage rates. Enhancing vaccine access and availability is vital for bridging this gap and ensuring that rural populations receive adequate immunization.

Efficient vaccine distribution is not only about improving health outcomes but also about cost-effectiveness. Minimizing the costs associated with vaccine distribution presents a substantial challenge, including reducing fuel costs, optimizing resource allocation, and increasing the efficiency of healthcare delivery. Reducing the financial burden on the Ministry of Health is essential to enable the reallocation of resources to address other pressing healthcare needs.

Driver fatigue and safety are critical concerns in healthcare logistics. Overly long and inefficient routes can lead to driver fatigue, potentially resulting in safety hazards and accidents. Optimizing routes to reduce journey duration and distance is crucial for promoting safer transportation practices and ensuring the well-being of drivers.

Access to accurate and up-to-date data is essential for effective vaccine distribution. This research addresses the challenge of utilizing field data collected by the Ministry of Health to transform it into actionable insights and make informed decisions regarding vaccine distribution strategies.

Selecting the appropriate optimization algorithms for solving the routing problem is another key aspect. This research focuses on comparing and evaluating multiple metaheuristic algorithms, each with its strengths and weaknesses. Choosing the most suitable algorithm for a specific problem instance is part of the broader problem-solving process.

Finally, assessing the impact of optimized distribution on vaccination coverage and healthcare services is an integral part of the research. This involves understanding how improved distribution influences healthcare outcomes and identifying potential areas for further improvement.

This article presents several significant contributions to the field of healthcare logistics optimization and vaccine distribution in rural areas.

1. Innovative Optimization Framework: The research introduces an innovative optimization framework tailored to address the complexities of vaccine distribution in rural regions. This framework considers the unique constraints associated with each healthcare center, including operating hours, vaccine availability, and storage requirements. It offers a novel approach to optimizing vaccine distribution, ensuring efficient delivery to intended recipients.
2. Comparative Analysis of Metaheuristic Algorithms: The study conducts a comprehensive evaluation of multiple metaheuristic algorithms, assessing their performance in solving the routing problem. By comparing these algorithms, the research provides valuable insights into their strengths and weaknesses. The findings suggest that the proposed optimization framework can substantially reduce travel distances and times, leading to improved cost-effectiveness and safer transportation practices.
3. Data-Driven Decision-Making: This research harnesses field data collected by the Ministry of Health to inform vaccine distribution strategies. A data-driven approach empowers decision-makers to gain a deeper understanding of the challenges and opportunities associated with vaccine distribution in rural areas, enabling them to make more informed decisions and adapt strategies to local conditions.
4. Impact on Vaccination Coverage and Healthcare Services: The research extends beyond optimization and assesses the real-world impact of optimized distribution on vaccination coverage and healthcare services. The findings highlight the potential for substantial improvements in vaccination coverage, particularly in underserved rural communities. By enhancing distribution strategies, this research contributes to narrowing the gap in vaccination rates between rural and urban areas, making significant strides in public health and healthcare delivery outcomes.

2. Background

The COVID-19 pandemic [6,7] has caused widespread disruptions and has had a profound impact on the lives of people around the world. Vaccination campaigns have emerged as a crucial strategy to combat the spread of the virus and protect public health. However, reaching remote and rural areas with limited infrastructure and resources presents significant challenges in effectively distributing vaccines.

In the context of Morocco, optimizing the trajectory of the COVID-19 vaccination campaign in rural areas becomes paramount. It is essential to maximize the coverage and efficiency of the campaign while minimizing the spread of the virus. This optimization involves not only addressing the challenges of vaccine distribution but also an efficient delivery of medications to these remote regions.

The distribution of medications in rural Morocco poses additional obstacles, including the reduction of transportation costs, optimizing the travel distance, minimizing the fatigue of drivers, and ensuring timely delivery to vaccination centers. The efficient distribution of medications is crucial to ensure that the necessary drugs reach the intended locations promptly, maintain the required temperature for their effectiveness, and support the overall success of the vaccination campaign.

To tackle these challenges, various metaheuristic algorithms have been proposed and applied in similar contexts [8,9]. These algorithms offer promising solutions by optimizing the trajectory and minimizing the distance traveled, allowing for the effective distribution of vaccines and medications in rural areas. However, a comprehensive review of the existing literature on the application of metaheuristic algorithms in optimizing the trajectory of COVID-19 vaccination campaigns is essential to identify the strengths, limitations, and potential areas for improvement in this domain.

Therefore, this literature review aims to examine the current state of research on metaheuristic algorithms for minimizing the trajectory of the COVID-19 vaccination campaign in rural Morocco, taking into account the specific challenges and constraints related to both vaccine distribution and medication delivery, By analyzing and synthesizing the existing literature, this review seeks to provide valuable insights and recommendations for the optimization of the vaccination campaign trajectory and medication distribution in rural areas of Morocco. Ultimately, these findings will contribute to enhancing the efficiency, coverage, and impact of the vaccination campaign while ensuring equitable distribution of healthcare resources and promoting the well-being of the population.

2.1. Metaheuristics algorithms

Metaheuristics algorithms are optimization techniques that use iterative search procedures to find optimal or near-optimal solutions to complex problems. There are various metaheuristics algorithms used for optimization problems, including genetic algorithms (GA), ant colony optimization (ACO), particle swarm optimization (PSO), simulated annealing (SA), tabu search (TS), and others. These algorithms have been successfully applied in various fields, including transportation. Logistics, and healthcare.

2.2. Vaccination and medication distribution campaigns

Vaccination and medication distribution campaigns pose complex logistical challenges that require efficient optimization strategies. In addition to optimizing the vaccination trajectory, the distribution of medications to healthcare centers plays a crucial role. This combined optimization problem involves selecting the most effective routes to maximize coverage, minimize travel distance and time, and consider resource availability, including healthcare facilities, vaccine doses, and healthcare workers.

2.3. Literature review

In the realm of optimizing COVID-19 vaccination and medication distribution efforts in rural areas, numerous studies have delved into the utilization of metaheuristic algorithms to enhance the efficiency and efficacy of such campaigns.

In 2021, Rodrigues and Lima [10] introduced a metaheuristic tailored to bolster vaccine distribution routing, with a particular focus on the Brazilian government's needs. Their approach, which blends GRASP and VND, demonstrated significant effectiveness in optimizing vaccine allocation and reducing distribution costs, especially in the state of Pernambuco. Meanwhile, Omar et al. [11] delved into the stochastic dynamics of COVID-19, utilizing fractional order dynamic models and a fractional-order-stochastic model. They explored various vaccination scenarios and employed the invasive weed optimization algorithm to optimize one of these scenarios, resulting in a more efficient utilization of vaccination doses in Saudi Arabia.

Shifting our focus to studies revolving around multi-period COVID-19 vaccination planning:

In 2021, Cowie et al. [12] conducted a comprehensive examination of the COVID-19 pandemic's impact on heart failure management. Their survey of national coordinators across 29 countries unveiled the challenges and organizational transformations in delivering heart failure care amid the pandemic.

Salinas et al. [13] embarked on a research journey titled "A Bi-Level Vaccination Points Location Problem that Aims at Social Distancing and Equity for the Inhabitants". This work addressed the intricate task of identifying vaccination locations while taking into consideration factors such as social distancing and equity for the local population. The paper introduced a bi-objective, bi-level program, and harnessed a cross-entropy metaheuristic to approximate the Pareto front of this complex issue, underscoring the significance of crafting efficient vaccination strategies that cater to the inhabitants' preferences.

