COVID-19 Vaccine's Distribution Routes with Bioinspired Metaheuristic Algorithms: Resoluteness

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Abstract— **The global emergency of COVID-19 caused by the SARS-CoV-2 virus at the end of 2019, it was without a doubt a critical and historical point for society in general; for instance, the effective development of vaccines, as well as the efficient distribution of them; They were an unprecedented challenge to slow down the spread or mitigate its impact on societies around the world. This article specifies three bio-inspired metaheuristic algorithms (genetic algorithm, particle swarm optimization algorithm, and artificial bee colony algorithm) that were used in the context of the capacitated vehicle routing problem to generate vaccine distribution routes, specifically, COVID-19 vaccine for over 18 years old the first and the second doses applications in Mexico, particularly in the State of Mexico. The quality of the solutions obtained by these algorithms is compared, and the performance of the particle swarm optimization (PSO) algorithm being superior in solution quality. The results show that the construction of vaccine distribution routes applying bio-inspired algorithms determines reliable scenarios that support the decision-making of the personnel dedicated to carrying out this activity.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/8709

Index Terms—**Artificial Bee Colony Algorithm, Bio-inspired, Capacitated Vehicle Routing Problem, Genetic Algorithm, Metaheuristics, Particle Swarm Optimization Algorithm.**

I. Introduction

At the end of 2019, the existence of a virus was announced that would gradually spread worldwide, giving rise to the COVID-19 pandemic (Corona Virus Disease). According to the World Health Organization (WHO), the disease is caused by a virus called SARS-CoV-2 [1].

The evolution of the pandemic was characterized from the next relevant aspects, the implementation of health measures in daily activities, isolation, distribution, and application of vaccines, and finally to recover daily routine. Today it is not possible to precisely determine how SARS-CoV-2 infections began, however, all evidence suggests that the virus has an animal origin which it is not a manipulated or constructed virus [2]. According to Banxico [3], in Mexico, the evolution of the pandemic was divided into three phases [3]: i. The installation of the National Day of Healthy Distance; ii: Non-essential economic activities were suspended; iii. The activities of the construction, mining, transportation, equipment manufacturing industries were reestablished. *Phase 1*. It began in February 2020, it is characterized by imported cases, the implementation of mitigation strategies has not yet been considered and ends with the installation of the National Day of Healthy Distance. *Phase 2*. Since March 2020, most cases and transmission were already local, limited to the suspension of in-person classes, mass events, and at the end of March non-essential economic activities were suspended. *Phase 3*. In April 2020 and is characterized by showing faster and more widespread transmission. In this phase, the activities of the construction, mining, transportation, equipment manufacturing industries were reestablished as essential activities if they could comply with health safety protocols. The new normal or the return to daily activities gradually involved changing personal care habits, the way of carrying out daily activities, and the way of communication, among others. The return to normality was carried out in accordance with criteria established by federal and state authorities, such as the usage of face masks, hand washing frequently, and healthy distance they are part of the gradual changes to the new routine [4]. The return to normality was carried out in accordance with criteria established by federal and state authorities, such as the usage of face masks, hand washing frequently, and healthy distance they are part of the gradual changes to the new routine [4].

To deal with the pandemic, the WHO issues the Emergency Use Listing (EUL) procedure. The procedure evaluates the suitability of the creation of medicines and vaccines as quickly as possible, respecting the criteria of safety, efficiency, and quality [5].

This involved a rigorous evaluation of clinical data from experimental trials corresponding to human trials, recruiting groups of volunteers [6]. Likewise, it required thorough analysis of data related to safety, efficiency, quality, and risk management plan by independent experts and WHO teams.

The technical advisory group for the COVID-19 vaccine in Mexico is a group of experts that defines a strategy focused on reducing the number of deaths associated with COVID-19 based on the mortality observed in the country. As a result, 4 prioritization axes were established for the application and distribution of the COVID-19 vaccine in Mexico [7]: 1) Age of individuals; 2) Personal comorbidities; 3) Priority care groups; and 4) Epidemic behavior.

Based on an analysis of population projections from National Council of Population (CONAPO, Consejo Nacional de Población; Mexico) and data from the National Epidemiological Vigilance System (SINAVE, Sistema Nacional de Vigilancia Epidemiólogica; Mexico) risk groups and vaccination stages were identified [7]:

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1. Stage 1 (December 2020 – February 2021): First-line healthcare personnel in COVID-19 control.
2. Stage 2 (February – April 2021): Remaining health personnel and people aged 60 and over.
3. Stage 3 (April – May 2021): People from 50 to 59 years old.
4. Stage 4 (May – June 2021): People from 40 to 49 years old.
5. Stage 5 (June 2021 – March 2022): Remaining population.

Plus, for the application of vaccines to be successful, it was necessary to carry out an exhaustive study to guarantee the timely administration of vaccines throughout the national territory. In Mexico, the distribution of vaccines against COVID-19 in accordance with the vaccination stages was carried out by the Ministry of Defense (SEDENA, Secretaría de la Defensa Nacional; Mexico) using land and air routes.

According to WHO, the spread of the virus at the beginning of October 2023 is defined by 771 million confirmed cases, including 6.9 million deaths, and a total of 13.5 billion vaccine doses administered [8].

At the same time, on 10 January 2023, there is 84% coverage in all age groups, highlighting 91% coverage for the group of people aged 18 years and over [9]. Vaccine distribution is a problem that can be approached as the classic Vehicle Routing Problem (VRP), which is a combinatorial optimization problem. The main objective of VPR is to define an optimal set of routes for a fleet of vehicle, which must satisfy the demand of a set of clients while satisfying some requirements and restrictions overall, that in most of the cases are the minimization of the total cost from the distribution. Delivery schedule and vehicle routing are important in supply chain operations. Supply chains are affected by multiple factors that become restrictions or variables of the problem, resulting in the creation of different variants of the VRP [10].

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Multiple articles have been published in relation to vaccine supply chains that belong to cold chains, even before the start of the pandemic [11], [12], [13], [14], [15]. The interest in these studies is due to the challenges involved in its implementation, also, the number of variables that must be considered, such as time windows, load capacity, conservation and temperature management of cargo transportation, fuel consumption, client satisfaction, delivery priority, traffic conditions just to mention a few.

