Multi-objective mathematical model of location-routing for the distribution of the Last Mile Delivery of post parcels with Co2 emissions consideration

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KEYWORDS
Location;
Routing;
Last Mile Delivery;
Co2 Emissions;
Multi-Objective Metaheuristic Algorithms

Abstract. In this article, a bi-objective location-routing mathematical model has been developed for the distribution of the Last Mile Delivery post parcels. The objectives of the model include minimization cost and tardiness penalty entered into the system due to the waiting of customers. In order to solving the purposed mathematical model, a multi-objective Whale Optimization Algorithm (WOA) based on the Pareto archive and a Non-Dominated Sorting Genetic Algorithm (NSGA-II) have been used. The mathematical model solved for a sample problem by each of the algorithms, and the results have been compared according to the multi-objective evaluation criteria such as Quality Metric (QM), Diversity Metric (DM), Spacing Metric (SM), Number of Solutions (NOS), Mean Ideal Distance (MID), and computational time. The reviews of results indicate that the proposed multi-objective WOA has a higher capability in achieving accurate, diverse, and high-quality solutions rather than NSGA-II. In other words, the proposed multi-objective WOA act more efficiently to explore the feasible solution area of the problem by spending more computational time to achieve optimal solutions.

1. Introduction

Nowadays, an increase in the development of urbanization has led to a growing complexity between industries, especially support service industries, and transportation systems for both people and goods. Moreover, urbanization has increased the demand resulting in the growth of distribution companies in the transportation industry. In this regard, distributors are looking for ways through which they can boost their profit although they face problems, such as traffic congestion, air pollution, long distances on people's daily travel routes, high fuel expenses, and vehicle depreciation..

In recent years, the products distribution in the retail industry has been altering rapidly due to customers' buying behaviors changes[١]. Delivery of post parcels to consumers has grown by more than

25% per year over the past 10 years [٢]. Delivery of packages and goods requires an efficient physical distribution structure [١]. The competition between package delivery services has been fierce, and success in this area has led relevant organizations to seek cost-effective and more sustainable solutions for the Last Mile delivery system in different cities [٣].

However, an increase in the distribution of packages has led to the growth of e-commerce, and consequently problems, such as traffic congestion or greenhouse gas emissions. As a result, companies must look for solutions to deliver packages that can reduce both expenses and gas emissions. So far, many researchers have studied the issue of delivery of post parcels to minimize costs (Zhou et al., 2016; [٤]; [٥]), whereas, minimizing pollutant emissions or customer waiting time have been left untouched.

Last-mile delivery has come out as a crucial operation in the dynamic and developing e-commerce era. These days, the economic crisis, which has led to an increase in fuel and other operating costs, has made last-mile delivery expensive. To dealing with this situation, optimizing vehicle delivery routing considering time windows to minimize the overall cost should be done in the e-commerce industry [٦]. Although there is many research in the field of optimization last-mile delivery, very few of them have considered customer's predicted time windows.

Therefore, given the importance of delivery of post parcels in recent years, as well as improving customer satisfaction and reducing emissions, this article aims to present a mathematical model for locating parcel pickup points, allocating them to demand points or centroids, and determining supply routes for the transportation of postal parcels to minimize costs, emissions of pollutants, and improving customer satisfaction when receiving their packages.

2. Literature review

No one can ignore the importance of an integrated supply chain and logistic fields. Many studies have focused on location, routing, and distribution in supply chain planning. Subramanian et al. (2010)[٧] solved the vehicle routing problem with Simultaneous Pickup and Deliveries (VRPSPD) using a parallel algorithm based on the sequential heuristic. Tlili et al. (2014)[٨] investigated vehicle routing problem with distance constraints and developed a mathematical model in which the capacity of vehicles is limited and also each vehicle can travel a predetermined distance. Sitek and Wikarek (2015)[٩] investigated the issue of multi-level capacitated vehicle routing, which includes depots and customers. They proposed a mathematical model for the problem and then solved it using a combined method.

Nagy et al. (2013)[10] introduced vehicle routing problem with mixed deliveries and pickups in which many customers want to send their goods to each other. In a general case, it is assumed that each customer sends a different product to another, which corresponds to sending the flow between customers. A network of hubs includes routing costs deployed (internal hub routes are assumed to be direct while client-to-hub routes have several stops).