Furthermore, a study conducted by Hassan et al. [8], titled "Optimum Location of Field Hospitals for COVID-19: A Nonlinear Binary Metaheuristic Algorithm", focused on the optimal positioning of field hospitals during the COVID-19 crisis. The authors proposed a modified maximal covering model replete with nonlinear constraints and developed a discrete binary gaining–sharing knowledge-based optimization (DBGSK) algorithm. This research unveiled the effectiveness of the DBGSK algorithm in tackling binary optimization challenges and provided valuable insights into the deployment of field hospitals in specific regions.

In 2022, Mohammadi et al. [14] set their sights on bi-objective optimization for a robust vaccine distribution network. Their model sought to minimize the anticipated number of deaths and distribution expenses while accounting for uncertain input variables and disruptions within the network. Tang et al. [15] delved into the intricacies of multi-period vaccination planning, optimizing the total travel distance of vaccine recipients and the associated operational costs. Their approach entailed a bi-objective mixed-integer linear program (MILP) and the development of a genetic algorithm to attain efficient solutions.

Fast forward to 2023, Fabbri et al. [16] contemplated the organization and scheduling of a vaccination campaign during a pandemic emergency. They introduced an optimization model that substantially streamlined the scheduling process, thereby reducing the time required to cover the target population. Meanwhile, Haixiang Guo and their team [16] tackled the allocation of vaccination demand and the creation of optimal distribution routes during pandemics. Their hierarchical decision mixed-integer linear program addressed a spectrum of issues related to vaccine distribution and vaccination efficiency.

Pino et al. [17] presented an optimization model designed for the optimal allocation of COVID-19 vaccines, considering variables such as vaccine efficacy, waning immunity, diverse age groups, population data, and vaccination rates. Their linear programming model aimed to minimize primary and breakthrough infections, thereby furnishing invaluable insights for vaccine distribution strategies. Meanwhile, Tu et al. [18] proposed a sub-healthy COVID-19 model that considers self-diffusion and cross-diffusion, delving into the impact of various factors on disease spread. Their work constructed an optimal control system, conducted a multi-objective optimization analysis, and elucidated the diverse parameters' effects on disease transmission.

Furthermore, Rodrigues and Lima [10] unveiled a metaheuristic-based vaccine distribution routing model (VDRM) in their study titled "A metaheuristic to support the distribution of COVID-19 vaccines". This innovative metaheuristic combined GRASP (Greedy Randomized Adaptive Search Procedure) with VND (Variable Neighborhood Descent) while factoring in various refinement operators. The research conclusively demonstrated the efficacy of this novel algorithm in planning the allocation of vaccine doses to combat COVID-19. It also provided a substantial boost in computational efficiency and distribution quality, outperforming existing procedures and ushering in a new era of optimized vaccine distribution.

3. Methodology

The methodology employed in this research encompasses the integration of both vaccination campaign and medication distribution problems, utilizing data obtained from the Ministry of Health in Morocco. Simulations of the campaign will be conducted to assess and compare the performance of various metaheuristic algorithms, (see Fig. 1 and Fig. 2). The algorithms selected for evaluation include rat swarm optimization [19], particle swarm optimization [20], genetic algorithms [21], and spotted hyena algorithm [22].

The simulations will focus on analyzing and optimizing the journey of the vaccination campaign, considering factors such as vaccination center operating hours, vaccine availability, medication demand, storage requirements, and distances between centers. The objective is to minimize the overall journey duration, reduce fuel costs, mitigate driver fatigue, and enhance the distribution efficiency of both vaccines and medications in rural areas.

The performance evaluation of the metaheuristic algorithms will be based on key metrics such as solution quality, computational time, and

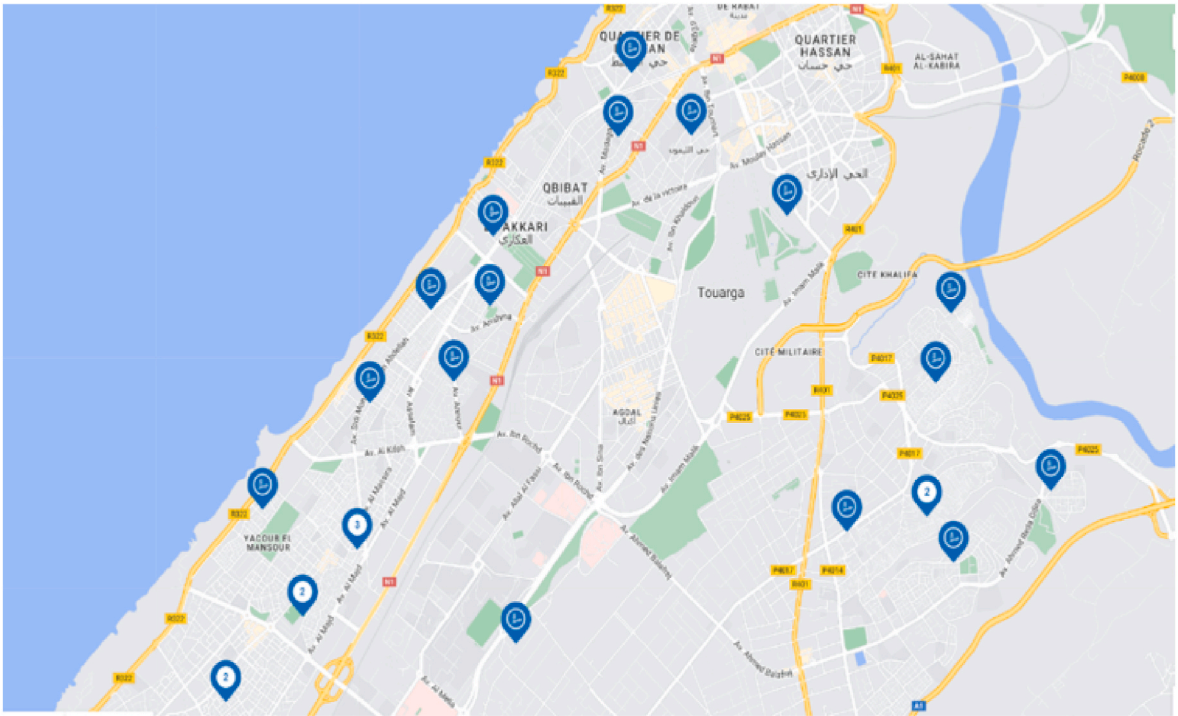


Fig. 1. Example of distribution of vaccination centers in the capital of Morocco.

Fig. 2. Mobile medical campaign reaches over 2200 individuals in the province of Chtouka Aït Baha.

scalability. Solution quality refers to the ability of each algorithm to produce optimal or near-optimal solutions for the vaccination campaign and medication distribution routes. Computational time measures the efficiency of the algorithms in finding solutions within acceptable timeframes. Scalability assesses how well the algorithms can handle larger problem instances, reflecting their applicability to real-world scenarios.

Through rigorous experimentation and analysis, the study aims to provide a comprehensive evaluation of each algorithm's effectiveness in optimizing the journey of the vaccination campaign and medication distribution in rural regions of Morocco. By comparing the performance of the different metaheuristic algorithms, their respective strengths and weaknesses can be identified, aiding decision-making processes for the Ministry of Health and other relevant organizations. The findings will offer valuable insights and guidance to healthcare authorities facing similar challenges in remote and rural areas, empowering them to select the most suitable metaheuristic algorithm for their specific requirements.