In the other hand, the state of the art shows the different solution approaches to solve the VRP. Those include exact methods, heuristics, and metaheuristics. Exact methods provide optimal solutions, in general, appropriately to solve problems in small scale but the heuristics and metaheuristics usually produce solutions close to the optimal without limits on the size of the problem. The heuristics produce solutions swifter than the exact method. Likewise, metaheuristics are high level algorithms that combine different heuristics [16], applicable to different kinds of problems of optimization with little modifications to adapt them to a specific problem. According to [16], the heuristics and metaheuristics algorithms are still the main solution methods.

Derived from the above, this article presents a comparative study of the use of bio-inspired metaheuristics as a proposal to carry out route planning in the transfer of biologicals, considering the variables of loading capacity, transportation cost and client demand.

The article is structured as follows: Section II provides a review of the works related to the study of the VRP according to the variables under consideration; the formulation of the distribution problem is explained in Section III; the description of the metaheuristics used is shown in Section IV; the strategy followed to validate the proposals is described in Section V; while the results are presented in Section VI, and finally the conclusions and open lines of study are included in Section VII.

II. Related Works

This section explains some works reported in the literature addressed to handling the VRP and the cold chain problem.

The *logistics of the cold chain* is studied by Zheng *et al*. [15] considering its fuel consumption and distribution period. The authors propose a solution based on the bi-objective location-routing problem. Furthermore, they use a multi-objective hyper heuristic (MOHH) to model and solve the problem. The results obtained provided a set of solutions with several options for a decision maker to select the distribution of interest.

On the other hand, a hybrid algorithm, *immune wolf colony hybrid algorithm* is proposed by Dou *et al.* [14] which reports rapid convergence of the global optimal solution and optimizes the logistics of vaccine distribution centers, considering restrictions such as the freshness and time windows.

Another approach to the cold chain, named as the location-routing problem-based low-carbon cold chain (LRPLCCC) where Leng *et al*. [13], develop the problem as a bi-objective mixed-integer programming (MIP) in addition to proposing a MOHH for the bi-objective model and obtain solutions. The study focused on two aspects: minimizing the total logistics cost that includes fixed costs of depots, leased vehicles, fuel consumption and carbon emissions; and improving client satisfaction and product conservation.

A distribution route optimization model using DNA computing and the Ant Colony Optimization (ACO) algorithm is proposed by Huang and Fei [17] based on an analysis of the special characteristics for the transport of biological such as room temperature and delivery in a certain range of time. The proposed DNA-ACO algorithm managed to minimize costs more efficiently than algorithms such as ACO and fish swarm ant colony optimization (FSACO).

Fu *et al.* [18] establish a *location model of cold chain logistics distribution center* with the objective of minimizing the total cost including manufacturers, distribution centers and clients. As a solution tool, the characteristics of the fireworks algorithm (FWA) are used to improve the fish swarm algorithm (FSA), the resulting algorithm is applied to the model.

The same way, Zhang *et al*. [19], suggest an FSA upgraded, including some FWA elements, and applying it to its *optimization model of location-routing problem-based low-carbon cold chain* that includes fixed costs, transportation cost, cost of load damage, cooling cost, emissions of carbon cost, and penalization cost.

Sujaree and Samattapapong [20] propose a hybrid algorithm called hybrid artificial chemical reaction optimization algorithm (HACROA), which was used to design a vaccine cold chain network with the objective of minimizing total travel distances. Finally, a mathematical model is proposed by Soria *et al*. [21] for the distribution of different COVID-19 vaccines in Mexico, resulting in an efficient strategy to satisfy demand in each period.

III. Capacitated Vehicle Routing Problem Method

The proposal suggested in this study considers a variant of the VRP known as the capacitated vehicle routing problem (CVRP) since the only restriction it considers is the capacity of the vehicles. The CVRP involves determining a set of vehicle routes with minimum cost in such that [22], [23]:

1. Each client is visited only once by a single vehicle.
2. All routes start and end at the depot.
3. The demand for any route does not exceed the capacity of the vehicles.

The problem can be expressed in the next graph theory. Let $G = (V, A)$ a complete graph where $V = \{0,1, \dots, n\}$ is the set of vertices and A is the set of arcs. The set of vertices $i = 1, \dots, n$ corresponds to the clients while the vertex 0 represents the deposit. Each arc $(i, j) \in A$ has an associated non-negative cost, c_{ij}, which represents the travel cost to go from the vertex i to the vertex j. Each client i $(i = 1, \dots, n)$ is associated with a non-negative demand, d_i, to be delivered, depot is assumed that $d_0 = 0$. A set of K similar vehicles with capacity C are in the depot and must be used to supply clients. It is assumed that $d_i \leq C$ for each $i = 1, \dots, n$ [22].

The mathematical formulation from the CVRP is described using the two-index vehicle flow formulation.

Let x_{ij} an integer variable that takes the value 1 if the arc $(i, j) \in A$ belongs to a solution and takes value 0 in opposite case.

In addition, to the notes mentioned, for a set $S \subseteq V$, let $\delta(S)$ and $A(S)$ the set of arcs $(i, j) \in A$ that have got uniquely one or both end vertices in S, respectively and $d(S)$ is the demand of total of set.

The CVRP can be formulated using the following integer linear programming model [22], [23]:

$$Minimizar \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij} \quad (1)$$

Subject to the following restrictions:

$$\sum_{i \in V} x_{ij} = 1 \quad \forall\, j \in V \setminus \{0\}, \quad (2)$$

$$\sum_{j \in V} x_{ij} = 1 \quad \forall\, i \in V \setminus \{0\}, \quad (3)$$

$$\sum_{i \in V} x_{i0} = K, \quad (4)$$

$$\sum_{j \in V} x_{0j} = K, \quad (5)$$

$$\sum_{i \notin S} \sum_{j \in S} x_{ij} \geq r(S) \quad \forall\, S \subseteq V \setminus \{0\}, S \neq \emptyset, \quad (6)$$

$$x_{ij} \in \{0,1\} \quad \forall\, i, j \in V. \quad (7)$$

The indegree and outdegree constraints (2) and (3) force that an arc enters and leaves each vertex associated to a costumer, respectively. As well as the restrictions (4) and (5) force the degree requirements for the depot vertex. The connectivity of the solution and the vehicle capacity requirements are both forced in the restriction (6). Given a set $S \subseteq V \setminus \{0\}$, it is defined $r(S)$ as the minimum number of vehicles needed to attend all the costumers in S. This problem is considered NP-hard because of the number of variables O(n2) and constraints.