Adulyasak et al. (2015)[11] presented an in-depth review of the product routing problem and investigated the relationship between production routing problem (PRP) and the two issues of lot-sizing with direct shipping and inventory routing. The findings indicated that most researchers have proposed innovative and meta-heuristic methods for this problem, while the use of precise algorithms, as well as robust optimization for this problem, has been ignored. Adulyasak et al. (2014)[12] designed a mathematical model of production routing and the solution. They provided a complicated combinatorial mathematical model for the supply chain production routing problem, which is a combination of the multi-level lot-sizing problem and the vehicle routing problem. Furthermore, they presented an innovative algorithm to solve their model for several numerical instances of the problem using the proposed model. Shiripour et al. (2016)[13] investigated the location-allocation-routing problem in a multilevel supply chain network under population-dependent travel times. They proposed a mixed-integer non-linear mathematical model for the problem in which the nodes are assumed to be capacitated. They also used a genetic algorithm and CPLEX software to solve the model.

With the advent of the Internet and new technologies in recent years, the concept of electric supply chain has emerged, which can be well observed in modern methods of distribution of goods. One of the concepts and approaches of modern distribution in the electronic supply chain is last-mile delivery, which is one of the most expensive stages of the entire supply chain of electronic supply chain. Due to its high operational cost, many researchers sought to provide models to optimize this stage of the supply chain. For instance, Gevaers et al. (2014) [14] tried to displayed last-mile delivery costs by providing a simulation tool that could significantly reduce the costs. Moreover, Boyer et al. (2009) [2] investigated factors affecting the cost of last-mile delivery, including customer density and delivery window length. The obtained results indicated delivery window length and customer density had a significant effect on route efficiency. In particular, greater density of customers in a given sales area and longer delivery windows causes facilitating greater performance. Wang et al. (2014)[15] conducted a quantitative study of the competitiveness of three delivery modes of attended home delivery, reception box, and collection-and-delivery points by analyzing the delivery cost structure and operational efficiency in different scenarios to identify the most appropriate mode. Hayel et al. (2016) [16] proposed a realistic queuing model to describe the Last Mile delivery system with HD and CP options. In their study, a game theory approach was designed to determine the optimal solution for the consumer considering the monetary and congestion effects of the two options.

Sawik (2024)[17] investigated multi-criteria optimization models and a practical example related to the integration of automated intelligent locking systems, capillary distribution networks, aggregation, last-mile delivery and supply chain management. The purpose of this article is to study logistics and transportation challenges with the aim of increasing efficiency, reducing costs and improving customer satisfaction.

Van Duin et al (2016) [3] examined the improvement of efficiency in home delivery using the principles of address intelligence for business-to-consumer (B2C) delivery. Their research indicated how intelligence can be used to predict future delivery results. They used the linear regression method for postal offices to identify and predict the delivery addresses. Zhou et al. (2016) [18] investigated the issue of location-routing for the distribution of goods to customers of online stores by considering the assumption of simultaneous home delivery and customer pickup. They have modeled a three-tier network including depots, pickup points, and customers, in which the locating pickup points and the vehicle routing is considered. The mathematical model presented was a single-purpose one which aimed to minimize the cost of location and transportation. They also used genetic and local search algorithms to solve the model.

Reyes et al. (2018) investigated the meal delivery routing problem. To solve the problems related to the food ordering and delivery system, they proposed dynamic delivery operations using an innovative algorithm to optimize the food delivery system. Amchang and Song (2018) [19] designed a distribution network for faster online retail delivery. Their purpose was to partition the Last Mile delivery network into zones and locate the Last Mile delivery centers (LMDCs) in Bangkok, Thailand. They provided a two-phase algorithm for zoning that could efficiently act as a Last Mile delivery network using network partitioning and facility location. The obtained results indicated that this approach could improve package delivery service and reduce overall delivery time.

Rohmer et al (2019) [4] addressed the problem of location-routing by considering time windows in the delivery system of the last mile delivery of fresh products. The product can be delivered directly to the customer's location or indirectly to a customer pickup point where they are stored until customer pickup takes place. The purpose was to minimize the total cost of transportation and storage. This research was done by formulating a mixed-integer linear program and solving it using a mixed-integer linear program.