This research contributes to the advancement of knowledge in the field of metaheuristics and its application in the healthcare sector, particularly in the context of vaccine and medication distribution. The results obtained from this study will enrich the existing body of literature and pave the way for improved optimization strategies in healthcare logistics. Ultimately, the study aims to enhance the efficiency and effectiveness of the vaccination campaign and medication distribution processes in rural areas, thus improving healthcare accessibility for the population in need.

3.1. Problem definition

Minimizing the travel distance for both the vaccination van and the medication distribution vehicle efficiently is a critical optimization problem to address in the context of the COVID-19 vaccination campaign in rural Morocco. This problem aims to identify the most optimal routes for these vehicles with the objective of reducing transportation costs, conserving fuel, and ensuring timely and effective delivery of vaccines and medications to the designated health centers.

The primary goal is to minimize the total distance traveled by the vaccination van and the medication distribution vehicle while upholding the quality of care and maximizing the campaign's efficiency. By minimizing travel distance, the campaign can optimize the allocation of resources, reduce transportation expenses, and extend coverage to a larger geographic area within a shorter timeframe.

To tackle this optimization problem effectively, several important constraints need to be considered. These include the operating hours of the vaccination centers, availability of vaccines and medications, and associated transportation costs. Incorporating these constraints into the optimization process allows for the identification of routes that are not only cost-effective but also ensure equitable access to life-saving vaccines and medications for all rural populations while minimizing resource utilization.

Additionally, managing team fatigue plays a pivotal role in enhancing the overall quality of care and operational efficiency of the vaccination campaign. By optimizing the trajectory of the vehicles, travel time and distance can be minimized for both the vaccination and distribution teams. This approach improves their well-being, mitigates fatigue-related risks, and ensures sustained performance throughout the campaign.

Furthermore, the optimization problem also addresses the crucial aspect of minimizing the trajectory for the medication distribution vehicle to maintain the required temperature conditions for medications. Proper storage and transportation under specific temperature requirements are essential to preserve the potency and efficacy of medications including vaccines. Optimizing the distribution routes helps minimize the time medications spend outside the prescribed temperature range, thereby safeguarding their effectiveness and maximizing their positive impact.

In summary, the optimization problem encompasses the identification of the most efficient and cost-effective routes for the vaccination van and medication distribution vehicle. By considering constraints such as vaccination center operating hours, vaccine and medication availability, transportation costs, team fatigue management, and temperature preservation, the campaign can optimize resource utilization, reduce expenses, improve accessibility to healthcare services, and significantly contribute to the success of the COVID-19 vaccination campaign in rural Morocco.

Mathematically, the problem can be modeled as follows:

Let G=(V, E) be a complete weighted graph where V represents the set of n vaccination stations CSs to visit and E represents the set of arcs between each pair of cities and CSs.

Let d_{ij} be the distance between city i and S_j.

Let CS_{ij} be a binary variable such that $CS_{ij} = 1$ if the route of the vaccination van goes from city i to CS_j. and $CS_{ij} = 0$ otherwise.

The objective is to minimize the following objective function:

$$min \sum_{i=1}^{n} d_{ij} * CS_{ij} \tag{1}$$

Under the following constraints:

Each city must be visited exactly once:

$$\sum_{i=1}^{n} CS_{ij} = 1, \forall i \in V \tag{2}$$

Each CS can be visited at most once:

$$\sum_{i=1}^{n} CS_{ij} \leq 1, \forall j \in CS \tag{3}$$

The vaccination van must return to its starting point:

$$\sum_{i=1}^{n} CS_{ij} = \sum_{i=1}^{n} CS_{ji}, \forall i \in V \tag{4}$$

The variables must be binary:

$$CS_{ij} \in \{0, 1\}, \forall i, j \in V\ U\ CS \tag{5}$$

4. Metaheuristics to solve the vaccination problem

To solve the vaccination and medication distribution problems, we will utilize a set of nature-inspired metaheuristic algorithms. Metaheuristics are powerful optimization algorithms that excel at finding optimal or near-optimal solutions in complex search spaces. Some of the utilized algorithms, which are inspired by animal behaviors like penguins and hyenas, employ mathematical models to mimic their hunting techniques and social relationships.

We have chosen these metaheuristic algorithms for their close resemblance in terms of inspiration and equations, ensuring a consistent transition to the discrete problem at hand. By harnessing their nature-inspired strategies, we can tackle the vaccination and medication distribution challenges with an innovative and efficient approach.

The selected metaheuristics offer a balanced exploration and exploitation of the search space, allowing us to effectively navigate the complex problem landscape and discover optimal solutions. Through their iterative refinement process, these algorithms gradually improve the administration and delivery of vaccines and medications, ensuring an optimized and resource-efficient approach.

In summary, by leveraging nature-inspired metaheuristics and customizing them for the vaccination and medication distribution problems, we can harness their inherent ability to explore and exploit the intricate search space. This approach enables us to achieve efficient and effective solutions, optimizing the delivery of vaccines and medications to rural areas.

4.1. Particle swarm optimization

Particle Swarm Optimization (PSO) [19] was first developed in 1995 by Eberhart and Kennedy for addressing optimization problems. It falls within the domain of computational intelligence and metaheuristic algorithms, drawing inspiration from the social behavior of birds flocking or fish schooling to solve optimization problems.

The algorithm revolves around a population of potential solutions called particles that traverse the search space. Each particle adjusts its movement through the space using a velocity vector, dynamically modified based on its own best-known position and the collective best position discovered by the entire swarm up to that point.

- **Mathematical formula**

Mathematically, the algorithm operates with vectors representing positions (x_i) and velocities (v_i) of particles in the search space. The update equations for velocity and position are crucial to how PSO evolves:

Velocity update formula:

$$v_i(t+1) = w * v_i(t) + c_1 * rand_1 * (p_i - x_i(t)) + c_2 * rand_2 * (g - x_i(t)) \tag{6}$$

Where.

- w represents the inertia weight, governing the impact of a particle's current velocity on its future movement. Typically, it linearly decreases from an initial value to a final one during the optimization process.
- c^1 *and* c^2 are acceleration coefficients controlling the influence of a particle's personal best position p_i and the global best position found by the entire swarm g on its velocity. These coefficients usually range between 0 and 2.
- $rand^1$ *and* $rand^2$ denote random numbers between 0 and 1, introducing stochasticity into particle movement.

Position update equation:

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{7}$$

Where t signifies the current iteration.

This approach fosters cooperation among particles, allowing them to communicate information about their positions and the best-known positions within the swarm, enhancing the exploration-exploitation balance in the search space to find optimal solutions for various optimization problems.

4.2. Genetic algorithm

Genetic Algorithm (GA) [20] is a metaheuristic optimization algorithm developed based on the principles of natural selection. It was first introduced in the early 1960s by John Holland and later popularized by his student David E. Goldberg. Genetic algorithms operate within the domain of evolutionary computation, simulating the process of natural selection to evolve a population of individuals towards optimal solutions for a given problem.

In a Genetic Algorithm (see Fig. 3), a population of individuals represents potential solutions to a problem. The algorithm evolves this population over successive generations using three fundamental genetic operators.

1. Selection:
   - Individuals in the population are chosen for reproduction based on their fitness. The fitness function assesses the quality of each individual.
   - The probability of selection is proportional to the fitness value of an individual. Fitter individuals have a higher chance of being selected.
2. Crossover:
   - Two parent individuals are selected from the population, and a crossover point is determined.
   - The genetic material beyond the crossover point is exchanged between the parents to create offspring.
   - This mimics the genetic recombination that occurs during sexual reproduction in nature.
3. Mutation:
   - A random mutation is applied to the offspring by altering one or more genes.
   - Mutation introduces small and random changes to the genetic material, contributing to diversity in the population.