IV. Metaheuristics

According to Konstantakopoulos *et al.* [10], local search metaheuristics are popular for offering efficient solutions and because of its utilization in conjunction with other algorithms, because their combination, the advantages of each algorithm are leveraged.

In the execution of the metaheuristics used in this research, a population of individuals is required $P = \{x_1, \cdots, x_n\}$, where each one represents a potential solution to the application problem. In its operation, each solution x_i is evaluated given a fitness function $f(x_i)$, which is expected to be maximized or minimized, whichever the case. Based on, the metaheuristics used in this research are described below.

A. Genetic Algorithm

Genetic algorithm (GA), it is an optimization algorithm inspired by the principle of natural selection, and the concept comes from the most survival fit and proper. As it works, new populations are generated through the usage of repetitive genetic operations in some cases from the individuals who are in the population. Each individual is evaluated to obtain its fitness measure; so, the ones with the best results, they are selected from the population. A crossover operator is applied, creating new individuals combining parts of the selected individuals. After that, a mutation operator is applied in the new individuals, thereby creating further new individuals. The selection, crossover and mutation operations will be repeated in the current population until the new population is completed [24]. The GA pseudocode is as follows [25]:

Algorithm 1 Basic Genetic Algorithm

Begin
 $t = 0$ // iterations
 Initialize $P(t)$ // initial population.
 While (no stop condition)
  $\forall\, x_i^t \in P(t)$ Assess its aptitude $f(x_i^t)$
  Select from $P(t)$ the best individuals $\{x'\}$
  Apply genetic operators (crossover and mutation) to $\{x'\}$ and obtain the new generation $P(t+1)$
  Set $t = t + 1$
 End While
End

B. Artificial Bee Colony

The Artificial Bee Colony (ABC) algorithm is inspired by the foraging behavior of bees and belongs to the group of swarm intelligence algorithms.

In this algorithm each candidate solution represents the position of the food source in the search space and the nectar quality of the food source is used to evaluate its fitness. In its operation, three groups of bees are considered to guide the process of exploration and exploitation: employees, onlookers, and scouts [26].

In the initialization phase, a population of food sources (solutions) are initialized by scout bees and parameters are assigned. A scout bee generates a random food source x_i (solución) and evaluates its nectar $f(x_i)$, then associates with this food source to become an employee.

After initialization, the interaction of three phases is required [25]:

1. **Employed bees' phase.** Employed bees search for new food sources with more nectar within the neighborhood of the food source x_i and when they find it, its aptitude is evaluated and compared with the previous one, and in case it is better, it is retained in the population (Greedy selection). The employed bees then share information about their food sources to the onlooker bees. If the amount of nectar decreases to a low level or depleted exhaust, the food source is abandoned, and the bee becomes unemployed. Otherwise, it may continue searching for food.
2. **Onlooker bees' phase**. Onlooker bees select a food source x_i depending on the probability obtained with the roulette selection method. As in the employed bees' phase, a greedy selection is applied, and new locations of all food sources are determined.
3. **Scout bees' phase**. The employed bees whose solutions did not improve after a specified number of attempts become scouts and their solutions are abandoned. The scout bee is then associated with a random solution x_i becoming an employed bee. If a food source has equivalent or better nectar than the old source, the old source is replaced and those initially poor or exploited sources are abandoned.

ABC algorithm has three control parameters: the bee colony size, the local search abandoning limit, and the maximum number of search cycles or a fitness-based termination criterion. The ABC pseudocode is as follows [26]:

Algorithm 2 ABC Algorithm

Begin
 Initialization phase
 While (no stop condition)
  Employed bees' phase.
  Onlooker bees' phase
  Scout bees' phase
  Memorize the best source of food found.
 End While
End

C. Particle Swarm Optimization

The particle swarm algorithm (PSO) considers an analogy of the collective behavior from groups of animals, such as the fish shoals and flocks of birds [27].

In PSO, a swarm of particles flies in a D-dimensional search space seeking an optimal solution from the consecutive updated of its trajectory based on the best positions previously visited. Each particle x_i has its own trajectory determined by its position vector $X_i = [x_{i1}, \dots, x_{iD}]$ and its velocity vector $V_i = [v_{i1}, \dots, v_{iD}]$.

The algorithm initializes a group of particles with random positions and then the individuals begin to move through the search space iteratively. At each iteration, the particles are updated in the following greater two values, the particle x_i^* is the best solution obtained so far for the particle x_i and the particle x^g is the best overall solution. The PSO pseudocode is as follows [27]:

Algorithm 3 PSO algorithm

Begin
 Initialize each particle by randomly selecting values for its position X_i and velocity V_i
 While (no stop condition)
  For each particle $i = 1$ a N
   Evaluate velocity v_{id} and update position x_{id}
   Calculate aptitude of the particle x_i
   If $(f(x_i) > f(x_i^*))$
    $x_i^* \leftarrow x_i$
   End If
   If $(f(x_i) > f(x^g))$
    $x^g \leftarrow x_i$
   End If
  End for
 End while
 Return x^g
End

In each iteration t the velocity of the particle is updated with the equation 8:

$$v_{id}(t+1) = wv_{id}(t) + c_1 r_1\big(x_{id}^*(t) - x_{id}(t)\big) +$$

$$c_2 r_2 \left(x_d^g(t) - x_{id}(t) \right) \quad (8)$$

Where w is the inertia factor, c_1 and c_2 are the cognitive and social acceleration coefficients, r_1 and r_2 are uniform random values between $(0,1)$. Finally, the position of the particle is updated with the equation 9:

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (9)$$

Generating solutions for routing problems with constraints can result in exhaustive searches that may take too much time to execute, or it is not possible to generate solutions that meet the constraints. To avoid the previously mentioned, a penalty cost is implemented if the solution exceeds the loading capacity of the vehicles. In this way the search space is also diversified. The following capacity overload penalty objective function is frequently used in CVRP study [28], [29], [30] (equation 10):

$$z(x) = c(x) + \alpha * q(x) \quad (10)$$

Where $c(x)$ is the cost of traversing the routes (distance) and $q(x)$ is the sum of the excess demand on the routes that make up the solution. The parameter α represents the penalty constant and is usually set to incorporate an additional cost into the objective function to guide the algorithm toward feasible solutions that satisfy the requirements of the problem.