Roosta et al. (2023) [20] studied the green capacitated location-routing problem (G-CLRP) under uncertainty of demand and the failure possibility in warehouses and routes. They purposed a robust two-objective mixed-integer linear programming (MILP) model for mentioned problem. Their research was aimed to set up the depots and choose the paths that offer the highest reliability (Maximizing network service) while imposing the lowest cost and environmental pollution. A Non-Dominated Sorting Genetic Algorithm (NSGA-II) was applied to solve the large-sized instances of the purposed model, doing a numerical analysis and a sensitivity analysis.

Rahmanifar et al. (2023) [21] proposed a two-level waste management system (WMS) aiming to minimize operational costs and environmental impact in the concept of the industry 4.0. They developed two models which both use modern traceability Internet of Thing-based devices to compare real-time information of waste level in bins and separation centers with the threshold waste level (TWL) parameter. The goal of first model is operational cost and CO_2 emission optimization which are led by waste collection from bins to the separation center with considering the time windows. Their second model was designed for capacitated vehicle routing problem as a to minimize the waste transportation cost to recycling centers. Additionally, new meta-heuristic algorithms and several novel heuristics based on the problem's specifications were engaged to solve the models and reach out optimized solutions. The results depicted that using IOT services embedded in bins has significant advantages for monitoring the waste level in bins continuously which make the system able to avoid visiting empty or overloaded bins.

Du, Jianhui et al. (2022) [22] investigated a multi-objective two-level joint delivery location routing problem considering carbon emission in online shopping. They purposed joint delivery (JD) model aiming operation costs and carbon emission minimizing via strengthening horizontal cooperation and resource sharing among express companies. They developed a multi-objective mathematical model for a multi-depot two-echelon joint delivery location routing problem (MD-2E-JDLRP) mathematic model and used a hybrid heuristic algorithm to solve mentioned model. Apart from that several benchmarks and a case study was tested to prove algorithm performance. The obtained results showed the JD model can effectively reduce costs and carbon emissions while ensuring higher customer satisfaction.

Rahmani Mokarrari et al. (2022) [23] proposed a stochastic-fuzzy multi-objective model for the last-mile delivery problem using drones and ground vehicles with objective to minimize the negative environmental effects and the total costs. They employed an exact method named AUGMECON2 to solve the proposed model, the model indicates locations and capacities of facilities where vehicles start their one-to-one trips to meet the customer demands. According to the findings, it was shown that increasing the reliability and decreasing the environmental impacts lead to the system's total cost increases. Moreover, when both drones and ground vehicles are considered for meeting the customer demands, the delivery system functions better regarding costs, environmental impacts, and reliability than when only one mode of delivery is considered.

Modiri et al. (2022)[24] proposed a multi-objective mixed integer mathematical programming model for designing a relief items distribution network in sustainable disaster relief logistics. The first objective function aimed to minimize the total network costs including the transportation, inventory, fixed costs of facilities and social costs. The second objective function intended to minimize the amount of environmental pollution (CO_2 emission) generated by the network. They concluded that by using the proposed model, decision-makers and managers would be able to make strategic and tactical decisions with the least cost and time, and in relief planning can enhance the structure of distribution networks and inventory and reduce clients' dissatisfaction.

Bosona (2020) [25] reviews the literature on the Last Mile delivery system, emphasizing the challenges and opportunities of this system in order to create sustainable development. The main purpose of this study was to identify the major challenges of urban transportation in the Last mile logistics and its opportunities. Boysen et al. (2021) [26] examined the concepts and theoretical foundations of Last Mile delivery from an operational perspective.

Zheng et al. (2020) [27] analyzed the optimal location of delivery points using Analytic Hierarchy Process (AHP) and Network Huff Model in Guangzhou, China. A hybrid GIS-based model was used in the study which was combined with AHP and Huff model of multi-criteria analysis of the hierarchical analytical process. In this model, the number of visiting customers to take the service as well as the delivery points were taken into account. Song and Han (2020) [28] designed a parcel delivery system for point-to-point delivery with IoT technology. They designed a new point-to-point delivery system using IoT technology and an IoT platform based on ThingPlug and LoRa technology for faster delivery and lower delivery costs. They designed an IoT device that can be part of or attached to packages that has various capabilities, including the ability to understand current delivery routes using location systems.

Ma et al. (2021)[29] developed a bi-level multi-objective location-routing model for municipal waste management considering government interests and the sanitation companies to minimize the logistics cost and environmental harms. The experimental results indicated that the improved operator had strong competitiveness and a better performance than previous methods, with the improved algorithm achieving the best average gaps of 0.18% and 0.24% and improving the best-known solutions in some instances.