Example:

Consider a scenario where the goal is to find the optimal sequence of centers to visiting. Each individual in the population represents a potential ordering of centers. The fitness function evaluates each individual based on the total distance traveled.

1. Selection:
   - Individuals with shorter total distances (higher fitness) have a higher chance of being selected as parents.
2. Crossover:
   - Two parents are chosen based on selection probabilities.
   - A crossover point is selected, and the genetic material beyond that point is swapped between parents to create two offspring.
3. Mutation:
   - Random mutations may involve swapping the positions of two centers in an individual's sequence.

This iterative process continues over generations, with fitter individuals more likely to be passed on to subsequent generations. The algorithm explores the solution space, converging towards an optimal solution for this problem.

4.3. Rat swarm optimization

The rat swarm optimization (RSO) [18] algorithm models the behavior of rat swarms to efficiently solve optimization problems. The algorithm consists of two main phases: exploration and exploitation. During the exploration phase, rats update their positions according to the best personal position found by the best searcher in the group, while during the exploitation phase, rats accept the position and evaluation of the prey they have found and fought with.

The mathematical equations for the RSO algorithm are as follows.

- **Pursuit of prey (exploration phase):**

$$P = A * P(t) + C * (Pbest(t) - P(t)) \tag{8}$$

The balance between exploration and exploitation:

$$A = R - \rho\left(\frac{R}{Max_{Iteration}}\right) \tag{9}$$

$$\rho = 1.\ 2.\ 3.\ \ldots\ Max_{Iteration} \tag{10}$$

- **Fighting prey (exploitation phase)**

$$P(t+1) = |Pbest(t) - P| \tag{11}$$

In these equations, P(t) represents the position of the rat at time t. Pbest (t) represents the best position of the rat at time t. A and R are parameters responsible for balancing exploration and exploitation, and $Max_{Iteration}$ represents the maximum number of iterations allowed in the algorithm.

The following sequence of steps outlines the core operations of the Rat Swarm Optimizer (RSO) algorithm for optimization.

- **Initialize Rat Population:** Create a population of rats denoted by Pi, where each rat is indexed from i = 1,2, …,n This forms the initial swarm of search agents.
- **Choose Initial Parameters:** Set the initial parameters A, C, and R for the RSO algorithm. These parameters play crucial roles in governing the exploration and exploitation dynamics within the optimization process.
- **Calculate Fitness Values:** Evaluate the fitness value of each search agent (each rat in the population). Fitness assessment determines the quality or suitability of a solution in the search space according to the objective function of the optimization problem.
- **Explore the Best Agent:** Identify the best search agent among the swarm. This typically refers to the rat with the highest fitness value, indicating the most promising solution found thus far.
- **Update Positions:** Utilize Equation (11) from the RSO algorithm to update the positions of the search agents (rats) based on the best solution found in the previous step. This step drives the swarm towards better solutions in the search space.
- **Boundary Limit Check:** Verify if any search agent has moved beyond the boundary limits of the search space. If any agent exceeds

these bounds, adjust its position to ensure it remains within the defined search space.

- **Update Best Solution Vector:** Re-calculate the fitness value for the updated search agents and compare them to the previous best solution vector (Pr). If a better solution is found among the updated agents, update the vector Pr to reflect this new optimal solution.

4.4. Spotted hyena optimizer

Spotted hyena optimizer (SHO) [21,22] is a swarm algorithm inspired by the social relationships and behaviors of spotted hyenas known for their complex behavior, hunting techniques, and communication. The algorithm mathematically models these hunting techniques and social relationships to effectively solve optimization problems.

The SHO algorithm exhibits four main behaviors: circling, hunting, attacking, and prey-seeking.

- **Encirclement behavior**

The encirclement considers the target objective as the best solution, allowing search agents to update their positions concerning this objective. The mathematical representation of this behavior is:

$$D_h = \left|A - P_{p(t)} - P(t)\right| \tag{12}$$

$$P(t+1) = P_{p(t)} - E - D_h \tag{13}$$

- **Hunting behavior**

The hunting behavior involves clustering the optimal solutions against the top search agent, mimicking the hunting behavior of spotted hyenas. The equations for this mechanism are

$$D_h = |A \,.\, P_h - P_k| \tag{14}$$

$$P_k = P_h - E - D_h \tag{15}$$

$$C_h = P_k + P_{k+1} + \ldots + P_{k+N} \tag{16}$$

- **Attacking behavior**

In this behavior, search agents update their positions according to the superior agent's position, while the spotted hyena continuously adjusts its position during the prey attack. The mathematical formulation for the prey attack is

$$P(x+1) = \frac{C_h}{N} \tag{17}$$

- **Prey seeking behavior**

This behavior exemplifies the algorithm's ability to explore, achieved by strategically incorporating random values—whether greater or less than 1—to ensure a robust exploration process. Through mathematical equations, the SHO algorithm precisely models these behaviors, empowering spotted hyenas to dynamically maneuver in response to their prey's whereabouts. The integration of random values serves as a crucial mechanism, finely balancing the algorithm's exploration and exploitation strategies. This delicate equilibrium facilitates a nuanced and adaptable pursuit of prey across the ever-evolving search terrain.

4.5. Whale optimization algorithm

The whale optimization algorithm (WOA) [23] is a metaheuristic optimization algorithm inspired by the social behavior and hunting strategies of humpback whales. The algorithm was designed to solve complex optimization problems by mimicking the whales' bubble-net hunting method which consists of a combination of encircling and spiraling behavior to trap prey effectively.

The mathematical equations for WOA are as follows.

- Encircling prey (exploration)

$$D = |C * X_{best} - X| \tag{18}$$

$$X_{new} = X_{best} - A * D \tag{19}$$

In Equation (18), D represents the distance between the current whale position (X) and the best solution found so far (X_{best}), C and A are random vectors generated within the range of [0.1]. In Equation (19), X_{new} represents the updated position of the whale in the search space.

- Spiral search (exploitation)

$$X_{new} = D * exp(b * l) * cos(2 * \pi * l) + X_{best} \tag{20}$$

In Equation (20), b is a constant that defines the shape of the logarithmic spiral, and l is a random number within the range of [0.1]. This equation describes the spiral search around the best solution found so far.

During the optimization process, WOA switches between the encircling prey and spiral search behaviors, depending on the value of A. If $|A| < 1$, the encircling prey behavior is employed. Otherwise, the spiral search behavior is used.

By applying these equations and behaviors, the WOA algorithm can effectively explore and exploit the search space, allowing it to find optimal or near-optimal solutions for a wide range of optimization problems.

4.6. Penguins search optimization algorithm

The Penguins Search Optimization Algorithm (PeSOA) [24] is inspired by the foraging behavior of penguins, aiming to replicate their hunting strategies for efficient food finding in a given environment. Penguins make decisions based on the energy gained from food compared to the energy expended during hunting, which forms the basis of this algorithm.

The algorithm operates based on several fundamental rules that emulate the complex foraging behaviors observed in penguins.

1. Penguins are grouped.
2. Group sizes vary according to food availability.
3. Grouped penguins explore randomly until they find food while ensuring their oxygen reserves are not depleted.
4. Penguins can simultaneously dive to the same depth during hunting.
5. Each group starts searching from a specific position and at random levels.
6. Penguins search individually within their groups and share successful food locations after a specific number of dives.
7. The number of penguins at a location depends on the abundance of food.
8. Inadequate food prompts a group or part of it to move to another location.
9. The group that consumes the most shares the location of rich food.