V. Methodology

The methodology used in this paper is described in Fig 1.

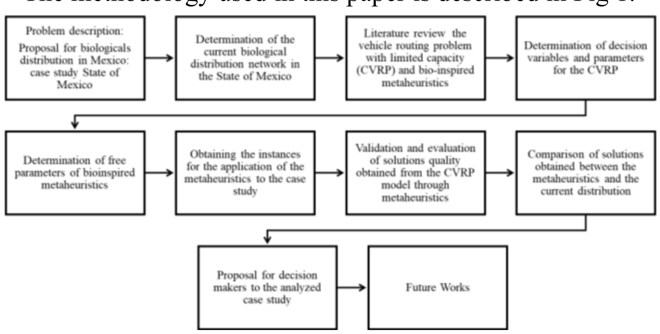


Fig. 1. Methodology for development of the work.

Next, the methodology for validating the proposal for the distribution of biological products in Mexico is described, specifically, for the State of Mexico. The data acquisition includes the identification of the different distribution centers (depot) and application sites (clients) for the transportation of vaccines, means of transport, vaccination stages, doses of vaccines acquired, among others. Therefore, in this study it is assumed that:

1. The demand for biologicals by application site corresponds to the population within the application age group and number of application sites in the municipality.
2. Time windows are not considered.
3. The vehicles have the same load capacity, and each vehicle leaves from the distribution center to various application sites and returns to the starting point.
4. Intermediate points (transshipment) between distribution centers and application sites are not considered.
5. There are no biological demands that exceed the capacity of vehicles.
6. The cost matrix is asymmetric, and the number of vehicles is unlimited.

The distribution network is made up of one depot and 261 application sites distributed in the age groups 18 to 29 years, 30 to 39 years, 40 to 49 years, 50 to 59 years, and 60 years and older.

The vaccine application sites were obtained from the official site of the Government of the State of Mexico [31] and are distributed in the 125 municipalities that make it up. The coordinates of the application sites were consulted from the map application server, Google Maps [32].

The required demand by application site was obtained from the National Institute of Statistics and Geography (INEGI, Instituto Nacional de Estadística y Geografía; Mexico) by consulting the population within the age range corresponding to the dose and area of the application site [33].

Regarding the cost of routes, the Distance Matrix API of Google Maps Platform was used [34] to obtain the travel distance between the application sites using their corresponding coordinates.

A. *Free Parameters of the Metaheuristics*

The performance of the metaheuristics is considerably affected by the parameter configuration because it controls some characteristics such as convergence, quality of the solution and execution time. Each algorithm was executed with different parameter configurations based on recommended ranges from the literature [28], [35], [36], [37], [38], [39], [40], [41], followed by an iterative process of adjustment and refinement. Specifically, for each algorithm, we started with standard or recommended parameter values, followed by a sensitivity and performance analysis where each parameter was adjusted independently while keeping the others constant across multiple executions. In each run, one hundred optimization cycles were carried out. Overall, parameter determination was carried out empirically, aiming to maintain similar initial conditions across the algorithms:

1. Genetic algorithm
   a) Population size = 50
   b) Crossover rate = 0.7
   c) Mutation rate = 0.1
   d) Elitist selection = 1
2. Artificial bee colony algorithm
   a) Scout bees = 50
   b) Food sources = 50
   c) Limit of abandon of local searching = 100
3. Particle swarm optimization algorithm
   a) Particles = 50
   b) Inertia = 0.5
   c) Acceleration coefficients C1 = 2.05 y C2 = 2.05

B. Solution Representation

The solution representation uses a vector of length $(n+m)$, where n elements representing customers are visited by m vehicle routes. Fig. 2 provides an example of an instance with five customers $(n=5)$ and three vehicles $(m=3)$. The sequence between two $0s$ is the sequence of customers to be visited by a vehicle. As shown in Fig. 2, customers 1 and 3 are assigned to the same route, and the vehicle visits customer 1 before customer 4. The solution representation is the same for all three algorithms.

0	1	3	0	4	5	0	2

Fig. 2. Solution representation which $n = 5$ y $m = 3$.

Regarding the generation of solutions in the initialization phase, a heuristic approach is used with the Greedy Randomized Construction Method. An initial solution is built by assigning one client at a time to a route of k vehicles. The client is randomly selected and assigned to the location that minimizes the cost of assigning the client on the current set of routes, while meeting the vehicle load capacity. In case it exceeds it, it is assigned to the next route that minimizes the cost and does not exceed the load capacity, the procedure is repeated until all clients are routed.

VI. Results

The performance of the algorithms was done in an equipment with AMD Ryzen 9 5950X 16 Cores processor and 32 GB of RAM with Windows 10 as Operating System. The algorithms were developed and compiled with JAVA programming language (JDK 8), multithreading programming with Spring Framework.

A. Quality Evaluation

In the literature, a frequently used measure to analyze both the effectiveness and quality of solutions obtained with metaheuristics is the percentage deviation between the best solution obtained (OS) and the best-known solution (BKS). Its calculation is as equation 11:

$$Percentage\ deviation = \left(\frac{OS-BKS}{BKS}\right) \times 100 \tag{11}$$

In Table I, the rows correspond to 3 instances of the Augerat problem set for the CVRP as reference values and the rows include the best solutions obtained by each algorithm implemented for the instances A-n32-k05 [42], B-n50-k08 [43] and P-n070-k10 [44] (where A, B and Pare the groups of the instances, n is the number of nodes and k is the number of vehicles), while the columns correspond to the performance of the algorithms and their percentage deviation from the best-known solutions. Each algorithm was run ten times for each instance and each run consisted of 100 iterations.

TABLE I
PERCENTAGE DEVIATION OBTAINED BY THE ALGORITHMS

Instance	Best solution obtained by each metaheuristic				Percentage deviation		
	BKS	GA	ABC	PSO	GA	ABC	PSO
A-n32-k05	784	1023	993	893	30.48	26.66	13.9
B-n50-k08	1312	1542	1525	1457	17.53	16.23	11.05
P-n070-k10	827	1296	1283	1190	56.71	55.14	43.89
	Average percentage deviation				34.91	33.52	22.95

Note: Where A, B and P are the groups of the instances, n is the number of nodes and k is the number of vehicles.

In Table I, it is possible to note that the average percentage deviation demonstrates the performance of the algorithms, the solutions close to the optimal can represent an efficient implementation of the algorithms, thus, the performance of the proposed algorithms is acceptable for the present study.

