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Presenting a Mathematical Programming Model for Routing and Scheduling of Cross-Dock and Transportation in Green Reverse Logistics Network of COVID-19 Vaccines

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Abstract

Cross-docking is the practice of unloading COVID-19 vaccines from inbound delivery vehicles and loading them directly onto outbound vehicles. Cross-docking can streamline supply chains and help them move COVID-19 vaccines to pharmacies faster and more efficiently by eliminating or minimizing warehouse storage costs, space requirements, and inventory handling. Regarding their short shelf-life, the movement of the COVID-19 vaccine to cross-dock and their freight scheduling is of great importance. Achieving the goals of green logistics to reduce fuel consumption and the emission of pollutants has been considered in this study. Accordingly, the present study developed mixed-integer linear programming (MILP) model for routing and scheduling cross-dock and transportation in the green reverse logistics network of COVID-19 vaccines. The model was multi-product (samples of COVID-19 vaccines produced by several manufacturers) and multi-level. This model focused on minimizing the logistics network costs to increase efficiency, reduce fuel consumption and pollution, maximize the consumption value of delivered COVID-19 vaccines and minimize the risk of injection complications due to COVID-19 vaccines corruption. Considering cost minimization as well as uncertainty in pharmacies demand for COVID-19 vaccines, the model was an NP-hard problem. In this model, the problem-solving time increased exponentially according to the problem dimensions; hence, this study proposed an efficient method using the NSGA II algorithm.

Keywords:
Mathematical Modeling
Routing
Scheduling Cross-Dock
Transportation
Green Reverse Logistics Network
COVID-19 vaccines

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INTRODUCTION

An outbreak of the deadly COVID-19 virus has taken many peoples' lives (Shirouyezad et al., 2020). Impacts of COVID-19 are observed ubiquitously in each type of unit from different sectors, especially the distribution of medicine between pharmacies (Adabavazeh et al., 2020; Singh et al., 2020). Corruption risk has long been an important aspect of logistics. This issue is especially prominent when the whole world is affected by COVID-19(Choi, 2020). After several manufacturers announced COVID-19 vaccine efficacy in clinical trials for protection against severe disease, a comprehensive post-efficacy strategy for the following steps to ensure vaccination of the global population is now required. These considerations should include how to manufacture billions of doses of high-quality vaccines. It supports vaccine purchase, coordination of supply, the equitable distribution of vaccines, and the logistics of global vaccine delivery, all of which are a prelude to a massive vaccination campaign targeting people of all ages. Furthermore, additional scientific questions about the vaccines remain that should be answered to improve vaccine efficacy, including questions regarding the optimization of vaccination regimens, vaccine effectiveness, safety, and enhanced surveillance. The timely and coordinated execution of these post-efficacy tasks will bring the pandemic to an effective and efficient close. Inventory flow control is one of the crucial concepts of COVID-19 vaccine supply chain management(Kim et al., 2021). Cross-docking has been assumed as an efficient method to control inventory flow, which is essential to COVID-19 vaccine supply chain management (Kim et al., 2021; Nalepa & Blocho, 2017; Taleghani & Taleghani, 2018). At the cross-dock, COVID-19 vaccines are directly shipped from the receiving dock-doors to shipping dock-doors – where COVID-19 vaccines are stored in a dock for a short time – and are then directly delivered to the pharmacies in at most 12 hours (Ardakani & Fei, 2020; Kim et al., 2021). In other words, although the cross-docking strategy removes the inventory operations of a traditional warehouse, it allows COVID-19 vaccines to be classified and unloaded via the integration process and then loaded in vehicles (Gelareh et al., 2020; Kim et al., 2021). If not all the vehicles of the pickup navy can arrive at the cross-dock simultaneously, the integration process is postponed after collecting all COVID-19 vaccines; as a result, the waiting time and inventory level increase exponentially. Most studies on cross-docking have addressed the exponential concept, its physical design, and its location (Babazadeh, 2020; Mousavi & Vahdani, 2017)**.** Green logistics is an effort to test ways to reduce environmental pollution and a more sustainable balance between the environment, economy, and society. As a result, green logistics's goal is to focus on helping sustainability and achieving it (Roshani Delivand & Shabgoo Monsef, 2020; Tirkolaee et al., 2020; Vaez-Ghasemi et al., 2021). The amount of waste of COVID-19 vaccines and environmental pollution are significantly affected by the time spent during logistics operations and environmental conditions of transportation and warehousing(Kim et al., 2021; Roshani Delivand & Shabgoo Monsef, 2020; Yazdanpanah et al., 2019).

Therefore, this study examined vehicle scheduling at cross-dock with multiple doors and vehicle routing to minimize the system's total cost and risk of injection complication due to COVID-19 vaccines corruption. The vehicles are designed so that inbound vehicles can be used as outbound vehicles. In addition to the vehicles used for exporting COVID-19 vaccines, inbound vehicles contain the COVID-19 vaccines of certain routes and unload other COVID-19 vaccines. After leaving the cross-dock, each vehicle serves only once at the specified destinations. Then it returns to the cross-dock after the service is offered to all destinations and goes to the designated destinations by selecting the shortest route. Assuming that inbound vehicles can be used as outbound vehicles can reduce the time needed to complete all activities. The inbound vehicle does not unload certain COVID-19 vaccines to deliver them to a destination as an outbound vehicle. This issue would reduce the total cross-docking completion time. Note that the model used in this study determines whether or not the use of inbound vehicles as outbound vehicles is cost-effective concerning the path to be taken by vehicles.

The remainder of this paper is structured as follows. Section II reviews previous relevant studies to detect the study gap. Then, parameters and variables affecting routing and scheduling, cross-docking, and transportation in the green reverse logistics network of COVID-19 vaccines are extracted to develop a mathematical model. Section III addresses the research method, including the proposed mathematical modeling. Section IV deals with the proposed solution method, including the solution algorithm of the proposed mathematical model. Section V presents the procedure adopted to solve the mathematical model presented in Section III using the algorithm in Section IV. Finally, Section VI concludes the study.

RESEARCH BACKGROUND

An investigation was performed on previous studies on scheduling and routing of cross-dock and transportation and green reverse logistics network of COVID-19 vaccines To provide a literature review and cover all the above-stated subjects.