The algorithm represents each penguin's search as a hole and level while keeping track of the number of fish eaten. Penguins are organized into groups and commence their search from random positions. After a predetermined number of dives, they communicate successful food locations. Less successful groups follow more successful ones in subsequent dives.

Equation (1) drives the adjustment of penguin positions within the algorithm:

$$D_{new} = D_{last} + rand() * \left|X_{local_{best}} - X_{local_{last}}\right| \tag{21}$$

Where.

- D_{new} represents the new position of a penguin.
- D_{last} signifies the penguin's last position.
- $rand()$ generates a random number for distribution.
- $X_{local_{best}}$ and $X_{local_{last}}$ denote the best and last local solutions found by the penguin, respectively.

This equation allows the algorithm to simulate movement, aiding in exploration and exploitation of the search space by adjusting penguin positions. It facilitates the efficient exploration of potential optimal solutions within the algorithm's iterative process.

5. Discrete metaheuristics to solve the vaccination problem

To solve this problem using the metaheuristics RSO, WOA, SHOA, PSO GA, and PSeOA, we need to adapt each of these algorithms to work on the vaccination problem as it is mathematically formulated (see Table 1).

We represent each solution as a sequence of cities and vaccination stations (CS) to visit. Each sequence corresponds to a possible route for the vaccination vehicle.

For each metaheuristic, we define a movement or position update operation to explore the space of possible solutions.

- **Genetic Algorithm (GA)**

In the context of the Genetic Algorithm (GA) addressing the optimization of the sequence of centers to be visited, each solution is represented as a sequence denoting the sequence of centers.

- **Crossover Operation:**

Crossover, a fundamental genetic operator, amalgamates two parent solutions to generate new offspring solutions.

Assuming two parent solutions.

Table 1
Initial parameter for Metaheuristics.

Metaheuristic	Parameter	Value
RSO	Population size	100
	Number of iterations	1000
WOA	Population size	50
	Number of iterations	1000
	A parameter	2
SHOA	Population size	100
	Number of iterations	1000
PSO	Population size	100
	Number of iterations	1000
	Inertia weight	0.2
GA	Population size	200
	Number of iterations	1000
	Crossover rate	0.7
PSeOA	Population size	150
	Number of iterations	1000

Parent 1:	2	1	3	4	5	6	7	8	9
Parent 2:	9	8	7	6	5	4	3	2	1

A one-point crossover at position 4 yields.

Offspring 1:	2	1	3	6	5	4	7	8	9
Offspring 2:	9	8	7	4	5	6	1	2	3

- **Mutation Operation:**

Mutation, another vital genetic operator, involves modifying one or multiple positions within a solution.

For instance, consider mutating a random position within Offspring 1.

Offspring 1(before mutation):	2	1	3	6	5	4	7	8	9
Offspring 1 (after mutation):	2	1	3	6	5	4	9	8	7

In this specific scenario, the mutation operation altered the sixth position in the sequence from 7 to 9.

- **The other population-based strategies**

In the case of other population-based strategies that operate in the continuous space such as RSO, WOA, SHOA, PSO, and PSeOA, a unique approach involves associating each individual in the population with a sequence of centers. These centers represent potential solutions in the context of the given problem, akin to checkpoints in a route.

Generally, the equations associated with these methods can be expressed using the following formula:

$$Xnew(t+1) = A * X(t) + C * (Xbest(t) - X(t)) \tag{22}$$

This equation signifies the evolution of a new solution at time t+1 based on a combination of $X(t)$, Xbest (t), and coefficients A and C.

5.1. Optimization process

During the optimization process, the movement of individuals within the population is dynamic. It encompasses subtle adjustments and permutations of center order along the path, resulting in incremental modifications to the current solution. Each move undergoes a solution check, accepting the new configuration if it outperforms the prior solution or discarding it otherwise.

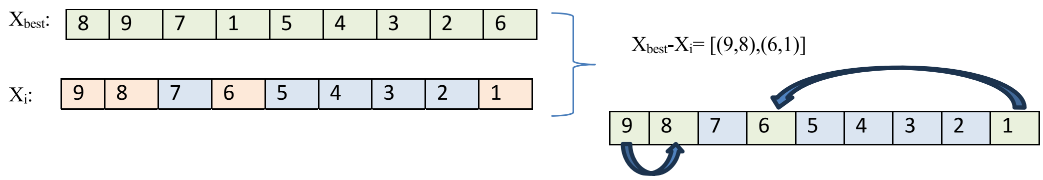
5.2. Adaptation for combinatorial problems

To address discrete combinatorial optimization problems like the vaccination campaign planning problem, a crucial transformation is required. This transformation involves substituting the continuous operators employed in the original algorithm with discrete counterparts.

5.3. The subtraction operator

The subtraction operator, which is responsible for calculating the difference between two positions in the search space, undergoes a distinctive adaptation. In the context of discrete combinatorial problems, the subtraction between two positions (*locBest-loci*) is redefined as a set of permutations. These permutations can be executed on one position, generating a new position that is closer to the other.

We evaluate each solution using the given objective function ($min \sum_{i=1}^{n} d_{ij} * CS_{ij}$) which measures the total distance traveled by the vaccination vehicle.



The representation of a discrete subtraction operator.

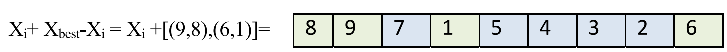
5.4. The addition operator

The addition operator, usually employed for continuous operations, takes on a new form when applied to discrete optimization problems. In this context, it's conceptualized as a collection of permutations capable of altering a path (or sequence of centers) within the current solution.

The chosen metaheuristic algorithm is executed until a stopping criterion is reached, such as a maximum number of iterations or a minimum improvement of the solution.

At the end of the algorithm execution, the best solution found represents the optimal route for the vaccination vehicle.

Here are some examples of permutations and insertions to generate new solutions.



5.5. The multiplication operator

The multiplication operator, typically associated with mathematical operations, takes on a distinct role when applied to optimization problems. In this context, it is conceptualized as an operator that acts upon a real number and a list of permutations, thereby reducing the number of permutations applied to a path.

For example.

- C x (X_{best}-X_i)
- C = 0,5
- C x (X_{best}-X_i) = 0,5 × [(9,8), (6,1)]= (9,8)

5.6. The constraints of the problem are enforced using repair or penalty mechanisms

For example, if a solution violates the constraint that a city must be visited exactly once, a penalty can be applied to the objective function for that solution, or the solution can be repaired by deleting duplicate visits and reinserting missing cities in a random or heuristic manner.

- **Permutations**: swap the position of two cities or CSs in the sequence. For example, if the current sequence is (1,2,3,4,5), a possible permutation would be (1,3,2,4,5) (swapping cities 2 and 3 as showing in Fig. 4).
- **Insert**: Remove a city or CS from the sequence and insert it at another position. For example, if the current sequence is (1,2,3,4,5), a possible insertion would be (1,3,2,4,5) (moving to a new city 2 after city 3).
- **Reverse**: Select a segment of the sequence and reverse the order of the cities or CSs within the segment. For example, if the current

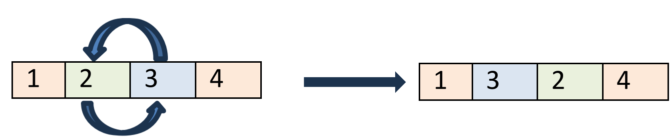


Fig. 4. Example of permutation.