B. Obtaining Instances for Vaccine Distribution

Considering the information on vaccination phases [31] and population census [33], Table II describes the number of vertices, number of arcs and total demand corresponding to each instance. In Table II, the instance E18A1 indicates the first dose of the 18–29-year age group, E40A2 indicates the second dose of the 40–49-year age group, and so on. Where for each instance the number of binary variables corresponds to the number of arcs and the restrictions to 3n+2 (n = number of vertices) in the model.

TABLE II
NUMBER OF APPLICATION SITES AND DEMAND FOR COVID-19 VACCINES FOR EACH INSTANCE

Instance	Vertices	Arcs	Demand (Vaccines)
E18A1	178	31506	3183223
E18A2	177	31152	3355937
E30A1	187	34782	2537527
E30A2	162	26082	2472808
E40A1	178	31506	2538297
E40A2	177	31152	2515270
E50A1	207	42642	1951408
E50A2	190	35910	1926948
E60A1	117	13572	1105234
E60A2	201	40200	1919417

According to the labelling and packaging of the Pfizer/BioNTech and Moderna vaccines [45], [46], the desired minimum capacities in the vehicles for distribution are described in Table III. The capacity C was defined by dividing the demand for vaccines of the instance between the $K = 10$ vehicles.

TABLE III
CHARACTERISTICS OF VEHICLES FOR DISTRIBUTION

Instance	C (Vaccines)	Pfizer/BioNTech		Moderna	
		m^3	kg	m^3	kg
E18A1	320000	4.88	9.55E-03	2.05	3.18E-02
E18A2	340000	5.14	1.01E-02	2.16	3.36E-02
E30A1	260000	3.89	7.61E-03	1.63	2.54E-02
E30A2	248000	3.79	7.42E-03	1.59	2.47E-02
E40A1	254000	3.89	7.61E-03	1.63	2.54E-02
E40A2	252000	3.85	7.55E-03	1.62	2.52E-02
E50A1	196000	2.99	5.85E-03	1.25	1.95E-02
E50A2	193000	2.95	5.78E-03	1.24	1.93E-02
E60A1	111000	1.69	3.32E-03	0.71	1.11E-02
E60A2	192000	2.94	5.76E-03	1.23	1.92E-02

C. *Analysis of Solution Quality*

Each algorithm was run ten times for each instance, likewise, each execution was carried out by twenty-five threads. Table IV compares the best solutions found by the algorithms; the best solutions obtained for each instance are highlighted.

TABLE IV
BEST SOLUTIONS OBTAINED BY THE ALGORITHMS

Instance	ABC	PSO	GA
E18A1	9.16E+06	**7.95E+06**	8.24E+06
E18A2	8.50E+06	**7.93E+06**	8.28E+06
E30A1	9.07E+06	**8.06E+06**	8.44E+06
E30A2	8.90E+06	7.99E+06	**7.94E+06**
E40A1	1.24E+07	**1.07E+07**	1.21E+07
E40A2	1.06E+07	**9.38E+06**	9.83E+06
E50A1	9.85E+06	**9.72E+06**	1.00E+07
E50A2	1.07E+07	**9.68E+06**	9.81E+06
E60A1	6.29E+06	**5.20E+06**	5.28E+06
E60A2	1.26E+07	**1.17E+07**	1.28E+07

From Table IV it is possible to note the efficiency of the PSO algorithm with respect to the other metaheuristics, by generating the best solutions in 90% of the instances, immediately followed by the GA.

When analyzing the quality of the solutions obtained by calculating the percentage deviation and considering those obtained with the PSO algorithm as the best values, it is possible to observe that the solutions obtained by the ABC algorithm range between 1.27 to 21.08 with an average of 11.6, whereas for the GA ranges between -0.66 and 12.6 with an average of 4.49 (the negative sign means that the genetic algorithm generated a better solution than PSO for instance E30A2). These values indicate that the ABC and GA algorithms are on average 11.6% and 4.49% higher in distribution cost.

D. *Execution Time Analysis*

The average computational time of the ten runs performed by the algorithms on each instance is illustrated in Fig. 3, it is clearly observed that the ABC algorithm is the one that obtains the solutions more quickly, while the PSO algorithm is the one that requires the most time.

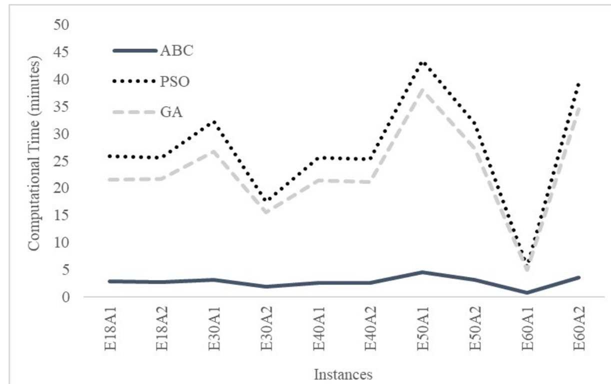


Fig. 3. Required execution time for each instance.

Once again, by calculating the percentage deviation with respect to the execution time and considering the ABC algorithm as optimal, it can be determined that the percentage deviation of the PSO algorithm ranges between 649.15 to 1001.44 with an average of 867.38 while for the GA it ranges between 566.24 and 868.43 with an average of 728.07, the above highlights the efficiency in terms of computational time of the ABC algorithm, in other words, the PSO algorithm is on average 867.38% greater while the GA is 728.07% greater in terms of computational time. However, it is necessary to clarify that the complexity of operations and the number of function evaluations conducted by the algorithms and their local search methods are not the same due to the inherent probability and/or randomness associated with each algorithm.

E. *Detailed Analysis*

Further analysis of the performance of the algorithms is carried out below, considering the E60A1 instance for the case study. Firstly, the obtaining of routes by each of the metaheuristics is observed in Fig. 4. In this it can be seen how from the first iterations the PSO and AG algorithms begin to approach the global minimum of 5.20E06 and 5.28E06 respectively, while the ABC algorithm does not present a lot of variation towards its global minimum of 6.29E06.

On the other hand, Fig. 5 shows the time in minutes required to obtain the solutions. From these results it is possible to observe the constant increase over time, however, the resource savings that the ABC algorithm requires are clear. The average duration of an optimization cycle for the ABC algorithm is 0.34 minutes, for the PSO algorithm 2.59 minutes, and for the GA 2.37 minutes.