Choi (2020) examined risk analysis research in logistics systems with special relevance to COVID-19. This study proposed a research agenda, which can help inspire more innovative risk analysis research to overcome challenges in logistics during and after the COVID-19 pandemic. Singh et al. (2020) proposed a public distribution system (PDS) model. Their model was developed with three different scenarios to demonstrate disruptions in the drug supply chain. Afra & Behnamian (2021) introduced the multi-product production routing problem with startup costs and environmental considerations. they integrated reverse logistics and remanufacturing decisions and chose the Relaxation Algorithm (LR) as the solution method. Tirkolaee et al. (2020) introduced a novel robust mixed-integer linear programming model for a green vehicle routing problem with intermediate depots considering different urban traffic conditions, fuel consumption, time windows of services, and uncertain demand for perishable products. To validate and solve the suggested model, they employed the CPLEX solver of GAMS as an exact method. Zulvia et al. (2020) introduced a green vehicle routing problem (VRP) for perishable products, optimizing operational cost, deterioration cost, carbon emissions, and customer satisfaction. they solved the proposed model using a many-objective gradient evolution (MOGE) algorithm. Sharafi & Bashiri (2016) presented two developed mixed-integer programming models for the GVRP with social and safety concerns. Moreover, they developed a Genetic Algorithm (GA) to deal efficiently with the problem in large size. Dagne et al. (2020) entroduced a designing and optimizing model for perishable product in stochastic demand, which comprises multiple levels from producer, local collector, wholesaler and retailers. they considered the quality deterioration rate of the product with increased order of transportation time in network model. Avakh Darestani & Pourasadollah (2019) presented an Integer Linear Programming model to design a multi-layer reverse leading, multi-product, and multi-period integrated logistics network by considering multi-capacity level for facilities under uncertainty condition. their model included three objectives: maximizing profit, minimizing the delay of goods delivering to the customer, and minimizing returned raw material from suppliers. they applied a nondominated sorting genetic algorithm II (NSGA-II). Jansen (2019) analyzed the logistics network concerning the effects of a new warehouse. They developed efficient routing and planning methods to use a complex logistics network. He & Li (He & Li, 2019) introduced a Mixed-Integer Programming (MIP) model to minimize distance in the routing process to describe the Dynamic Schedule Problem (DSP). Rahmandoust & Soltani (2019) proposed a nonlinear multi-product Vehicle Routing Problem (VRP) with heterogeneous vehicles to find the probable minimum number of cross dockings among the available sets of discrete locations. This problem minimizes the total cost of establishing cross-docking centers and vehicle transportation costs (i.e., distribution and operation cost) as well. Küçükoğlu & Öztürk (2019) addressed the VRP and packing problem with cross-docking and proposed an MILP model. LIU & And (2019) studied the problem of location routing with the limitation of the payment time window. They also applied the fuzzy processing method to define customer satisfaction performance to reduce costs, improve customer satisfaction, and enhance efficiency by selecting cross-docking centers and arranging routes properly. Baniamerian et al. (2019) designed a Profitable Heterogeneous Vehicle Routing Problem with Cross-Docking (PHVRCD) to increase the total benefit of a cross-docking connected system. Rahbari et al. (2019) proposed a bi-objective MILP model for the problem of routing and programming vehicles with cross-docking for perishable products under the uncertainty in the travel time. Nikolopoulou et al (2019) presented a new routing problem of the public vehicle with cross-docking using an adaptive memory programming method coupled with a Tabu Search algorithm. They designed a set of pick-up and delivery routes with the minimum travel distance. Nasiri et al (2018) introduced a MILP model wherein the selection and allocation of the order were incorporated into the Vehicle Routing Problem with Cross-Docking (VRPCD) to minimize total costs, including purchasing, inventory, transportation, cross-docking, and early/tardy delivery penalty costs. Mancini (2017) introduced and formulated the hybrid VRP, which is a developed form of VRP. In their proposed model, Hiassat et al. (2017) added location decision as a strategic decision to the model developed by Lee et al. (2006). The latter discussed the warehousing and transfer of blood units from hospitals to specialized centers. This study addressed a location-inventory-routing model for perishable goods. Shuang et al. (2019) introduced a reverse logistics production routing model. The researcher assumed a reverse supply chain with remanufacturing options under various greenhouse gas emissions policies. Kuşakcı et al. (2019) studied the optimization reverse logistics network under fuzzy demand to prevent the rapid consumption of natural resources and convert generated waste into value for the economy. Yavari & Geraeli (2019) investigated the design of a green closed-loop supply chain network for degradable products under uncertain conditions using a MILP model to minimize costs and environmental pollution. Zhang et al. (2018) studied a stochastic reverse production routing model with environmental considerations. Furthermore, they incorporated the reverse supply chain model with the remanufacturing option to reduce greenhouse gas emissions. Gardas et al. (2018) examined reverse logistics in the automobile service sector to reduce exploration and production of oil using the multi-criteria decision-making method. Liao (2018) proposed the reverse logistics network design for recycling products and remanufacturing. They developed a generic Mixed-Integer Nonlinear Programming (MINLP) to maximize total profit by controlling the return of products for repair, remanufacturing, recycling, reuse, or burning/disposal. Yu & Solvang (2018) proposed a model to provide Pareto solutions between benefit and environmental performance. They investigated the effect of system flexibility on the sustainable reverse logistics system design. Rahimi & Ghezavati (2018) proposed a multi-period multi-objective MILP model to design and program the network benefit, increase social effects, and decrease environmental effect in a reverse logistics network. Trochu et al (2018) evaluated the design problem of a reverse logistics network under environmental policies to recycle wood waste in construction, renovation, and demolition industry. Khodaparasti et al. (2018) presented a modified allocation model to avoid unwanted defects in criteria. This problem was expressed as a covering model involving the facility capacity and demand elasticity.

Much research has been conducted on reverse logistics concerning specific goals and constraints. The assumptions of these studies are not similar to what occurs in real life, especially in the current global crisis, namely the COVID-19 outbreak. Moreover, the practical aspect of the subject has received less attention due to the simplification of the used models. In a green reverse logistics network of COVID-19 vaccines, delivery time plays a critical role concerning several goals, including Just-in-Time (JIT) logistics. Failure to deliver on time or delayed delivery of COVID-19 vaccines for any reason at any stage of the logistics network process may lead to injection risk. It is due to corruption and endangering human lives, as well as financial and environmental losses. The goals are considered to reduce procurement time and costs and increase popular satisfaction under conditions where COVID-19 vaccines have maximum consumption value at the time of delivery and are spoiled COVID-19 vaccines. Accordingly, it was aimed to develop, solve, and analyze a mathematical programming model to remove the problem. Including these goals in the study, the model would help the green reverse logistics network of COVID-19 vaccines achieve the highest efficiency and productivity. Scientifically and theoretically, many researchers have examined vehicle scheduling at cross-docking. However, the present study addressed a combination of routing, scheduling, cross-docking, and transportation according to the green reverse logistics network goals of COVID-19 vaccines, less studied in recent years.

RESEARCH METHOD

In the problem introduced in this research, in order and replenishment cycles, pharmacies provide logistics network decision-makers with information about the amount, type, and delivery time of COVID-19 vaccines according to demand elasticity. Then, at cross-dock, they prepare a schedule for inbound and outbound shipments based on the orders. This schedule shall minimize costs and time of routing, scheduling, cross-docking, transportation, environmental costs, and risk of COVID-19 vaccines corruption To increase the efficiency of the green reverse logistics network of COVID-19 vaccines. It should also allow for the timely delivery of COVID-19 vaccines to pharmacies such that their consumption value is maximized and endangering human lives is minimized.

According to this schedule, inbound vehicles at the cross-dock are unloaded at receiving dock doors concerning orders and defined schedules. Unloaded COVID-19 vaccines can be sent directly to shipping doors for loading operations or be stored in the cross-dock intermediate warehouse and remain there until they are consolidated with other received orders of the cross-dock. Consolidated orders are loaded onto outbound vehicles at shipping dock-doors based on the pre-specified orders and schedules. Furthermore, outbound vehicles leave cross-dock and meet pharmacies after loading all the orders based on the scheduled routing sequence. Then, they return to the central collection center after delivering the orders and collecting the returned COVID-19 vaccines from pharmacies. Accordingly, decision-makers would make the following decisions regarding inbound vehicles from manufacturers to receiving dock-doors:

- Procedures to assign inbound vehicles to receive dock-doors: Accordingly, the sequence of inbound vehicles entering each specified receiving door determines when the inbound vehicles should arrive at receiving doors and the release time for the inbound vehicles and orders.

Additionally, the decision-makers make the following decisions about shipping doors and outbound vehicles:

- Assignment of the orders to the outbound vehicles (determining consolidation of COVID-19 vaccines for each outbound vehicle);
- Assignment of outbound vehicles to shipping dock-doors: In this regard, the sequence of outbound vehicles at each specified shipping door determines the arrival time of the outbound vehicles at shipping doors and the time allocated to the outbound vehicles.
- Routing and scheduling the outbound vehicles in the delivery process and collecting COVID-19 vaccines returned by pharmacies.
- reducing emissions of greenhouse gases according to green logistics goals.

Once these decisions are made, the consumption value of COVID-19 vaccines delivered to the pharmacies is calculated according to scheduling, routing, cross-docking, and transportation in the green reverse logistics network of COVID-19 vaccines.

The development of this model relies on the following assumptions:

- Manufactured COVID-19 vaccines are transported to the cross-dock by inbound vehicles. Once delivered to the cross-dock, they are loaded onto outbound vehicles by consolidating COVID-19 vaccines following pharmacies' demands. Finally, the outbound vehicles deliver the COVID-19 vaccines according to the pharmacies' orders, collect the returned COVID-19 vaccines, and return them to the central collection center.
- Each of the shipping or receiving dock-doors is exclusively specified for a vehicle at the service time;
- The crossover time of the unloaded COVID-19 vaccines at receiving and shipping doors is highly short (almost zero), compared to loading and unloading times; therefore, no inventory holding cost is considered for the COVID-19 vaccines at this time;
- The loading time of outbound vehicles starts when all relevant orders are unloaded and received at receiving dock doors and moved to the shipping doors;
- Outbound vehicles are available at the beginning of the planning horizon, i.e., T=0
- Each outbound vehicle can be used only once during the planning horizon;
- Both the delivery routes of the ordered COVID-19 vaccines and the collection of returned COVID-19 vaccines start from the cross-dock and ends with the central collection center;
- In addition to the transfer time of vehicles, the load weight of vehicles also affects the amount of fuel consumption. It should be noted that the addition of vehicles will also add costs such as fuel consumption and environmental costs to the fixed costs of the logistics network. So in this mathematical planning model, we are looking for an optimal answer that, in addition to considering all aspects of the problem, seeks to reduce fuel consumption as a result of reducing environmental pollution to achieve green logistics goals.
- All the orders of the pharmacies are delivered by an outbound vehicle. The returned COVID-19 vaccines are received and collected from the pharmacies by the same outbound vehicle;
- The number of returned COVID-19 vaccines is smaller than that of the ordered COVID-19 vaccines; therefore, the outbound vehicle is not limited in capacity to collect the returned COVID-19 vaccines from each pharmacy receiving orders; and
- The consumption value of the COVID-19 vaccines is greater than the planning horizon.