In their research, Tan et al. (2019)[30] investigated the capacitated pollution-routing problem with pickup and delivery (CPRPPD) to find an optimal route to minimize operational and environmental costs, as well as a set of optimal speeds over each arc, while respecting capacity constraints of vehicles and pickup sites. To verify the proposed CPRPPD model and algorithm, a real-world instance was conducted. Comparing with the scenario including HD service only, the scenario including both HD and PS option was more economical, which indicated that the CPRPPD model was more efficient.

Table 1 is a brief summary of previous studies conducted in the field. As can be seen, recent studies have focused on last mile delivery and pickup points. These include the research of Bosona (2020) [25] and Boysen et al. (2021) [26], who have reviewed the literature. Some researchers, such as Song and Han (2020) [28] and Zheng et al. (2020) [32], have used IOT and GIS techniques to analyze the problem.

Since in this paper, we present a mathematical model for locating pickup points in last mile delivery system, we have paid close attention to articles with a mathematical optimization model. In this regard, some have presented a mathematical model for locating pickup points in the last mile delivery system [5]. In addition to locating pickup points, some have also considered routing vehicles and goods (e.g. Zhou et al., 2016; [4]). However, as **Table 1** shows, the mathematical models presented by Rohmer et al. (2019) [4] and Zhou et al. (2016) [18] did not take into account factors, such as pollutant reduction, dispersion principle, and coverage radius, and the optimization model is a single-purpose one.

Therefore, the present research aims to fill this gap by making the following contributions to the field:

- Considering reducing emissions of hazardous pollutants or green routing
- Considering the dispersion principle to observe the dispersion of pickup points in the investigated areas of the current study
- Considering the coverage radius
- Presenting a two-objective mathematical model with the purpose of minimizing customer waiting time (maximizing customer satisfaction) and minimizing the cost of location-allocation, routing and hazardous pollutant emission of vehicles.

3. Methodology

This paper aims to present a bi-objective location-allocation-routing model and to determine delivery points in a distribution system. Since the positioning-routing problem is an NP-HARD problem [9] in this paper, whale optimization algorithm (WOA) and NSGA-II are used to solve the model.

3.1. Mathematical model

The issue under consideration in this article is the location of pickup points for sending postal parcels to customers. The central post office sends postal parcels to the pick-up points by using a fleet of vehicles, and customers can receive their parcels from these points at the mentioned time. This problem includes a set of candidate (potential) locations for pickup points and a set of demand points. Therefore, the model seeks to locate pickup points from among those candidates, and assign pickup points to demand so that demands are met. Of note, the located pickup points can only be assigned to demand points that are within their coverage radius. Moreover, this model considers vehicle routing and a vehicle picks up the goods from the central post office and delivers them to the pick-up points. A vehicle may travel to several pickup points. Vehicle fuel and emissions are also included in the cost of pollution in this model. Another issue that is included in this model is dispersion principle, which ensures that the pickup points are scattered in the investigated area.

For the problem described, a bi-objective mathematical model aiming to minimize costs (location, vehicle use, and emissions) and the imposed costs to the system caused by late delivery to the customers.

In the following section, the components of the mathematical model, including sets, indices, parameters, variables, and model structure (objective functions and model constraints) are described.

Model sets and indices are as follows:

I: set of pickup points (i and j: indexes of pickup points)
C: set of demand points (c: index of demand points)
V: set of vehicles (v: index of vehicles)
0: index of company or depot

Also, according to **Table 2** the variables of the mentioned model include three binary variables and three numerical variables with positive values as follows:

Binary variables

X_{ij}^{v} =Equal to 1 if vehicle v travels from location i to j; otherwise is equal to 0.

Z_{ic} =Equal to 1 if demand point c allocates to pick up point i; otherwise is equal to 0.

W_i =Equal to 1 if pickup point i is allocated to at least one of the demand points; otherwise is equal to 0.

Numerical variables: Arrival time of the vehicle at the location of each node ia_i

Yl_c: Maximum customer waiting time of customers from demand point c for picking from the allocated pickup point (starts counting from the announced time)

Y_{ij}^{v} : The amount of commodity that is transported by vehicle *v* from location *i* to location *j*.