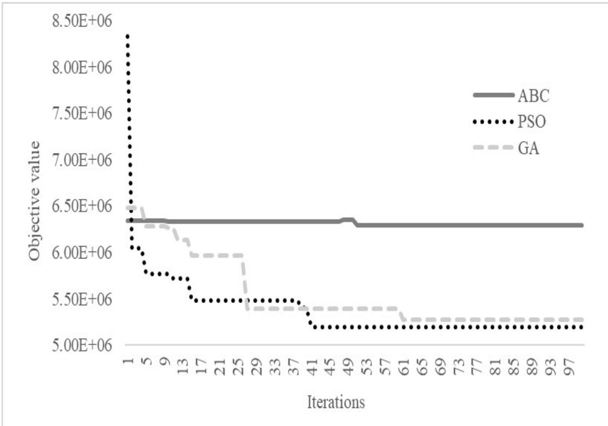


Fig. 4. Obtaining solutions for E60A1 instance.

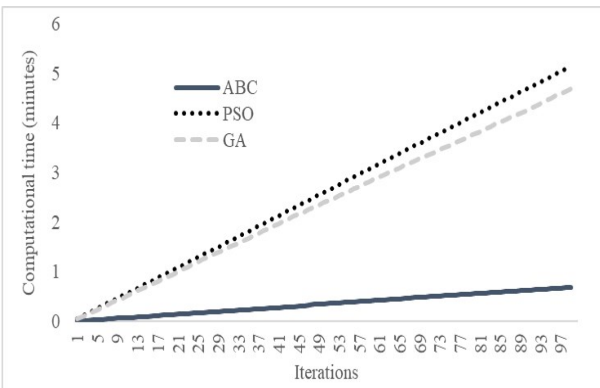


Fig. 5. Computational time of best solutions for E60A1 instance.

Finally, Fig. 6 presents the graph of the best solution obtained for the E60A1 instance by the PSO algorithm, Table V shows its corresponding routing of application sites, where each route belongs to vector of the best solution and node 262 is the distribution center which correspond to the node 0 in Fig. 2.

TABLE V
BEST SOLUTION FOR E60A1 INSTANCE

Route	Application sites	Nodes
1	262, 119, 81, 75, 80, 74, 115, 22, 8, 127, 151, 162, 24, 71, 82, 121, 262	16
2	262, 194, 158, 130, 46, 99, 45, 177, 44, 77, 182, 262	11
3	262, 26, 94, 88, 101, 112, 87, 120, 188, 47, 174, 43, 207, 147, 262	14
4	262, 67, 126, 116, 6, 181, 124, 190, 218, 7, 186, 187, 157, 92, 95, 93, 191, 145, 65, 183, 262	20
5	262, 11, 84, 61, 152, 103, 171, 86, 85, 66, 13, 165, 149, 32, 262	14
6	262, 5, 184, 96, 110, 16, 163, 15, 262	**8**
7	262, 213, 123, 97, 161, 100, 42, 91, 193, 173, 148, 262	11
8	262, 76, 146, 98, 64, 14, 164, 23, 29, 137, 79, 262	11
9	262, 133, 205, 125, 48, 134, 132, 175, 176, 262	9
10	262, 180, 117, 28, 144, 70, 69, 41, 68, 30, 2, 102, 262	12

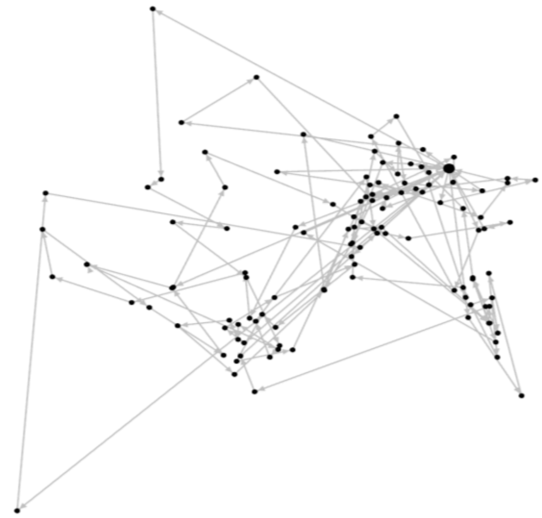


Fig. 6. Best solution graph for E60A1 instance.

VII. CONCLUSIONS

In this work, three bio-inspired metaheuristic algorithms were used to generate COVID-19 vaccine distribution routes in the State of Mexico, Mexico. For this, ten instances were determined corresponding to the age groups and the application of vaccines considering the vaccination phases proposed by the federal government. The analysis carried out includes both the quality of the solution and the required execution time, using the percentage deviation as a measure of the performance of each algorithm to determine the difference between the solutions obtained between them.

To validate the reliability of the solutions obtained, the same approach was used in each algorithm so that each solution complies with the CVRP restrictions by overcapacity penalty, initialization of feasible solutions, among others.

From the results, it is concluded that the PSO algorithm generates the best solutions that require the most computational time, immediately followed by the genetic algorithm. The elements that determined this result were the exploration and exploitation of the search space. On the one hand, the PSO algorithm emphasizes exploration. In this algorithm, particles explore the search space, adapting their positions in response to interactions with other particles, making easier the discovery of regions in the search space.

On the other hand, The GA based on the genetic crossover and mutation operators explores the search space and exploits favorable solutions, facilitating the probability of discovering superior solutions.

Something quite different happens with the ABC algorithm. This algorithm is based on employed and scout bees as local search mechanisms. The ABC algorithm places more emphasis on exploitation and neglects exploration.

In the context of CVRP, determining optimal routes involves the exploration of various combinations of client visit sequences, in the case of bio-inspired algorithms and especially the swarm behavior, offers a means to explore numerous combinations of routes approaching the optimal ones. However, in terms of computational time, the ABC algorithm is faster in all instances, due to the lower complexity in its development stages and operations; therefore, the decision maker can select the best solution with greater computational effort or a quick solution under the risk that a better solution may exist.

Future work is oriented towards the application of this type of algorithms to the transfer of other types of products, the use of other restrictions such as delivery time windows, costs of cooling systems, multiple depots, product conservation and others specific to cold supply chains.