Modeling changes in the consumption value of COVID-19 vaccines and endangering human lives over time due to COVID-19 vaccines corruption

devaluation of the COVID-19 vaccines is imperceptible because the COVID-19 vaccines are shipped under the right temperature conditions from their manufacturers. Accordingly, the consumption value of COVID-19 vaccines is maximum when unloading COVID-19 vaccines at cross-dock. However, the activity and growth of the COVID-19 vaccine perishability factors and, consequently, devaluation of the COVID-19 vaccines are accelerated due to temperature changes and cross-dock conditions at the time of unloading COVID-19 vaccines in the cross-dock. In this model, the COVID-19 vaccines consumption is modeled according to a time-dependent linear piecewise function from the delivery time of COVID-19 vaccines to the cross-dock. Finally, as COVID-19 vaccines lose their consumption value after this period, the value of this function is considered to be zero, which means no consumption value. If the vaccine is injected, it poses a risk to human life.

Research problem model

This section introduces the indices, parameters, decision variables, objective functions, and model constraints.

A) Sets and Indices

i: Set of manufacturers, $i = \{1,2,3, \dots, I\}$, indexed by i

j: Set of nodes, indexed by *j*, where *j* = 0 denotes the cross-dock, $j = \{1,2,3, \dots, n\}$ denoted pharmacies, and $j = n + 1$ denotes the central collection center.

k: Set of outbound vehicles at the cross-dock, indexed by *k*, where $k = \{0,1,2,3, \dots, K+1\}$ such that $k = 0$ and $K + 1$ are considered as dummy outbound vehicles at cross-dock.

l: Set of inbound vehicles at the cross-dock, indexed by *l*, where $l = \{0,1,2,3, \dots, L+1\}$ such that $l = 0$ and $L + 1$ are considered as dummy inbound vehicles at cross-dock.

f: Set of receiving dock-doors, $f = \{1,2,3, \dots, F\}$, indexed by *f*.

h: Set of shipping dock-doors, $h = \{1,2,3, \dots, H\}$, indexed by *h*.

p: Set of samples of COVID-19 vaccines produced by several manufacturers, $p = \{1,2,3, \dots, P\}$, indexed by *p*.

B) Parameters

TT_{il}: Travel time from manufacturer *i* to the cross-dock for inbound vehicles *l*.

x_{li}: 1 if inbound vehicle *l* carries COVID-19 vaccines to the cross-dock from manufacturer *i*, and 0 otherwise.

u_{jl}: 1 if some/all parts of order *j* are carried by inbound vehicle *l*, and 0 otherwise.

TU_{jl}: Time required to unload order *j* carried to cross-dock by inbound vehicle *l*.

Tl_{jk}: Time required to load order *j* carried to cross-dock by outbound vehicle *k*.

a_j: Minimum delivery time of order *j*.

b_j: Maximum delivery time of order *j*.

$TT_{jj'k}$: Travel time between Node *j* and node j' for outbound vehicle k $((j \neq j')\ j, j' = \{0,1,2, \dots, n = 1\})$.

FC_k: Fixed cost of using outbound vehicle *k*.

ST_{jk}: Service time for pharmacies *j* by outbound vehicle *k*.

D_{jp}: Quantity of COVID-19 vaccine type *p* packages ordered by pharmacies *j*.

CV_p: The consumption value time of COVID-19 vaccine type *p* from the delivery time to the cross-dock.

V_p: Volume of each COVID-19 vaccine type *p* packages.

PT: Planned time for routing.

α_p: Earliness cost per COVID-19 vaccine type *p* packages.

β_p: Tardiness cost per COVID-19 vaccine type *p* packages.

γ_p: Inventory holding cost of each COVID-19 vaccine type *p* packages at cross-dock.

LC_k: The additional cost of fuel consumption of the outbound vehicle *k*, per unit load weight carried by it, will lead to environmental costs due to increased emissions.

C_k: Crossover cost of outbound vehicle *k*.

Q_k: Volume capacity of outbound vehicle *k*.

W_p: Weight of each COVID-19 vaccine type *p* packages.

M: Big number.

C) Variables of inbound vehicles route from manufacturers to a cross-dock

at_{li}: Movement time towards cross-dock from manufacturer i of vehicle *l*.

rt_l: Release time of inbound vehicle *l*.

r_j: Release time of order *j*.

y_{lf}: 1 if inbound vehicle *l* is processed at the receiving dock-door f, and 0 otherwise.

$x_{lj'}$: 1 if inbound vehicles j' is processed at the same the receiving dock-door, and inbound vehicle *l* immediately precedes inbound vehicle j', and 0 otherwise $((l \neq j')\ l, j' = \{0,1,2, \dots, L+1\})$.

D) Variables of outbound vehicles from cross-dock to pharmacies and delivery process:

$z_{jj'k}$: 1 if outbound vehicle *k* travels from node *j* to node j',and 0 otherwise $((j \neq j')\ j, j' = \{0,1,2, \dots, n+1\})$

v_{jk}: 1 if outbound vehicle *k* carries order *j*, and 0 otherwise.

τ_k: 1 if outbound vehicle *k* is used, and 0 otherwise.

s_{jk}: Time at which outbound vehicle *k* leaves node *j*.

s_j: Time at which order *j* is delivered.

dt_j: Departure time of order *j*.

Y_{kh}: 1 if outbound vehicle *k* is processed at the shipping dock-door *h*, and 0 otherwise.

$X_{kj'}$: 1 if outbound vehicles k and j' are processed at the same shipping dock-door, and outbound vehicle k immediately precedes Outbound Vehicle j', and 0 otherwise ($(k \neq j')$ $k, j' = \{0,1,2,\dots,K+1\}$).
e_j: Order j earliness.
t_j: Order j tardiness.
CV_{jp}: Consumption value of COVID-19 vaccine type p ordered by pharmacy j when it is delivered to the pharmacy, ($0 \leq CV_{jp} \leq 1$). The closer CV_{jp} is to 1, risk of injection complication due to COVID-19 vaccines corruption is closer to 0.)
CVs_{jp}: Auxiliary variable for the consumption value piecewise linear function of COVID-19 vaccines, ($-\infty \leq CVs_{jp} \leq 1$)
δ_{jp}: 1 if ($CVs_{jp} \leq 0$), and 0 otherwise.
la_{jk}: The load weight of outbound vehicle k, when it arrives the node j.

E) Objective functions:

$$Minimize\ F_1 = \sum_{j=1}^{n}\sum_{p=1}^{P}\sum_{l=1}^{L}\sum_{f=1}^{F}\sum_{k=1}^{K}\sum_{h=1}^{H} y_{lf}Y_{kh}v_{jk}\,\alpha_p L + \sum_{j=1}^{n}\sum_{p=1}^{P}\sum_{l=1}^{L}\sum_{f=1}^{F}\sum_{k=1}^{K}\sum_{h=1}^{H} y_{lf}Y_{kh}v_{jk}\,\beta_p L + \sum_{j=1}^{n}\sum_{p=1}^{P}\sum_{l=1}^{L}\sum_{f=1}^{F}\sum_{k=1}^{K}\sum_{h=1}^{H} y_{lf}Y_{kh}v_{jk}\,\gamma_p D - r_j) + \sum_{j=0}^{n}\sum_{\substack{j'=1\\ j\neq j'}}^{n+1}\sum_{k=1}^{K} C_k z_{jj'k}TT_{jj'k} + \sum_{k=1}^{K} FC_k\tau_k + \sum_{j=0}^{n}\sum_{\substack{j'=1\\ j\neq j'}}^{n+1}\sum_{k=1}^{K} LC_k.\,la_{jk}.\,z_{jj'k} \quad (1)$$

$$Maximize\ F_2 = \sum_{p=1}^{P}\sum_{j=1}^{n}\sum_{k=1}^{K}\sum_{h=1}^{H} v_{jk}Y_{kh}\,CV_{jp} \quad (2)$$

The objective function (1) is to minimize costs and increase the efficiency of a logistics network. The following costs are considered here. The first and second sections of the function calculate the earliness and tardiness penalty costs of pharmacies' orders to achieve just-in-time logistics goals, respectively. The third section calculates the cost of temporary storage at cross-dock. The fourth section calculates the cost of the crossover outbound vehicle. The fifth section estimates the environmental cost of using each outbound vehicle. Finally, the sixth part is the added cost of fuel consumption and environmental pollution, related to the load weight carried by outbound vehicles, according to green logistics goals. The objective function (2) maximizes the consumption value of delivered COVID-19 vaccines and minimizes the risk of injection complications due to COVID-19 vaccines corruption.