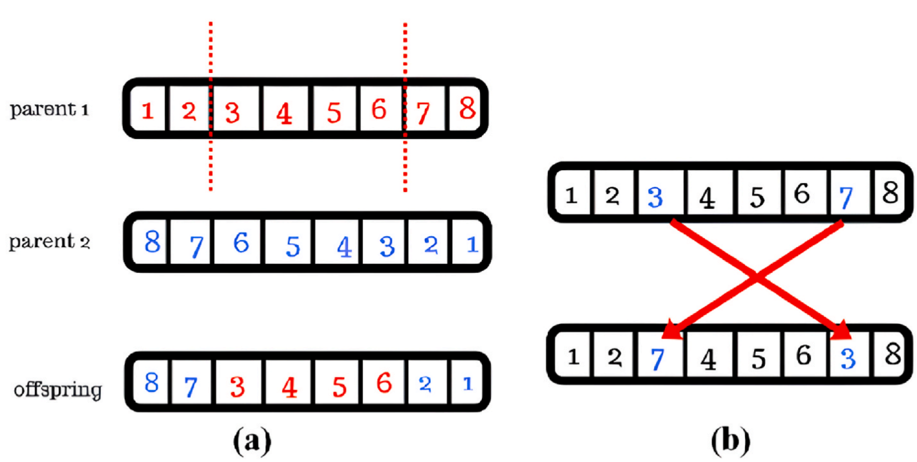


Fig. 3. a) crossover, b) mutation.

Table 2
Metaheuristics and their corresponding best distance (in km) achieved.

Province	Center Count	RSO	WOA	SHOA	PSeOA	PSO	GA
Agadir Ida Ou Tanan	36	245.922	271.314	331.974	350.552	379.084	412.559
Al Haouz	73	504.650	521.581	589.567	640.213	680.858	729.101
Al Hoceima	59	406.707	411.053	464.042	499.002	536.282	583.619
Aousserd	6	35.523	77.593	111.522	142.144	173.054	220.829
Assa Zag	9	56.167	64.165	123.313	147.105	159.810	170.799
Azilal	80	553.503	583.968	636.054	654.834	659.754	706.300
Beni Mellal	49	336.841	373.614	438.856	458.246	484.511	530.679
Benslimane	22	147.989	163.417	182.063	194.720	223.757	255.878
Berkane	21	140.415	179.257	237.989	261.410	271.137	272.249
Berrechid	30	203.619	217.963	228.647	259.411	299.456	311.253
Boujdour	11	70.476	82.185	104.286	135.021	172.473	182.099
Boulemane	40	273.938	289.326	342.369	389.679	431.335	435.317
Casablanca	108	749.655	750.471	759.529	763.557	775.533	790.460
Chefchaouen	54	371.573	392.730	436.715	474.233	480.078	510.211
Chichaoua	46	315.666	317.037	413.125	456.236	469.167	509.157
Chtouka Ait Baha	34	231.560	261.411	314.274	342.360	362.353	363.053
Driouch	26	175.975	213.414	241.348	273.025	279.439	311.316
El Hajeb	23	154.404	190.984	246.386	278.662	305.930	306.801
El Jadida	39	266.144	272.492	320.891	359.466	393.771	414.408
El Kelaa Des Sraghna	67	462.497	495.389	575.712	597.967	633.453	655.290
Errachidia	57	392.969	413.697	426.697	472.587	476.633	523.200
Es Semara	9	56.528	78.290	96.973	127.969	156.925	180.960
Essaouira	70	483.493	514.661	572.257	586.413	593.153	622.390
Fahs Anjra	8	49.365	55.195	129.822	139.286	145.749	186.794
Fes	43	294.703	340.621	402.236	408.135	424.996	449.519
Figuig	27	182.516	225.263	241.273	243.811	273.606	273.823
Fkih Ben Saleh	40	273.266	314.056	360.613	361.597	407.395	420.243
Guelmim	42	287.385	315.820	355.399	375.939	407.111	443.201
Guercif	19	126.143	126.583	184.976	193.339	222.259	236.727
Ifrane	26	175.368	208.505	253.970	300.605	336.147	342.161
Inezgane Ait Melloul	18	119.502	143.357	191.049	211.681	223.096	231.336
Jerada	19	126.205	171.953	255.930	265.312	267.838	284.883
Kenitra	49	336.342	363.275	460.224	494.169	502.225	506.639
Khémisset	49	336.843	378.756	443.016	469.458	493.393	516.909
Khenifra	45	308.580	333.793	373.234	393.836	395.100	421.958
Khouribga	52	357.934	400.531	457.433	466.398	468.803	497.578
Laayoune	11	70.419	81.622	140.285	177.454	193.276	229.133
Larache	36	245.997	285.807	366.754	410.420	435.320	435.908
Marrakech	68	469.341	509.650	558.048	573.606	591.024	625.095
Mdiq-Fnideq	4	21.930	43.159	78.321	122.642	168.068	184.973
Mediouna	6	35.311	85.598	111.263	140.467	180.770	211.873
Meknès	66	455.532	473.831	551.097	573.120	596.306	642.288
Midelt	49	336.779	365.043	387.045	431.753	466.980	495.391
Mohammedia	14	91.225	112.491	172.242	184.965	209.882	235.592
Moulay Yacoub	17	112.700	151.132	185.456	232.222	268.911	317.849
Nador	33	224.200	251.930	292.341	318.300	347.798	387.234
Nouaceur	10	63.826	81.818	137.332	185.767	223.855	243.928
Ouarzazate	41	280.385	286.008	347.866	365.690	371.744	403.737
Oued Ed-Dahab	12	77.989	104.979	167.709	184.163	222.432	243.000
Ouezzane	36	245.475	292.698	333.911	371.471	410.954	425.950
Oujda Angad	32	217.275	239.655	326.046	364.981	371.017	402.649
Rabat	31	210.429	228.964	284.108	316.675	330.298	345.622
Rehamena	31	210.824	255.136	310.247	354.809	376.553	396.483
Safi	46	315.838	317.979	354.831	381.473	393.863	439.911
Salé	28	189.511	222.235	273.883	310.009	312.983	324.487
Sefrou	32	217.750	234.900	301.651	333.001	349.725	392.863
Settat	80	553.728	575.480	602.260	621.757	636.737	677.565
Sidi Bennour	28	189.508	202.650	293.848	307.892	336.356	369.562
Sidi Ifni	31	210.581	215.135	255.140	283.815	317.073	365.361
Sidi Kacem	39	266.794	309.030	389.041	401.621	442.603	471.514
Sidi Slimane	22	147.477	154.224	207.539	208.429	211.201	236.821
Skhirate-Temara	19	126.378	163.696	210.625	258.640	280.728	325.033
Tan Tan	10	63.496	102.899	125.798	129.228	153.551	170.950
Tanger Assilah	33	224.755	228.590	298.720	305.058	351.702	384.164
Taounate	71	490.622	513.408	594.272	609.271	643.024	670.584
Taourirt	17	112.932	134.976	163.136	171.454	199.908	200.949
Tarfaya	5	28.386	65.914	118.702	131.886	140.103	163.185
Taroudant	109	756.402	787.828	865.283	911.989	932.434	959.101
Tata	35	238.737	243.636	261.407	309.156	317.022	358.669
Taza	72	497.472	534.717	540.304	559.315	600.512	622.318
Tetouan	41	280.997	326.450	388.865	417.661	445.896	481.448
Tinghir	42	287.967	293.801	350.966	364.464	373.748	377.662
Tiznit	56	385.804	409.918	429.612	467.553	475.232	499.998
Youssoufia	15	98.795	147.719	192.304	223.162	263.745	273.869
Zagora	32	217.884	240.625	279.732	309.492	334.853	375.966

Table 3
Comparison of metaheuristic algorithms' performance in optimizing province distances.