REFERENCES

[1] World Health Organization. “Coronavirus disease (COVID-19).” World Health Organization. Accessed: Feb. 2022. [Online]. Available: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/question-and-answers-hub/q-a-detail/coronavirus-disease-covid-19

[2] World Health Organization. “Origins of the SARS-CoV-2 virus.” World Health Organization. Accessed: Mar. 2022. [Online]. Available: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/origins-of-the-virus

[3] Banxico, “Reportes sobre las economías regionales Enero - Marzo 2020,” Banxico, Mexico, Accessed: Feb. 2022. [Online]. Available: https://www.banxico.org.mx/publicaciones-y-prensa/reportes-sobre-las-economias-regionales/%7BAC9C8A70-ECC0-7B77-EE44-BE087567CB83%7D.pdf

[4] Procuraduría Federal del Consumidor. “Nueva normalidad. Cuidarte es cuidar a los tuyos.” Gobierno de México. Accessed: Mar. 2023. [Online]. Available: https://www.gob.mx/profeco/documentos/nueva-normalidad-cuidarte-es-cuidar-a-los-tuyos?state=published

[5] World Health Organization. “WHO lists 9th COVID-19 vaccine for emergency use with aim to increase access to vaccination in lower-income countries.” World Health Organization. Accessed: Feb. 2022. [Online]. Available: https://www.who.int/news/item/17-12-2021-who-lists-9th-covid-19-vaccine-for-emergency-use-with-aim-to-increase-access-to-vaccination-in-lower-income-countries

[6] World Health Organization. “Vaccines and immunization: Vaccine safety.” World Health Organization. Accessed: Mar. 2023. [Online]. Available: https://www.who.int/news-room/questions-and-answers/item/vaccines-and-immunization-vaccine-safety

[7] R. Cortés Alcalá, R. Gómez Torres and X. Alba Ricaño, “Política nacional rectora de vacunación contra el SARS-CoV-2 para la prevención de la COVID-19 en México,” Gobierno de México, Mexico, Version 4.0, Accessed: Feb. 2022. [Online]. Available: https://coronavirus.gob.mx/wp-content/uploads/2021/01/PolVx_COVID_-11Ene2021.pdf

[8] World Health Organization. “WHO Coronavirus (COVID-19) Dashboard.” World Health Organization. Accessed: Oct. 2023. [Online]. Available: https://covid19.who.int/

[9] Secretaría de Salud de México. “Análisis situacional de la epidemia en México.” Gobierno de México. Accessed: Mar. 2023. [Online]. Available: https://coronavirus.gob.mx/analisis-situacional-de-la-epidemia-en-mexico/

[10] G.D. Konstantakopoulos, S.P. Gayialis, and E.P. Kechagias, “Vehicle routing problem and related algorithms for logistics distribution: a literature review and classification,” Oper. Res., vol. 22, no. x, pp. 2033–2062, July. 2022, doi: 10.1007/s12351-020-00600-7.

[11] X. Sun, C.-C. Wu, and L.-R. Chen, “Cold Chain Logistics Distribution Optimization for Fresh Processing Factory Based on Linear Programming Model,” in IAEAC., 2018, pp. 593-597, doi: 10.1109/IAEAC.2018.8577759.

[12] B. Zhao, H. Gui, H. Li, and J. Xue, "Cold Chain Logistics Path Optimization via Improved Multi-Objective Ant Colony Algorithm," IEEE Access, vol. 8, pp. 142977-142995, 2020, doi: 10.1109/ACCESS.2020.3013951.

[13] L. Leng, J. Zhang, C. Zhang, Y. Zhao, W. Wang, and G. Li, “Decomposition-based hyperheuristic approaches for the bi-objective cold chain considering environmental effects,” Computers & Operations Res., vol. 123, no. 105043, 2020, doi: 10.1016/j.cor.2020.105043.

[14] S. Dou, G. Liu, and Y. Yang, "A New Hybrid Algorithm for Cold Chain Logistics Distribution Center Location Problem," IEEE Access, vol. 8, pp. 88769-88776, 2020, doi: 10.1109/ACCESS.2020.2990988.

[15] W. Zheng, L. Leng, S. Wang, G. Li, and Y. Zhao, “A Hyperheuristic Approach for Location-Routing Problem of Cold Chain Logistics considering Fuel Consumption,” Comput. Intell. and Neuroscience, vol. 2020, no. 8395754, Jan. 2020, doi: 10.1155/2020/8395754.

[16] W.-C. Yeh and S.-Y. Tan, “The Vehicle Routing Problem: State-of-the-Art Classification and Review,” Appl. Sci., vol. 11, no. 10295, 2021, doi: 10.3390/app112110295.

[17] J. Huang and T. Fei, “Optimization of Distribution Routes by Hybrid DNA-ACO Algorithm,” in AIAM., 2019, pp. 397-404, doi: 10.1109/AIAM48774.2019.00084.

[18] M. Fu, T. Fei, L. Zhang, and H. Li, “Research on Location Optimization of Low-Carbon Cold Chain Logistics Distribution Center by FWA-Artificial Fish Swarm Algorithm” in CISCE., 2021, pp. 529-533, doi: 10.1109/CISCE52179.2021.9446043

[19] L. Zhang, M. Fu, T. Fei, and X. Pan, “Application of FWA-Artificial Fish Swarm Algorithm in the Location of Low-Carbon Cold Chain Logistics Distribution Center in Beijing-Tianjin-Hebei Metropolitan Area,” Scientific Program., vol. 2021, no. 9945583, 2021, doi: 10.1155/2021/9945583.

[20] K. Sujaree and N. Samattapapong, “A Hybrid Chemical Based Metaheuristic Approach for a Vaccine Cold Chain Network,” Operations and Supply Chain Management: An Int. J., vol. 14, pp. 351-359, 2021, doi: 10.31387/oscm0460307.

[21] R. Torres, H. Perez, G. Perea, and I. Soria-Arguello, “A Proposal Mathematical Model for the Vaccine COVID-19 Distribution Network: A Case Study in Mexico”, Math. Problems in Eng., vol. 2021, 2021, Art. no. 5484101, doi: 10.1155/2021/5484101

[22] P. Toth and D. Vigo, THE VEHICLE ROUTING PROBLEM. PA, USA: SIAM, 2002.