F) Constraints:

$$x_{li}rt_l = x_{li}at_{li} + x_{li}TT_{il} + x_{li}\sum_{j=1}^{n} TU_{jl}u_{jl} \quad l = \{1,2\dots,L\};\ i = \{1,2,\dots,I\} \quad (3)$$

$$rt_{j'} \geq rt_l - M(1 - x_{lj'}) \quad l = \{1,2\dots,L\};\ j' = \{1,2\dots,L\} \quad (l \neq j') \quad (4)$$

$$r_j \geq rt_l - M(1 - u_{jl}) \quad j = \{1,2\dots,n\};\ l = \{1,2\dots,L\} \quad (5)$$

$$\sum_{f=1}^{F} y_{lf} = 1 \quad l = \{1,2\dots,L\} \quad (6)$$

$$x_{lj'} - 1 \leq y_{lf} - y_{j'f} \leq 1 - x_{lj'} \quad l, j' = \{1,2\dots,L\}\ (l \neq j');\quad f = \{1,2\dots,F\} \quad (7)$$

$$\sum_{\substack{l=0\\ l\neq j'}}^{L} x_{lj'} = 1 \quad j' = \{1,2\dots,L\} \quad (8)$$

$$\sum_{\substack{j'=1\\ l\neq j'}}^{L+1} x_{lj'} = 1 \quad l = \{1,2\dots,L\} \tag{9}$$

$$\sum_{j'=1}^{L} x_{0j'} = F \tag{10}$$

$$\sum_{l=1}^{L} x_{l,L+1} = F \tag{11}$$

$$x_{0l} + x_{0j'} + y_{lf} + y_{j'f} \leq 3 \quad l,j' = \{1,2\dots,L+1\}, (l \neq j'); \quad f = \{1,2\dots,F\} \tag{12}$$

$$s_{0k} \geq r_j + TL_{jk} - M(1 - v_{jk}) \quad j = \{1,2\dots,n\};\ k = \{1,2\dots,K\} \tag{13}$$

$$s_{0j'} \geq s_{0k} - M(1 - X_{kj'}) \quad k,j' = \{1,2\dots,K\};\ (k \neq j') \tag{14}$$

$$dt_j \geq s_{0k} - M(1 - v_{jk}) \quad j = \{1,2\dots,n\};\ k = \{1,2\dots,K\} \tag{15}$$

$$\sum_{h=1}^{H} Y_{kh} = 1 \quad k = \{1,2\dots,K\} \tag{16}$$

$$X_{kj'} - 1 \leq Y_{kh} - Y_{j'h} \leq 1 - X_{kj'} \quad k,j' = \{1,2\dots,k\}; (k \neq j') \quad h = \{1,2\dots,H\} \tag{17}$$

$$\sum_{\substack{k=0\\ k\neq j'}}^{K} X_{kj'} = 1 \quad j' = \{1,2\dots,K\} \tag{18}$$

$$\sum_{\substack{j'=1\\ k\neq j'}}^{K+1} X_{kj'} = 1 \quad k = \{1,2\dots,L\} \tag{19}$$

$$\sum_{j'=1}^{K} X_{0j'} = H \tag{20}$$

$$\sum_{k=1}^{K} X_{k,K+1} = H \tag{21}$$

$$X_{0k} + X_{0j'} + Y_{kh} + Y_{j'h} \leq 3 \quad k,j' = \{1,2\dots,K+1\} \ (k \neq j');\ h = \{1,2\dots,H\} \tag{22}$$

$$\sum_{k=1}^{K}\sum_{\substack{j=0\\ j\neq j'}}^{n} z_{jj'k} = 1 \quad j' = \{1,2\dots,n\} \tag{23}$$

$$\sum_{j'=1}^{n} z_{0j'k} = 1 \quad k = \{1,2\dots,K\} \tag{24}$$

$$\sum_{j=1}^{n} z_{j,n+1,k} = 1 \quad k = \{1,2\dots,K\} \tag{25}$$

$$\sum_{j=0}^{n} z_{jhk} - \sum_{j'=1}^{n+1} z_{hj'k} = 0 \quad h = \{1,2\dots,n\};\ k = \{1,2\dots,K\} \tag{26}$$

$$\frac{1}{M}\sum_{\substack{j=0\\ j\neq j'}}^{n} z_{jj'k} \leq v_{j'k} \leq \sum_{\substack{j=0\\ j\neq j'}}^{n} z_{jj'k} \quad j' = \{1,2\dots,n\};\ k = \{1,2\dots,K\} \tag{27}$$

$$\sum_{j=1}^{n}\sum_{p=1}^{P} v_{jk}.D_{jp}.V_p \leq Q_k \quad k = \{1,2\dots,K\} \tag{28}$$

$$s_{j'k} \geq s_{jk} + TT_{jj'k} + ST_{j'k} - M(1 - z_{jj'k}) \quad j = \{0,1,2\dots,n\}, j' = \{1,2,\dots,n+1\}, (j \neq j'); \quad k = \{1,2,\dots,K\} \tag{29}$$

$$s_j \geq s_{jk} - M(1 - v_{jk}) \quad j = \{1,2\dots,n\};\ k = \{1,2\dots,K\} \tag{30}$$

$$s_j \leq s_{jk} + M(1 - v_{jk}) \quad j = \{1,2\dots,n\};\ k = \{1,2\dots,K\} \tag{31}$$

$$s_j \leq PT \quad j = \{1,2\dots,n\} \tag{32}$$

$$t_j \geq s_j - b_j \quad j = \{1,2\dots,n\} \tag{33}$$

$$e_j \geq a_j - s_j \qquad j = \{1,2 \dots, n\} \tag{34}$$

$$CVs_{jp} CV_p \leq CV_p - (s_j - r_j) \qquad j = \{1,2 \dots, n\}; \quad p = \{1,2 \dots, P\} \quad \forall \ D_{jp} \neq 0 \tag{35}$$

$$CVs_{jp} + M\delta_{jp} \geq 0 \qquad j = \{1,2 \dots, n\}; \quad p = \{1,2 \dots, P\} \quad \forall \ D_{jp} \neq 0 \tag{36}$$

$$CV_{jp} \geq CVs_{jp} \qquad j = \{1,2 \dots, n\}; \quad p = \{1,2 \dots, P\} \quad \forall \ D_{jp} \neq 0 \tag{37}$$

$$CV_{jp} \leq CVs_{jp} + M\delta_{jp} \qquad j = \{1,2 \dots, n\}; \quad p = \{1,2 \dots, P\} \quad \forall \ D_{jp} \neq 0 \tag{38}$$

$$CV_{jp} \leq 1 - \delta_{jp} \qquad j = \{1,2 \dots, n\}; \quad p = \{1,2 \dots, P\} \quad \forall \ D_{jp} \neq 0 \tag{39}$$

$$v_{jk} \leq \tau_k \qquad j = \{1,2 \dots, n\}; \quad k = \{1,2 \dots, K\} \tag{40}$$

$$\left(la_{jk} - \sum_{p=1}^{P} D_{jp}.W_p - la_{j'k} \right).z_{jj'k} = 0 \qquad j = \{0,1,2 \dots, n\}; \quad j' = \{1,2 \dots, n+1\}; (j \neq j'); \quad k = \{1,2 \dots, K\} \tag{41}$$

$$y_{lf} \in \{0,1\} \qquad l = \{0,1,2 \dots, L+1\}; \quad f = \{1,2 \dots, F\}$$

$$x_{lj'} \in \{0,1\} \qquad l = \{0,1,2 \dots, L\}; \quad j' = \{1,2 \dots, L+1\} \quad (l \neq j')$$

$$Y_{kh} \in \{0,1\} \qquad k = \{0,1,2 \dots, K+1\}; \quad h = \{1,2 \dots, H\}$$

$$X_{kj'} \in \{0,1\} \qquad k = \{0,1,2 \dots, K\}; \quad j' = \{1,2 \dots, K+1\} \quad (k \neq j')$$

$$z_{jj'k} \in \{0,1\} \qquad j = \{0,1,2 \dots, n\}; \quad j' = \{1,2 \dots, n+1\}; (j \neq j'); \quad k = \{1,2 \dots, K\}$$

$$v_{jk} \in \{0,1\} \qquad j = \{1,2 \dots, n\}; \quad k = \{1,2 \dots, K\}$$

$$at_l, r_j, rt_l, DT_k, s_{0k}, dt_j, s_{jk}, la_{jk}, s_j, e_j, t_j \in R_+$$

$$CV_{jp} \in R_+; CVs_{jp} \in R; \quad \delta_{jp} \in \{0,1\} \qquad j = \{1,2 \dots, n\}; \quad p = \{1,2 \dots, P\}$$