Metaheuristic	Mean distance (km)	Median distance (km)	Minimum distance (km)	Maximum distance (km)
RSO	315.24	275.20	21.93	756.40
WOA	345.15	334.79	43.16	787.83
SHOA	400.59	367.05	78.29	865.28
PSeOA	423.24	409.14	125.80	911.99
PSO	441.07	434.32	140.10	932.43
GA	468.39	464.25	170.80	959.10

sequence is (1,2,3,4,5), a possible inversion would be (1,4,3,2,5) (inversion of segment 2–4).

By combining these operations with the previously mentioned metaheuristics, we can explore the space of possible solutions.

6. Experimental results

The selected algorithms have been implemented to address the vaccination problem using a dataset consisting of 2.331 health centers. Each health center is characterized by its name, province, city, category, and coordinates (x and y). By applying the algorithms to this comprehensive dataset, we can assess their effectiveness in solving the vaccination problem in a real-world scenario.

We tested the basic and improved algorithms using C++ as a programming language under the 64-bit Windows 10 operating system. The tests were performed on a Dell laptop with a 2.00 GHz Intel Core i5 processor and 16 GB of RAM.

The values of the parameters of the proposed algorithm are chosen based on some preliminary tests. We are going to make this comparison on several criteria such as the best value which designates the best solution obtained by each algorithm and the mean value which designates the average value of the 20 solutions obtained after 20 executions of an algorithm.

Based on the data provided, we can see that each of the six metaheuristics RSO, WOA, SHOA, PSeOA, PSO, and GA was tested on 65 different provinces in Morocco, each with a variable number of health centers (see Table 2). Table 3 shows the best distance (in km) obtained by each metaheuristic for each province.

To analyze the performance of these algorithms, we can calculate some basic statistics.

First, we can find the mean, median, minimum, and maximum of the best distances obtained by each algorithm in all provinces.

Table 3 provides detailed statistics on the performance of different metaheuristic algorithms in terms of the best distance (in kilometers) obtained for each province in Morocco. The statistics include the mean distance, median distance, minimum distance, and maximum distance.

1. Mean distance: The mean distance represents the average best distance obtained by each algorithm across all provinces. It indicates the overall performance of the algorithms. Among the algorithms tested, RSO has the lowest mean distance of 315.24 km, indicating generally better performance in achieving shorter distances compared to other algorithms. GA has the highest mean distance of 468.39 km, suggesting relatively poorer performance on average.
2. Median distance: The median distance represents the middle value in the sorted list of best distances. It gives an indication of the central tendency of the data. RSO has the lowest median distance of 275.20 km, indicating that approximately half of the provinces achieved a best distance below this value. GA has the highest median distance of 464.25 km, suggesting a relatively higher central tendency towards longer distances.

Table 4
Metaheuristics Dunn's multiple comparisons test.

Dunn's multiple comparisons test	Rank sum diff.	Significant?	Summary	Adjusted P Value
RSO vs. WOA	−75,00	Yes	*	0,0159
RSO vs. SHOA	−150,0	Yes	****	<0,0001
RSO vs. PSeOA	−225,0	Yes	****	<0,0001
RSO vs. PSO	−300,0	Yes	****	<0,0001
RSO vs. GA	−375,0	Yes	****	<0,0001
WOA vs. SHOA	−75,00	Yes	*	0,0159
WOA vs. PSeOA	−150,0	Yes	****	<0,0001
WOA vs. PSO	−225,0	Yes	****	<0,0001
WOA vs. GA	−300,0	Yes	****	<0,0001
SHOA vs. PSeOA	−75,00	Yes	*	0,0159
SHOA vs. PSO	−150,0	Yes	****	<0,0001
SHOA vs. GA	−225,0	Yes	****	<0,0001
PSeOA vs. PSO	−75,00	Yes	*	0,0159
PSeOA vs. GA	−150,0	Yes	****	<0,0001
PSO vs. GA	−75,00	Yes	*	0,0159

3 .Minimum distance: The minimum distance represents the smallest value observed among the best distances. It indicates the best performance achieved by each algorithm in at least one province. RSO has the smallest minimum distance of 21.93 km, indicating the best performance among all algorithms in terms of achieving the shortest distance in at least one province. GA has the largest minimum distance of 170.80 km, suggesting that it performed relatively poorly in terms of achieving the shortest distance.

4. Maximum distance: The maximum distance represents the largest value observed among the best distances. It indicates the worst performance or the presence of outliers in terms of the longest distances achieved. GA has the largest maximum distance of 959.10 km, suggesting that it performed relatively poorly in terms of achieving the longest distance among all the algorithms.

6.1. Statistical comparison

In this study, we will use Dunn's test [25,26] to compare the performance of different algorithms and metaheuristics in solving this optimization problem. The aim is to check whether there are statistically significant disparities in the quality of the solutions obtained by these algorithms.

Dunn's multiple comparison test is a widely used statistical method for validating the results of metaheuristic algorithms.

The test evaluates rank sum differences between pairs of algorithms which reflect variations in performance based on objective or fitness values acquired across a set of problem instances or test functions.

Statistical hypothesis testing is used to determine the significance of rank sum differences. It is used to determine whether the observed disparities are unlikely to have occurred at random. Adjusted p-values are used as an indicator of significance, often designated by asterisks or other symbols.

Table 4 presents the results of Dunn's multiple comparisons test conducted to evaluate the performance of different metaheuristics algorithms. The test compares the rank sum differences between pairs of algorithms and determines whether there are statistically significant differences in the quality of the solutions obtained.

Each row in the table represents a pairwise comparison between two metaheuristics algorithms. The "Rank sum diff." column shows the difference in rank sums which reflects the difference in performance between the algorithms. A negative value indicates that the first algorithm performed better than the second algorithm.

The "Significant?" column indicates whether the observed rank sum difference is statistically significant. In all cases, the significant column is marked as "Yes", indicating that there are statistically significant differences between the algorithms.