[23] H. Zhang, H. Ge, J. Yang, and Y. Tong, “Review of Vehicle Routing Problems: Models, Classification and Solving Algorithms,” Archives of Comput. Methods in Eng., vol. 29, pp. 195–221, 2022, doi: 10.1007/s11831-021-09574-x.

[24] S. Katoch, S. S. Chauhan, and V. Kumar, “A review on genetic algorithm: past, present, and future,” Multimedia Tools and Appl., vol. 80, pp. 8091–8126, 2021, doi: 10.1007/s11042-020-10139-6.

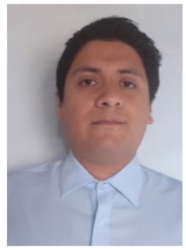
[25] K.-L. Du and M. N. S. Swamy, Search and Optimization by Metaheuristics: Techniques and Algorithms Inspired by Nature. Switzerland: Birkhäuser Cham, 2016.

[26] N. Bacanin et al., "Artificial Neural Networks Hidden Unit and Weight Connection Optimization by Quasi-Refection-Based Learning Artificial Bee Colony Algorithm," IEEE Access, vol. 9, pp. 169135-169155, 2021, doi: 10.1109/ACCESS.2021.3135201.

[27] T. M. Shami, A. A. El-Saleh, M. Alswaitti, Q. Al-Tashi, M. A. Summakieh, and S. Mirjalili, "Particle Swarm Optimization: A Comprehensive Survey," in IEEE Access, vol. 10, pp. 10031-10061, 2022, doi: 10.1109/ACCESS.2022.3142859.

[28] C. So-In, K. Rujirakul, P. Aimtongkham, and C. Punriboon, “A Bio-Inspired Capacitated Vehicle-Routing Problem Scheme

Using Artificial Bee Colony with Crossover Optimizations," J. of Internet Services and Inf. Secur., vol. 9, pp. 21-40, 2019, doi: 10.22667/JISIS.2019.08.31.021.
[29] J. Pasha et al., "Exact and metaheuristic algorithms for the vehicle routing problem with a factory-in-a-box in multi-objective settings," Adv. Eng. Inform., vol. 52, no. 101623, 2022, doi: 10.1016/j.aei.2022.101623.
[30] J. Pasha, M. A. Dulebenets, M. Kavoosi, O. F. Abioye, H. Wang, and W. Guo, "An Optimization Model and Solution Algorithms for the Vehicle Routing Problem With a "Factory-in-a-Box"," IEEE Access, vol. 8, pp. 134743-134763, 2020, doi: 10.1109/ACCESS.2020.3010176.
[31] Gobierno del Estado de México. Portal Cuidadano del Gobierno del Estado de México. Accessed: 2022. [Online]. Available: https://edomex.gob.mx/vacunacion.
[32] Google. "Google Maps." Google. Accessed: 2022. [Online]. Available: https://www.google.com.mx/maps/preview.
[33] Sistema Nacional de Información Estadística y Geográfica. Instituto Nacional de Información Estadística y Geográfica - INEGI. Accessed: 2022. [Online]. Available: https://www.inegi.org.mx/temas/estructura/
[34] Google. "Google Maps Platform." Google. Accessed: 2022. [Online]. Available: https://developers.google.com/maps
[35] H. Seidgar, M. Kiani, and H. Fazlollahtabar, "Genetic and artificial bee colony algorithms for scheduling of multi-skilled manpower in combined manpower-vehicle routing problem," Prod. Manuf. Res., vol. 4, pp. 133-151, 2016, doi: 10.1080/21693277.2016.1224986.
[36] N. Niazy, A. Elsawy, and M. Gadallah, "Solving Capacitated Vehicle Routing Problem Using Chicken Swarm Optimization with Genetic Algorithm," Int. J. Intell. Eng. and Syst., vol. 13, pp. 502-513, 2020, doi: 10.22266/ijies2020.1031.44.
[37] W.Y. Szeto, Y. Wu and S.C. Ho, "An artificial bee colony algorithm for the capacitated vehicle routing problem," Eur. J. Oper. Res., vol. 215, no. 1, pp. 126-135, 2011, doi: 10.1016/j.ejor.2011.06.006.
[38] I. Brajevic, "Artificial Bee Colony Algorithm for the Capacitated Vehicle Routing Problem," presented at the Eur. Comput. Conf., Paris., France, April 28-30, 2011, 43.
[39] Kao Y. and Chen M, "A HYBRID PSO ALGORITHM FOR THE CVRP PROBLEM," in Proc. Int. Conf. Evol. Comput. Theory Appl., 2011, pp. 539-543, doi: 10.5220/0003724005390543.
[40] T.J. Ai and V. Kachitvichyanukul, "Particle swarm optimization and two solution representations for solving the capacitated vehicle routing problem," Computers Ind. Eng., vol. 56, no. 1, pp. 380-387, 2019, doi: 10.1016/j.cie.2008.06.012.
[41] C. Pornsing, "A PARTICLE SWARM OPTIMIZATION FOR THE VEHICLE ROUTING PROBLEM," Ph.D. dissertation, Mechanical, Industrial and Systems Engineering., University of Rhode Island., Kingston., NY, USA, 2014. [Online]. https://digitalcommons.uri.edu/oa_diss/246/
[42] P. Augerat, 1995, "Augerat 1995 - Set A," VRP-REP. [Online]. Available: http://www.vrp-rep.org/datasets/item/2014-0000.html
[43] P. Augerat, 1995, "Augerat 1995 - Set B," VRP-REP. [Online]. Available: http://www.vrp-rep.org/datasets/item/2014-0001.html
[44] P. Augerat, 1995, "Augerat 1995 - Set P," VRP-REP. [Online]. Available: http://www.vrp-rep.org/datasets/item/2014-0009.html
[45] World Health Organization. "Pfizer-BioNTech COVID-19 Vaccine, COMIRNATY® (Tozinameran)." World Health Organization. Accessed: Sept. 2023. [Online]. Available: https://www.who.int/publications/m/item/comirnaty-covid-19-mrna-vaccine
[46] World Health Organization. "COVID-19 Vaccine Moderna (mRNA-1273)." World Health Organization. Accessed: Sept. 2023. [Online]. Available: https://www.who.int/publications/m/item/covid-19-vaccine-moderna-mrna-1273



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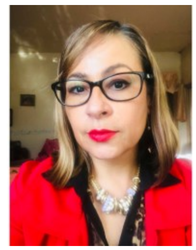

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