Constraints (3) - (12) related to inbound vehicles at cross-docking operations are as follows:

Constraint (3) schedules the movement of inbound vehicle l from the manufacturer to cross-dock as well as unloading completion and release time. Constraint (4) ensures that if an inbound vehicle precedes another inbound vehicle, the release time of the latter should ensure that there is enough time for the former to complete its unloading. Constraint (5) calculates the release time of pharmacy's order, which is the maximum release time of the vehicles that bring some/all parts of the pharmacy's order. Constraint (6) states that each inbound vehicle is serviced at only one receiving door. Constraint (7) ensures that if an inbound vehicle precedes another inbound vehicle, they should be at the same receiving door. Constraints (8) and (9) indicate that each non-dummy inbound vehicle is exactly ahead of an inbound vehicle (it may be a dummy vehicle). Constraints (10)- (12) restrict the dummy inbound vehicles '0' and 'L+1' to be the first and the last inbound vehicles at each receiving dock-doors, respectively.

- Constraints (13) - (22) related to the outbound vehicles from the cross-dock for the delivery orders and the collection of returned COVID-19 vaccines at the central collection center are as follows:

Constraint (13) applies the dependency of an outbound vehicle on its related incoming pharmacy's orders. It connects the departure time of an outbound vehicle to the release time of its related pharmacy's orders. Constraint (14) ensures that if an outbound vehicle precedes another outbound vehicle, then the departure time of the latter should ensure that there is enough time for the former to complete its loading. Constraint (15) calculates the departure time of each pharmacy's order, which is the departure time of the vehicle that delivers the same order. Constraint (16) stipulates that each outbound vehicle can be processed at only one shipping door. Constraint (17) ensures that they should be at the same shipping door if an outbound vehicle precedes another outbound vehicle. Constraints (18) and (19) each non-dummy outbound vehicle is exactly precisely ahead of another outbound vehicle (it may be a dummy outbound vehicle). Constraints

(20)-(22) restrict the dummy outbound vehicles '0' and 'K+1' to be the first and the last outbound vehicles at each shipping dock-doors, respectively.

- Constraints (23) - (41) related to the delivery process are as follows:

Constraint (23) determines that each pharmacy's orders are delivered by only one outbound vehicle (this constraint prevents split delivery). Constraints (24) and (25) enforce each outbound vehicle to leave cross-dock and return to the central collection center. Constraint (26) ensures the continuity of the outbound vehicle route from the cross-dock. Constraint (27) determines that the pharmacy's order must be delivered by one outbound vehicles. Constraint (28) limits the load of the outbound vehicle to its capacity. Constraint (29) schedules the order delivery process. Constraints (30) and (31) compute the delivery time of the order to the pharmacy. Constraint (32) indicates that the delivery process of all orders should be carried out within the planning time horizon. Constraint (33) specifies the tardiness in the delivery of the order. Constraint (34) specifies the earliness in the delivery of the order. Constraint (35) models the Consumption value of the COVID-19 vaccine delivered to the pharmacy as a linearly decreasing function since unloading of the COVID-19 vaccine at the cross-dock COVID-19 vaccine has a maximum consumption value. Constraint (36) specifies whether a COVID-19 vaccine ordered by a pharmacy is delivered after its consumption value period. Constraints (37)-(39) model the consumption value function and ensure that the consumption value of the COVID-19 vaccines delivered after their consumption value period should be equal to zero to minimize the risk of injection complication COVID-19 vaccines corruption. Constraint (40) specifies whether a vehicle is used. Constraint (41) calculates each outbound vehicle's load weight when it arrives at each related node.

PROPOSED SOLUTION

Survival of the Fittest! This issue is the same hypothesis of evolution and inheritance, which inspired the GA formation. As a random search algorithm, its advantage is considering a population of search space points as the initial population to start and improve subsequent generations using genetic operators rather than starting the search from an earlier point. In the simplest versions of this algorithm, a limited population of fixed-length chromosomes consisting of genes is processed. The two main operators of the algorithm are crossover and mutation. The crossover operator is to visit different parts of a justified area by combining the genes of two chromosomes.

On the other hand, the mutation operator keeps the search process away from local optima by applying minor changes to a selected chromosome. The efficiency algorithm encompasses the combined use of these two operators. The present study used an advanced GA to solve the two-stage stochastic programming problem.

Non-Dominated Sorting GA II (NSGA-II)

The NSGA-II algorithm is one of the most widely used and robust existing algorithms to solve multi-objective optimization (MOO) problems, proven to solve various problems. Srinivas and Deb(1994) introduced the NSGA optimization method to solve MOO problems. Regarding this optimization method, note the following highlights:

- One solution, definitely unrivaled by no other solution, scores higher. Solutions are ranked and sorted based on the number of better solutions;
- The fitness value is assigned to the solutions following their ranks, and other solutions do not dominate them;
- The fitness sharing method is used for close solutions to optimally adjust the distribution of solutions and ensure the uniform distribution of solutions in a search space.

Due to the relatively high sensitivity and performance of the solutions provided by the NSGA algorithm to fitness sharing and other parameters, the second version of the NSGA algorithm, NSGA-II, was introduced by Kalyanmoy Deb et al. (2000). In addition to the efficiency of NSGA-II, it is considered as a model forming many MOO algorithms. Different researchers used this algorithm and its unique approach to MOO problems many times to develop newer MOO algorithms (Coca et al., 2019; Abdi et al., 2020). Undoubtedly, this algorithm is considered one of the most basic members of the collection of evolutionary MOO algorithms, which can be named the second generation of such methods. The main features of this algorithm are:

- Defining crowding distance as an alternative to methods such as fitness sharing;
- Using binary tournament selection operators; and
- Saving and archiving non-dominated solutions obtained in the previous steps of the algorithm (elitism).

In the NSGA-II algorithm, several options are selected from the solutions of each generation using the binary tournament selection method. In the binary selection method, two solutions are selected randomly from the population and compared to reach a better solution. In the NSGA-II algorithm, the solutions are selected based on their rank and crowding distance. The lower the rank of the solution is, and the longer the crowding distance is, the better the option would be. A set of individuals from the same generation are selected to participate in crossover and mutation. It is due to the iteration of the binary selection operator on the population. The crossover operation is performed on a portion of the selected set of individuals. The mutation operation is performed and leads to the generation of an offspring population. Then, this population is consolidated with the main population. Newly formed members of the population are first ranked in ascending order, and the members of the population with the same rank are also ranked in descending order in terms of crowding distance. Afterward, the population members are first sorted by rank and then by crowding distance. Some of the top members of the sorted list are selected, and the rest are discarded. The selected members form the next generation population, and the cycle introduced in this section is repeated until the stopping condition is met. Non-dominated solutions, known as MOO, are often referred to as Pareto front. None of the Pareto front solutions takes precedence over the other, and each can be considered an optimal decision, depending on the circumstances.

NSGA-II algorithm steps

Step 1: Produce the initial population as usual, based on the scale and problem constraint;

Step 2: Assess the produced population from the perspective of the defined objective functions;

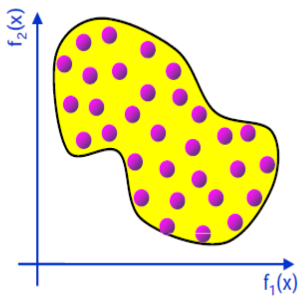


Fig.1. Second step in NSGA-II Algorithm

Step 3: Apply the non-dominated sorting method;

The population members are placed in a series of categories, as the members of the first category are a completely non-dominated set by the other members of the current population. In other words, the members of the second category are dominated only by the members of the first category. This process continues in other categories until all the members are ranked based on the category number.