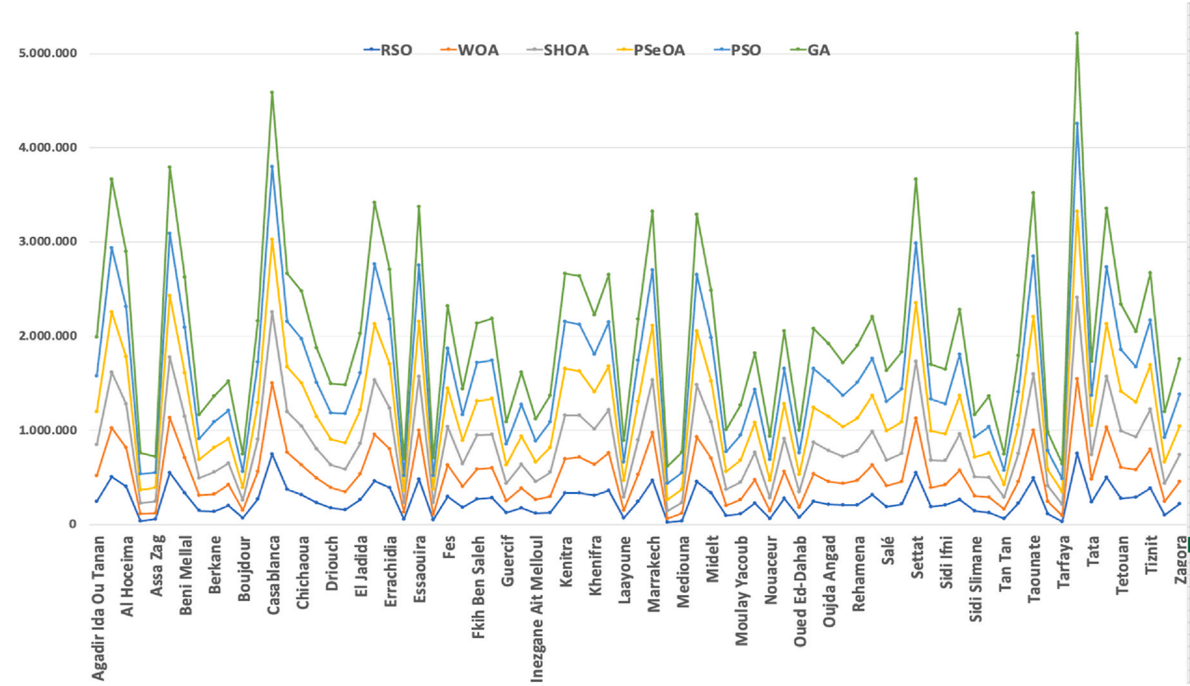


Fig. 5. Metaheuristics and their corresponding best achieved distances (in kilometers) per province.

The “Summary” column provides a summary of the significance level represented by asterisks. The number of asterisks corresponds to the level of significance, with more asterisks indicating higher significance. For example, "*" denotes a significance level of 0.05, while "****" represents a significance level below 0.0001.

The “Adjusted P Value” column displays the adjusted p-values, which measures the level of significance after adjusting for multiple comparisons. A lower adjusted p-value indicates a higher level of significance.

Dunn’s multiple comparisons test yielded significant insights into the performance disparities among various metaheuristic algorithms. By scrutinizing rank sum differences between algorithm pairs, the test discerned statistically notable variations in solution quality.

Among the array of metaheuristics scrutinized, RSO emerged as the top performer, boasting an impressive mean distance of 315.24 km, closely trailed by WOA at 345.15 km. SHOA and PSeOA secured mean distances of 400.59 km and 423.24 km, respectively, while PSO and GA recorded slightly higher mean distances of 441.07 km and 468.39 km.

When focusing on median distances, RSO maintained its dominance, showcasing a median distance of 275.20 km, while WOA and PSO followed suit with median distances of 334.79 km and 434.32 km, respectively.

Analyzing the minimum and maximum distances achieved, RSO demonstrated supremacy with the lowest minimum distance of 21.93 km and the highest maximum distance of 756.40 km. Conversely, GA exhibited the highest minimum distance of 170.80 km, while PSO attained the highest maximum distance of 932.43 km.

These findings unequivocally highlight RSO and WOA as consistent frontrunners, continuously surpassing other algorithms. Following in a descending order, SHOA, PSeOA, PSO, and GA exhibit progressively higher mean and median distances.

These revelations from the analysis furnish invaluable insights into the relative efficacy of metaheuristic algorithms for the specific problem at hand. Additionally, Fig. 5 corroborates the preceding analysis.

7. Conclusion

In summary, the integration of metaheuristic algorithms in conjunction with a comprehensive tour planning system presents a highly promising avenue for optimizing vaccination campaigns and medication distribution in the rural regions of Morocco. By conscientiously accounting for critical field constraints and intricacies such as transportation costs, these algorithms facilitate the determination of efficient routes for trucks responsible for transporting vaccines and medications, all while minimizing the overall duration of the journey. The inclusive tour planning system further bolsters this optimization framework by factoring in essential elements like fuel expenses and vehicle maintenance costs.

Moreover, this research extends its impact far beyond the scope of vaccination campaigns by tackling the intricate matter of medication distribution to rural healthcare facilities. By proficiently utilizing the proposed metaheuristic algorithms and the tour planning system, a meticulously optimized delivery route for medications can be executed. This process involves careful consideration of key factors, including medication availability, storage prerequisites, and expiry timelines. This holistic approach ensures the timely and uninterrupted access of vital healthcare resources to the underserved rural population, thereby significantly fortifying the healthcare system in these areas.

The amalgamation of metaheuristics and the tour planning system, as illuminated in this study, not only promises substantial cost reductions, and enhanced operational efficiency but also underscores the commitment of Morocco’s Ministry of Health towards embracing innovative strategies aimed at elevating healthcare delivery standards in the rural regions. By adopting this robust, data-driven solution, the Ministry of Health is poised to augment the efficiency of its vaccination and medication distribution initiatives, culminating in the overall enhancement of the rural populace’s well-being.

Furthermore, the findings of this research confer a substantial contribution to the field of healthcare logistics optimization. By spotlighting the immense potential harbored by metaheuristic algorithms and tour planning systems in the context of rural healthcare endeavors, this study proffers invaluable insights to global policymakers and practitioners. The optimization framework presented herein serves as a pivotal reference for designing and implementing resource-efficient and cost-effective vaccination and medication distribution strategies, not confined to Morocco but extendable to analogous contexts worldwide. Through the interchange of knowledge and adaptable strategies, the impact of this research can traverse borders, benefiting underserved populations and propelling the field of healthcare logistics optimization on a global scale.

7.1. Limitations

Data Accessibility and Confidentiality: Our study's foundation is the field data furnished by the Ministry of Health, bearing inherent limitations that we, as researchers, cannot rectify or control. Factors such as data accuracy, comprehensiveness, and timeliness are beyond our purview, and any potential lacunae or inaccuracies within the dataset could conceivably influence the dependability of our conclusions. Additionally, specific data pertinent to our study may pose accessibility challenges due to confidentiality and security constraints.

Stationary Parameter Assumption: Our optimization models make the assumption that certain variables, such as vaccine demand and clinic operational hours, remain relatively consistent throughout the planning period. However, real-world scenarios frequently deviate from this assumption due to unanticipated events, such as disease outbreaks, local incidents, or shifts in health center policies. These variations have the potential to exert an impact on the model's performance.

Fine-Tuning Algorithm Parameters: The precision of adjusting the parameters of metaheuristic algorithms is pivotal for their efficacy. Nonetheless, our study predominantly relied on default or widely accepted parameter values, which may not be universally optimal for every distinct instance of the routing problem. Consequently, the modification of parameter settings could yield divergent outcomes.

7.2. Perspectives

Dynamic Optimization: Delving into the development of dynamic optimization models that can adeptly adapt to changing parameters and unforeseen events presents a promising avenue for further research. This could involve predictive modeling grounded in historical data and real-time inputs.

Multi-Objective Optimization: The broadening of research horizons to encompass multiple objectives, such as cost minimization, vaccine coverage maximization, and carbon emissions reduction, could furnish a more comprehensive solution that accounts for the broader societal and environmental impacts of vaccine distribution.

CRediT authorship contribution statement

Toufik Mzili: Conceptualization, Data curation. **Ilyass Mzili:** Conceptualization, Investigation, Methodology. **Mohammed Essaid Riffi:** Project administration, Supervision, Writing – review & editing. **Mohamed Kurdi:** Formal analysis, Investigation, Writing – original draft. **Ali Hasan Ali:** Project administration, Software, Writing – review & editing. **Dragan Pamucar:** Supervision, Validation, Writing – review & editing. **Laith Abualigah:** Data curation, Formal analysis, Investigation, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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