Based on the defined notations and problem description, the multi-objective mathematical model is designed as follows:

(1)

Equation 1

$$\min z1=\sum_{j}\sum_{v} fv_v X_j^v + \sum_{i\in IU0}\sum_{j\in I}\sum_{v\in V} tc_{ij} X_{ij}^{v} + \sum_{i\in I} fc_i W_i + \sum_{i\in I}\sum_{c\in C} t_{ic} Z_{ic} + \sum_{i\in IU0}\sum_{j\in I}\sum_{v\in V} dl_{ij} X_{ij}^{v} v_f \,(pf + pc + wc + Y_{ij}^{v})$$

First Objective Function: Minimization of vehicle usage costs and fuel costs is calculated based on carbon emissions and location costs. Therefore, minimizing fossil fuel costs means minimizing carbon emissions.

(2)

Equation 2

$$\min z2 = \sum_{c \in C} pl_c Y l_c$$

Second Objective Function: Minimizing customer wait time

Then constraints have been defined as below;

Subject to:

(3)

Equation 3

$$\sum_{i \in I} z_{ic} = 1$$

$$\forall c \in C$$

Allocating each demand point to exactly one pickup point.

(4)

Equation 4

$$Z_{ic} \le R_{ic}, W_i$$

$$i \in I, c \in C$$

Allocating each demand point to only one of the pickup points, if this pickup point is established and also the demand point is under the coverage radius of this pickup point.

(5)

Equation 5

$$\sum_{c \in C} d_c, Z_{ic} \le cap_i$$

$$\forall i \in I$$

Capacity constraint of pickup points based on the demand of demand points.

(6)

Equation 6

$$\sum_{i \in IU} X_{ij}^{v} \leq 1$$

$$\forall v \in V , j \in I$$

(7)

Equation 7

$$\sum_{j \in I} X_{ij}^{v} \leq 1$$

$$\forall v \in V , i \in IU\,0$$

Each vehicle shouldn’t visit each node more than once.

(8)

Equation 8

$$\sum_{k \in IU\,0} X_{ik}^{v} = \sum_{l \in IU\,0} X_{li}^{v}$$

$$\forall i \in I , v \in V$$

Conjunction constraint of routing paths.

(9)

Equation 9

$$X_{ij}^{v} \leq W_{j}$$

$$\forall i \in IU\,0, j \in I$$

Constraint (9) ensures that vehicles travel only to places where a pickup center is located.

(10)

Equation 10

$$Y_{ij}^{v} \leq q_{v} , X_{ij}^{v}$$

$$\forall i \in IU\,0, j \in I, v \in V$$

Vehicle capacity constraint.

(11)

Equation 11

$$\sum_{l \in I} Y_{li}^{v} \geq \sum_{k \in I} Y_{ik}^{v}$$

$$\forall i \in I, v \in V$$

Constraint of avoiding the sub tour.

(12)

Equation 12

$$\sum_{v \in V} \left(\sum_{l \in I} Y_{li}^{v} - \sum_{k \in I} Y_{ik}^{v} \right) = \sum_{c \in C} d_c, Z_{ic}$$

$$\forall i \in I$$

Constraint of inventory balance.

(13)

Equation 13

$$\sum_{j=1, j \neq 0}^{I} X_{0,j}^{v} \geq 1$$

Constraint (13) indicates that vehicles may travel from the central post office to one or more pickup points :(14) (15) (16)

Equation 14

$$a_0 = 0$$

Equation 15

$$a_j \geq a_i + (t_{ij} + p_i)X_{ij}^{v} - M\,(1 - X_{ij}^{v})\forall i \in IU\,0, j \in I, v \in V$$

Equation 16

$$a_j \leq a_i + (t_{ij} + p_i)X_{ij}^{v} + M\,(1 - X_{ij}^{v})\forall i \in IU\,0, j \in I, v \in V$$

Constraints (14), (15), and (16) calculate the time it takes for the vehicle to reach the pickup point.

(17)

Equation 17

$$Yl_c = \max\left\{0, \sum_{j \in I} a_j Z_{jc} - l_c\right\}$$

$$\forall c \in C$$

Constraint 17 calculates the (maximum) customer wait time for picking:(18)

Equation 18

$$\sum_{i=1}^{I} \min\left(dl_i\right) \geq DL$$

$$\forall i \in I$$

Constraint (18) is related to the dispersion principle and ensures that the minimum distance between centers is observed.