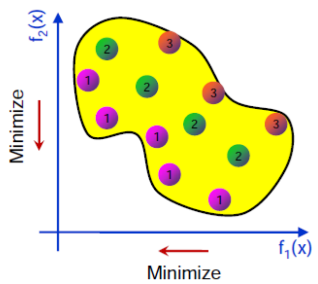


Fig2. Third step in NSGA-II Algorithm

Step 4: Calculate the control parameter' population distance';

This parameter is calculated for each group member, indicating the proximity of the sample. The larger value of this parameter results in better divergence and range in the set of population members.

$$d_j(k) = \sum_{i=1}^{n} \frac{f_i(k-1) - f_i(k+1)}{f_i^{max} - f_i^{min}} \qquad (4-1)$$

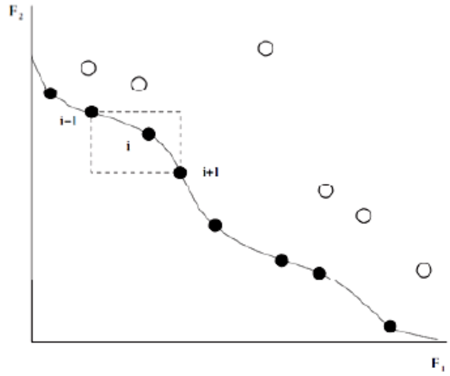


Fig. 3. Calculation of population distance (Deb et al., 2000)

Step 5: Select parent population for reproduction; and

One of the selection mechanisms is based on the binary tournament between the two randomly selected population members.

Step 6: Perform mutation and crossover operations.

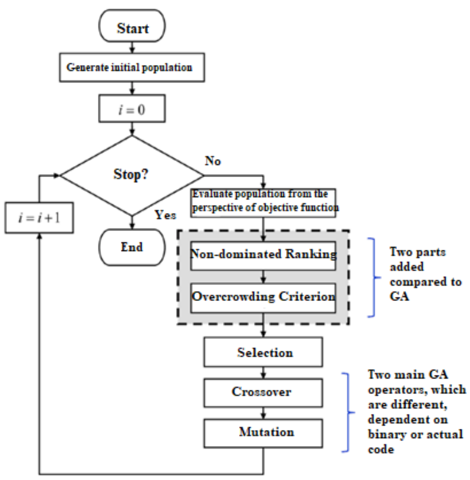


Fig. 4. NSGA-II algorithm performance (Deb et al., 2000)

To describe the proposed algorithm, six important features of this algorithm are described below.

Solution Encoding (Chromosome Structure)

The chromosome structure or the feasible solution of the third proposed model consists of two separate parts; however, the two parts are interconnected, and one affects the feasibility of the other.

A) Genes related to variables

As the title implies, this part of the chromosome is related to the first-stage variables, also known as design variables. These variables must be decided before the actual values of the uncertain parameters are determined.

B) Initial Population

A periodic strategy is used to obtain an initial feasible solution. Gene X is generated randomly from the chromosome based on resource constraints and mathematical expectations in the first step. Then, the other parts, i.e., XS, XM, and XP of the chromosome, are randomly filled. Afterward, the second chromosome is generated randomly to meet each scenario's model constraints and requirements. Note that the chromosomes are adjusted in each of the above steps if needed. Each chromosome is compared with the other chromosomes in the mating pool to prevent the production of similar chromosomes in each generation.

C) Fitness Function

In GA, fitness assessment is usually performed based on the value of the objective function of the problem. According to the relevant explanations, one of the functions in this algorithm is considered as the main objective function, and the other functions are included in the model as constraints. Accordingly, in the proposed GA, the first objective function, i.e., the total weight of the mathematical expectations and the variability of the overall system costs, is considered as a fitness function.

D) Selection Strategy

The proposed GA uses two selection strategies. In the first strategy, the best chromosome is passed directly from parents to the next generation. A mating pool is first generated for the displacement operator, and the parents are then selected from the same pool. Finally, the parents are selected for the mutation operator. It is better to select the best and the most promising parents because better parents have better offspring, on average, To perform a crossover operation. Accordingly, a normalization operation is performed on the produced mating pool. The mean and standard deviation of the objective function is calculated for each generation. Then, a chromosome with an average better than that of the generation is transferred to the mating pool for crossover or mutation operations to guarantee that the best chromosomes create the next generations.

E) Improved GA operators

The Chromosome Structure Section mentions that this structure consists of two-dimensional (2D) matrices; hence, the classical GA operators cannot implement these chromosomes. For this purpose, the classical GA operators are improved to be applied to the 2D matrices. The improved operators are divided into three categories (namely columnar, districted, and erratic), as described below:

- **Columnar Operator:** This operator is applied as columnar. First, two random numbers are generated in the corresponding row and column of the chromosome. Then, the mutation or crossover operation is applied to the selected part. For example, in Figure 5, the red and green columns of the two chromosomes A and B are chosen randomly, and the mutation operator is applied.

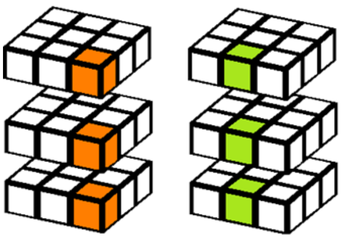


Fig. 5. Columnar displacement operator

- **Districted Operator:** This operator is applied as districted. First, a few random numbers are generated within the corresponding column and row of chromosomes. Then, the operators (mutation or displacement) are applied to the block formed by these random numbers. For example, in Figure 6, the red and green blocks are randomly selected from two chromosomes, and the displacement operator is then applied to them.

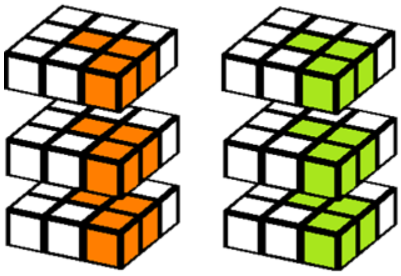


Fig. 6. Districted displacement operator

- **Erratic Operator:** This operator is applied erratically. Several valves of the chromosome are selected randomly, and the crossover or mutation operation is applied to them (Figure 7).

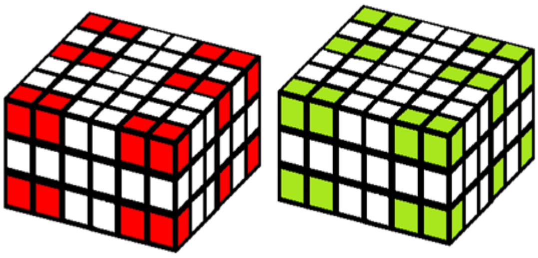


Fig. 7. Erratic displacement operator

F) Modification operations

Following the application of each operator in section A, the composition of the index will change. Sometimes it makes the capacity of the transferred product exceed the available capacity and result in an unjustified chromosome. In this case, a modification operation is required to convert this unfeasible solution to a feasible solution. In this section, a modification operation is designed to change the solution randomly to obtain a feasible chromosome. Importantly, by setting up a counter, one can set the desired chromosome to be removed if it remains unfeasible after a certain number of the subsequent iterations of the operator. Afterward, an alternative chromosome is re-generated based on the feasible solution production strategy.

Comparison criteria for evaluating solution quality

Some comparison criteria are introduced to evaluate the proposed algorithm. In general, converging to Pareto optimal solutions and providing diversity among the resulting solutions are two distinct and almost contradictory goals in multi-objective evolutionary algorithms (MOEAs). Accordingly, no single criterion to decide solely and absolutely on the performance of algorithms has not been presented yet. This research pursues two goals; therefore, at least two criteria are introduced to evaluate the algorithm's performance.

- **Mean Ideal Distance (MID):** This criterion is used to calculate the average distance of Pareto solutions from the origin of coordinates.
- **Maximum Spread or Diversity (D):** This criterion, proposed by Zitzler, measures the length of the space cube used by the end values of the targets for a set of non-dominated solutions. For example, this criterion equals the Euclidean distance between two boundary solutions in the target space in a bi-objective mode. The larger values provide better results.
- **Spacing (S):** This criterion, proposed by Schott, is the relative distance between successive solutions. The measured distance is equal to the minimum sum of the absolute values of the difference in the values of the objective functions between the *i*th solution and the solutions located in the final non-dominated set. This criterion measures the deviation of the criteria of different values. If the solutions are uniformly sided-by-side, the value of S will be small too. Therefore, the algorithm, with its final non-dominated solutions, will have slightly better spacing.
- **The number of Pareto solutions (NPS):** The NPS value indicates the number of Pareto optimal solutions observed in each algorithm.
- **CPU Time:** Algorithm execution time is one of the main indicators in determining the efficiency of any metaheuristic algorithm.

Parameter Setting

The results of metaheuristic algorithms depend on the values of their input parameters. Accordingly, we describe how to set the values of the proposed algorithm parameters. Meanwhile, stopping conditions are considered to reach 20 iterations.

Parameter setting methods and Taguchi method

The Design of Experiments is widely used in many systems as an essential tool in determining and correcting process performance. Parameter setting methods are:

- Referring to previous studies;
- Trial and error method;
- How to perform complete tests;
- Taguchi method;
- Response Surface Method (RSM);
- Fuzzy neural network; and
- Metaheuristic algorithms (before or during execution).

The Taguchi method was used in this study. Dr. Genichi Taguchi contributed to expanding the experimental design knowledge. The parameter design method presents an engineering method for the product or process design to minimize changes and sensitivity of turbulence factors. The first goal of an efficient parameter design is to identify and adjust the factors minimizing the response variables. The next goal is to identify controllable and uncontrollable factors.

Taguchi specifically addresses the concept of the loss function. A loss function combines cost, target, and diversity and achieves a measurement criterion. It further aims to set specification limits. He also expanded the concept of robustness. Taguchi defined quality as a loss transferred to the population from the moment the product is shipped. The ultimate goal of this method is to find the optimal combination of some controllable factors. Taguchi's philosophy is based on a solid and stable design. This method performs calculations using Minitab software version 16 using the DOE option and then Taguchi sub-option. The number of factors required to determine the number and combination procedure of laboratory levels should be specified (Table 1).

Table 1: Candidate factors and levels of NSGA-II algorithm

Algorithm Parameters	Low	Medium	High
nPop	15	30	**45**
P Crossover (Pc)	0.5	0.7	**0.9**
P Mutation (Pm)	0.2	0.3	**0.4**

The Taguchi L9 standard is selected as an appropriate experimental design to set the proposed parameters according to orthogonal arrays. The L9 array is a practical design with nine experiments. Table 2 shows the test designs for the proposed algorithm.

Table 2: Test designs with orthogonal array L9 for NSGA-II algorithm

Execution Order	Algorithm Parameters			Solution Values
	nPop	Pc	Pm	MID
1	1	1	1	6.9517
2	1	2	2	37.162
3	1	3	3	3.0812
4	2	1	2	9.465
5	2	2	3	5.6565
6	2	3	1	9.5747
7	3	1	3	16.3752
8	3	2	1	14.2128
9	3	3	2	7.9231

The proposed metaheuristic algorithm runs for each Taguchi test. Figure 8 shows the average Signal to Noise (S/N) ratio obtained for each level of the algorithm. Table 2 presents the optimal levels of input parameters for this algorithm.

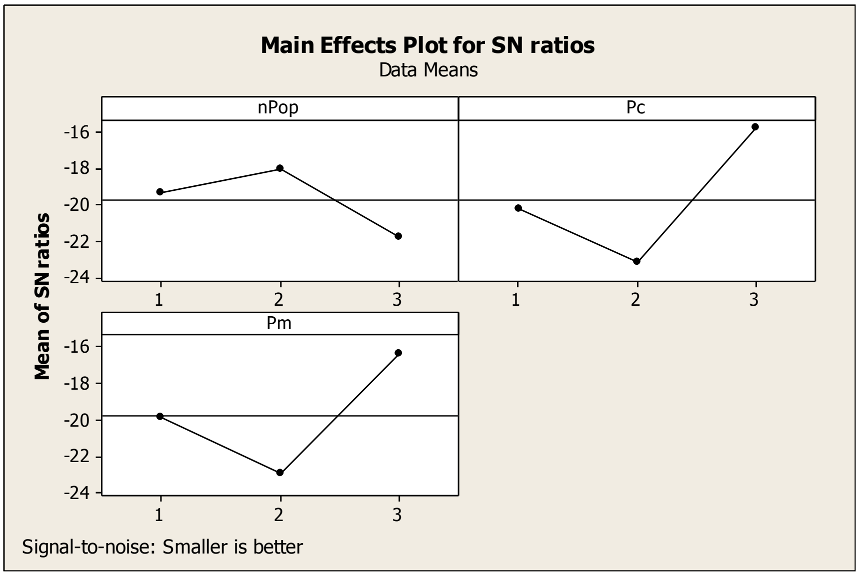


Fig. 8. S/N ratio of NSGA-II algorithm parameters

A multi-objective mathematical model is solved for routing, scheduling, cross-docking, and transportation in the green reverse logistics network of COVID-19 vaccines. The results are described in the next section.

SOLVING THE MODEL

As seen in Section III, a mathematical model was developed to solve the model optimally. The concerned mathematical model was solved by determining the inputs for a group of manufacturers, the total inbound and outbound vehicles, dock-doors (for shipping and receiving), and a set of pharmacies. Accordingly, three small, medium, and big problems were designed and implemented to solve the mathematical model of the research problem. The number of manufacturers was considered 3, 6, and 10 for the three problems above (namely small, medium, and big), respectively. Accordingly, for Index j, which is set to zero in this study at the beginning of the problem, $j = n$ represents the number of pharmacies.

Additionally, the number of outbound vehicles for small problems is initially considered 1, so k = 0 and K + 1 are considered dummy outbound vehicles at cross-docking operations. The maximum value for the number of vehicles in a large-scale solution is deemed to be 10. This process is also valid for outbound vehicles.

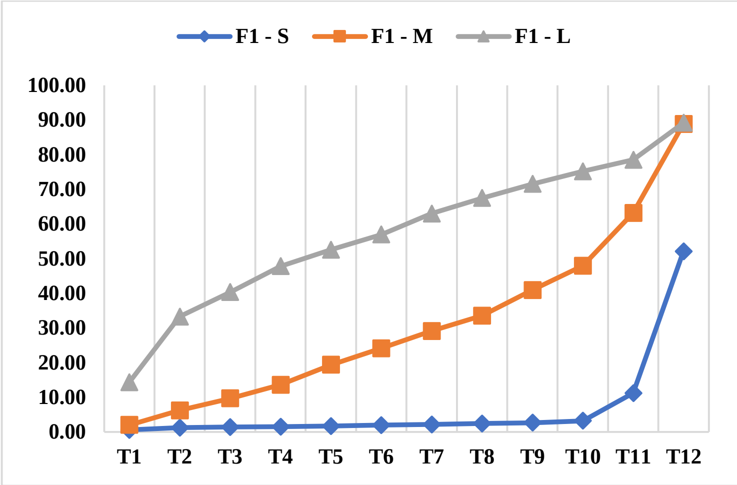
The numbers of shipping and receiving dock-doors are 3, 6, and 10 for small, medium, and big problems, respectively. Finally, the number of COVID-19 vaccine packages in solving small, medium, and big problems are 5, 10, and 15, respectively.

NSGA optimization was used in the MATLAB environment to solve this model. Accordingly, as described in Sections IV and V in detail, the parameters of the solution method were set based on the Taguchi method (Section 4.5.1). Moreover, the input values of the problem were generated as random numbers and fed to the model as inputs. After solving this problem, the output is as follows:

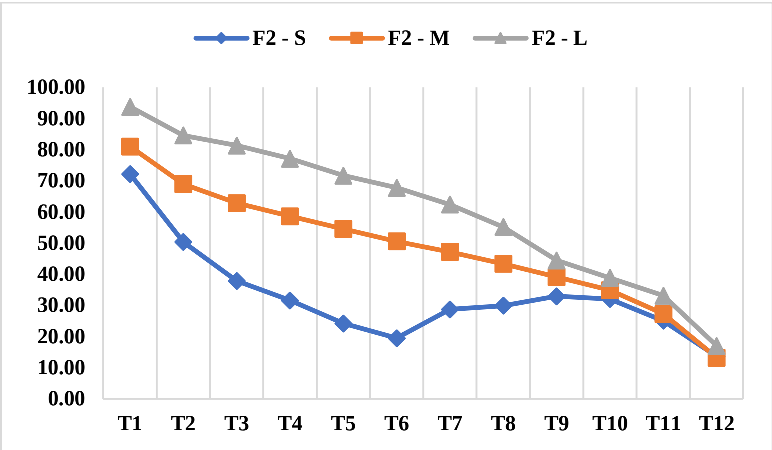
Table 3: Solution results for the objective functions of the small, medium, and big problems