4. Solution method

One of the largest finned whales is the humpback whale. An adult humpback whale is about the size of a school bus. Their favorite prey is krill and small groups of fish. The most interesting thing about humpback whales is their special hunting method. This exploratory behavior is known as net bubble feeding. Humpback whales prefer to hunt groups of krill or small fish near the surface of the water. It has been observed that this exploration and hunting is done by creating indicator bubbles along a circle or paths.

The WOA algorithm is one of the optimization algorithms inspired by nature that can be used in various fields.

In order to solve the purposed model, we have employed multi-objective whale optimization algorithm (WOA) which is based on the Pareto archive. The algorithm begins with a set of random solutions. Humpback whales can detect prey and surround them. Since the location of the optimal design in the search space is not known by analogy, the WOA algorithm assumes that the current best candidate solution is hunting the target or is close to the optimal state. After the best search agent is identified, other search agents try to update their location relative to the best search agent.

In this study, the algorithm is designed based on the Pareto archive which is updated at the end of each iteration of the algorithm. What is more, in each iteration of the algorithm, an improvement procedure is employed. The flowchart of the proposed WOA algorithm is shown in Fig. 1.

4.1. Solution representation

In this paper, the solution representation method consists of 4 matrices corresponding to the variables of the model, where two three-dimensional matrices are considered to display the variables X_{ij}^{v} and Y_{ij}^{v} . the values of the matrix related to the variable X_{ij}^{v} is equal to 0 or 1 according to the definition of the variable, the values of the houses of the matrix related to the variable Y_{ij}^{v} are numerical values according to the definition of the said variable; A two-dimensional matrix is defined to represent the Z_{ic} variable with the values of 0 and 1, as well as a one-dimensional matrix to represent the W_i variable with the values of 0 and 1.

4.2. Generating initial solutions initialization

In this research, a parallel neighborhood search method is used to generate initial solutions.

A) Parallel neighborhood search

The parallel neighborhood search method designed in this paper consists of three neighborhood search operators that operate in parallel (simultaneous). The way the parallel neighborhood search method works is that first a feasible solution is randomly generated and then this generated solution is given as an input to the parallel neighborhood search method. finally, if the output solution of the parallel neighborhood search method isn't repeated, is added to the set of generated solutions.

The first neighborhood search operator: two indexes i and j in the uniform interval [1..I] (I number of delivery and pick-up points) are randomly generated and the values of elements i and j in the variable W_i are exchanged with each other.

The second neighborhood search operator: two indices c1 and c2 are randomly generated in the uniform interval [1..C] (C is the number of demand points) and the values of the columns c1 and c2 in the Z_{ic} variable are exchanged.

The third neighborhood search operator: two indices i and j in the uniform interval [1..I] (I number of delivery and pick-up points) are randomly generated and if a trip has been made between these two points using vehicle v, The trip is assigned to another vehicle.

It should be noted that after applying each of the explained operators, the values of the model variables are checked based on the model's constraints and the new and feasible values are determined based on the changes made.

The parallel neighborhood search method is executed 2N times and generates 2N non-repeated feasible solutions. Afterwards, in order to select N solutions as initial solution population, the whole 2N obtained solutions of two methods are considered as a set and get ranked using c_s criteria (Eq.19). In the following equation, solution ranks and crowding distances are calculated based on Deb (2002). Then c_s criteria is calculated for each solution. Finally, N solutions that have less c_s criteria are selected.

(19)

Equation 19

$$C_s = \frac{RANK}{CROWDING\ DISTANCE}$$

As it can be seen in Eq.19, both solution ranks (quality) and crowded distances (diversity) are considered for choosing the population. Therefore solutions with highest quality and diversity will go for executing the algorithm, because the lower the value of c_s for a solution means the higher the quality and diversity of that solution.

4.3. Improvement method

We purpose a procedure to improve previous step's selected solutions in WOA. Then improved solutions are selected as the next generation's population.

The proposed improvement procedure is based on the variable neighborhood search (VNS). VNS uses three neighborhood search structures. The used neighborhood search structures are explained in the previous section.