Problems	First Objective			Second Objective		
	F1 – S	**F1 - M**	**F1 - L**	**F2 - S**	**F2 - M**	**F2 – L**
T1	0.59	2.03	14.34	72.18	81.02	93.76
T2	1.25	6.20	33.27	50.30	68.94	84.53
T3	1.41	9.70	40.37	37.80	62.80	81.30
T4	1.53	13.59	47.85	31.55	58.56	77.10
T5	1.70	19.39	52.57	24.14	54.54	71.62
T6	1.96	24.14	56.99	19.39	50.51	67.74
T7	2.14	29.12	63.04	28.66	47.12	62.35
T8	2.42	33.56	67.49	29.87	43.31	55.12
T9	2.65	40.97	71.55	32.88	39.07	44.38
T10	3.24	47.96	75.21	32.00	34.83	38.78
T11	11.21	63.20	78.55	25.00	27.21	33.10
T12	52.11	88.89	89.24	13.59	13.15	16.97

According to the explanations mentioned above, the data generated for the solution were considered input problems. Table 3 and figure 9 show the results of solving the objective functions for the three research problems. This table shows that the first objective function, indicating the increased logistics and efficiency network's minimized cost, is presented in 12 time periods. Table 3, T1 shows the results of the objective functions for the problems in the first period. In this course, the problem is solved in three sizes: small, medium, and big, and the results are expressed for the first objective function. The remarkable difference is caused by the costs imposed on the research problem, resulting in increased penalties for delays. This issue is because the early delivery of demands increases the cost of stopping and wasting time, holding costs, and problem failure. For the problem of tardiness and the problem tardiness cost, it also imposes pharmacy dissatisfaction costs. According to table 3 and figure 9, as the number of periods for the system operations increases (Period 6 et seq.), the costs of the medium and big problems in the green reverse logistics network system become closer. This issue implies that more COVID-19 vaccine flows in the network make the delivery time more balanced as such, the costs become closer. As observed, in periods 11 and 12, the system costs get closer to each other for any size problems. This subject presents a rise in the increasing demand and flow of COVID-19 vaccines among producers, a cross-dock, and pharmacies; thus, the system cost is optimal. The right column in Table 3 shows the values for the second objective function of the three research problems. As stated in the research model, the second objective function indicates the maximum consumption value of the delivered COVID-19 vaccines and minimizes the risk of injection complication due to COVID-19 vaccines corruption. Accordingly, this table shows the consumption value of COVID-19 vaccines to pharmacies.

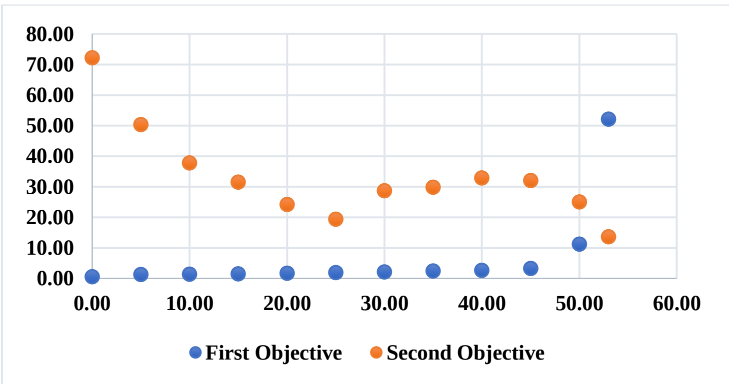


(A): Convergence of first objective function

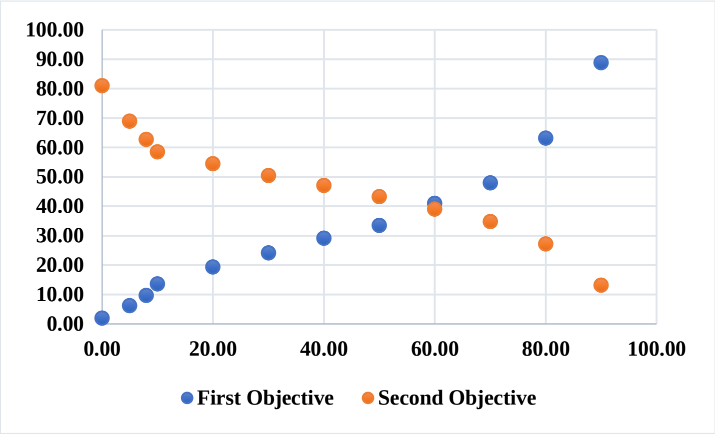


(B): Convergence of the second objective function

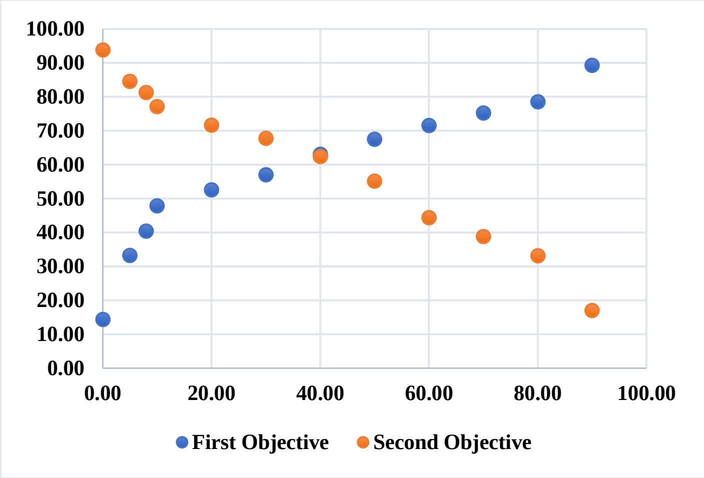
Figure 9: Convergence of the objective functions



(A): Small Pareto front



(B): Medium Pareto front



(C): Large Pareto front

Fig. 10. Non-dominated solutions in the first test problem

To analyze the algorithms, we have defined different tests with small and large complexities. Twelve tests are generated concerning benchmarks in the literature. For each test problem as given in Table 3, based on the Pareto solutions of the metaheuristics, we have considered the upper and lower bound of the solutions as well as the optimal solution, which is the average of the Pareto fronts.

To further analyze the performance of the algorithms statistically, the interval plots for each assessment metric are provided. In this regard, we first normalize the data and then depict the data to show the robustness of the algorithms. In these plots, as shown in Figures 10 (A) to (C), the lower value brings the better accuracy and robustness of the algorithms.

CONCLUSION

An outbreak of deadly COVID-19 has taken the lives of many peoples. Various manufacturing companies are looking to produce the COVID-19 vaccines after it is discovered. Making these vaccines available to the public is one of the most important challenges today. Deciding on transportation and vehicle routing is one of the main decisions in the category of short-term decisions in logistics management and supply chain for COVID-19 vaccines. Transportation is one of the most critical components affecting the total cost of the final COVID-19 vaccine produced, as well as one of the integral components of any society and one of the key sectors of any country's economy. The vehicle routing problem is one of the most challenging problems in COVID-19 vaccines supply chain management. It is a type of combinatorial optimization problem and integer programming, one of the practical concepts of operational research. Much research has been conducted on the types of vehicle routing problems and how to solve them. The present study looked at routing, scheduling, cross-docking, and transportation in the green reverse logistics network of COVID-19 vaccines. It minimizes costs and time, maximizes the consumption value of delivered COVID-19 vaccines, and minimizes the risk of injection complication due to COVID-19 vaccines corruption during logistics operations by manufacturers. Ignoring these goals would lead to an increase in the time and cost of logistics operations, an increase in the environmental costs, and a reduction in the consumption value of delivered COVID-19 vaccines, consequently maximizing the risk of injection complication due to COVID-19 vaccines corruption and getting away from green logistics goals. Then, an efficient method was demonstrated using the NSGA II algorithm. The algorithm provides a series of convergent solutions to solve three small, medium, and big problems for two objective functions of the mathematical model: minimizing costs and maximizing the consumption value of delivered COVID-19 vaccines. The present study assumed that there was no uncertainty in the input parameters of the problem. Accordingly, future researchers can investigate the effect of uncertainty in input parameters on design and problem-solving. The proposed model and the results of this study can be used in all the reverse logistics networks, especially the COVID-19 vaccines logistics in the current global crisis, namely the COVID-19 outbreak. Moreover, the mathematical model can be generalized to the supply chains of most manufacturing companies.

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