These structures are applied in the form of VNS which is as follows:

The pseudo-code of our VNS is as follows:

```
{For each input solution
K=1
While stopping criterion is meet do
        New solution=Apply NSS type k

        If new solution is better  then
           K=1
        Else
           K=k+1
           If k=4 then
              K=1
           Endif
        Endif
Endwhile
}
```

Each solution of the population enters the VNS algorithm, and an improved solution is obtained as an output. Then, the correction procedure is applied to the rest of the solution matrices and replaced by the input solutions.

The general structure of the improvement procedure is as follow:

```
Improvement method
{For each si in input population
Si=apply VNS procedure on si.
Si=check feasibility method.
}
```

4.4. Solutions and searching parameters update

In the whale optimization algorithm (WOA), following formulates are used to update the solutions and searching parameters: (20) & (21)

Equation 20

$$\overrightarrow{D} = \left| \overrightarrow{C} , \overrightarrow{X^*}(t) - \overrightarrow{X}(t) \right|$$

Equation 21

$$\overrightarrow{X}(t+1)=\overrightarrow{X^*}(t)-\overrightarrow{A},\overrightarrow{D}$$

Where $\overrightarrow{D}$ is searching space, $\overrightarrow{C}$ and $\overrightarrow{A}$ are the coefficients, $\overrightarrow{X^*}(t)$ is the optimal solution in iteration t, $\overrightarrow{X}(t)$ is the solutions for iteration t, and $\overrightarrow{X}(t+1)$ is the solution for iteration $t+1$.

The following relations are also used to update $\overrightarrow{A}$ and $\overrightarrow{C}$: (22) & (23)

Equation 22

$$\overrightarrow{A}=2\vec{a},\vec{r}-\vec{a}$$

Equation 23

$$\overrightarrow{C}=2\vec{r}$$

In the formulas as mentioned (22) and (23), $\vec{a}$ is initialized with a value of 2 and decreases linearly in each iteration; also, $\vec{r}$ is a random value in the interval [0,1].

Moreover, to update the optimal solution, if there is a solution among all the obtained solutions better than $\overrightarrow{X^*}$, it is replaced with $\overrightarrow{X^*}$. Otherwise, it remains unchanged.

4.5. Pareto archive update

In this research, the proposed solution method is based on the Pareto archive. The proposed algorithm uses a set called the Pareto archive, which holds non-dominated solutions generated by the algorithm since the first iteration and this set is updated in each iteration. The produced solutions in the last iteration and the Pareto archive solutions are put into a pool and get ranked. In the next step, solutions in pareto front (non-dominated solutions) are selected as the new Pareto archive set.

4.6. Selecting the next-generation solutions

In each iteration, the algorithm requires a population of solutions. Thus, in order to choose population for the next iteration, the last iteration and the newly generated solutions by the algorithm are poured into the same set named solution pool. After that, solutions get ranked and their crowding distances are calculated (Deb, 2002). Afterwards, N solutions with the highest quality and diversity are selected as the population of the next iteration.

5. Computational results

In this paper, to solve the multi-objective mathematical model, the Whale Optimization Algorithm (WOA) and Non-dominate Sorting Genetic Algorithm (NSGA-II) have been employed. In this regard, a problem was selected for 40 candidate points in 22 part of Tehran, to locate the delivery and collection points. In the next stage, the problem is solved by the algorithms and the results of the two mentioned algorithms are compared using comparative metrics.

5.1. Comparative metrics

For evaluating the proposed algorithms' efficiency, some criteria such as Number of Pareto solutions (NOS), Mean Ideal Distance (MID), Quality Metric (QM), Spacing Metric (SM), and Diversity Metric (DM) are used.

The Number of Pareto solutions: Since the algorithms are designed based on the Pareto archive, the set of obtained solutions is the same as the final Pareto archive. One of the comparison criteria is the number of final obtained solutions.

Mean Ideal Distance: This criterion is equal to the sum of the Euclidean distances of the solutions from the ideal point. In this study, the ideal point is a matrix including two cells, which the value of the first cell is equal to the minimum value of the first objective function of all solutions, and the value of the second cell is equal to the minimum value of the second objective function of all solutions.

Quality Metric: This criterion is equal to the number of Pareto (non-dominated) solutions.

Spacing Metric: This criterion calculates the uniformity of the distribution of the obtained Pareto solutions at the Pareto fronts, and it is defined as follows: (24)

Equation 24

$$S = \frac{\sum_{i=1}^{N-1} \left| d_{mean} - d_i \right|}{\left(N-1\right) \times d_{mean}}$$

Where d_i represents the Euclidean distance between two adjacent non-dominated solutions and d_{mean} represents the mean value of d_i .

Diversity Metric: This criterion is used to determine the number of non-dominated solutions of the optimal front. The definition of diversity metric is as follows: (25)

Equation 25

$$D = \sqrt{\sum_{i=1}^{N} \max\left(\left\| x_t^i - y_t^i \right\|\right)}$$

Where $\left\| x_t^i - y_t^i \right\|$ represents the Euclidean distance between two adjacent solutions of x_t^i and y_t^i on the optimal front.

5.2. Setting algorithms and model parameters

In order to implement WOA and NSGA-II algorithms, the algorithm parameters are set as follows:

- For executing the whale optimization algorithm, the size of population is considered 200; the number of variable neighborhood search algorithm iteration is 10 and the number of algorithm iterations is considered equal to 300.

- In order to execute NSGA-II, crossover and mutation rates are set to 0.8 and 0.1 respectively.

- Furthermore, to run NSGA-II, the number of algorithm iterations is set to 300 and the population size is considered 200.

The model parameters to solve and optimize objective functions are as described in the following **Table 3**:

5.3. Results

In this section, the proposed meta-heuristic algorithms' results are presented and compared. The mathematical model is solved by the multi-objective whale optimization algorithm based on Pareto archive and NSGA-II, and the values of the objective functions for the solutions in the Pareto archive are as described in Tables 4 and 5.

As can be seen in **Table 4**, the values of the objective functions of the solutions in the Pareto archive are non-dominated to each other, which indicate the same level of quality of the solutions and the contradiction between the two objective functions.

In **Table 5** the answers obtained from the NSGA-II algorithm are presented.

As can be seen in Figure (2), the quality level of the solutions obtained from the whale optimization algorithm is higher than the quality level of the solutions obtained from the NSGA-II algorithm. The comparison of two algorithms based on the comparative indices is presented in **Table 6.**

According to **Table ۶**, WOA is able to achieve solutions with higher quality compared to NSGA-II. Moreover, the MID criterion shows that the solutions generated by WOA are closer to the ideal point than NSGA-II. The proposed WOA enables to find out solutions with higher diversity, which means it has more efficient to explore and extract the solution feasibility area than the NSGA-II. On the other hand, NSGA-II generates more uniform solutions.

In the following, we have presented the results of the variables based on the first solution of the whale optimization algorithm.

The results of locating pickup points showed that pickup points were considered in places 7, 14, 15, 18, and 26. Moreover, the allocation of demand points to localized pickup points is also presented in **Table 7.**

Table 7. Allocation of demand points to localized pickup pointsAccording to the travel time between the two nodes and the service time as well as the route of the vehicles, the time for the vehicles to reach the pickup points is as described in the following **Table 8:**

The route of the vehicles to deliver the parcels from the head office to the pickup points is shown in the **Figure 3**.

Table 9 shows the due time, announced time to the demand points (according to the allocation solution), The announced time coincides with the arrival time .and the corresponding delay for each demand point (a_i), determined by the model tacking in account the travel time between the two nodes, service time, and routing of vehicles.

Table 9. Delivery delay of parcels to the demand point In the table 9, the first row shows the time announced to the demand points; the second row is the arrival time of the package, which corresponds to the time of the vehicle's arrival at the pick-up points assigned to the demand points. Finally, the third one calculates the amount of delay for each demand point.

6. Conclusion

In this article, the problem of distribution of postal packages in the Last Mil V3, Y=0 em is discussed. In order to optimally plan this system in Tehran, a bi-objective mathematical model has been presented that locates pickup points and vehicle routing so that transportation costs, location costs, and emissions costs in the transportation system. It also helps to minimize the waiting time of customers. To solve the model, whale optimization algorithm based on Pareto archive and NSGA-II are used. The solution results showed that the solutions obtained from solving the model by two algorithms are non-dominated to each other and are at the same level in terms of quality. Also, the values of the objective functions indicate the contradiction between the objectives functions considered in the model.

The proposed structure of the whale algorithm is based on the Pareto archive, and in order to improve the solutions, an improvement procedure based on variable neighborhood search (VNS) is used. Also, in the proposed structure of the multi-objective whale optimization algorithm, Deb's (2002) rule, which is the basis of the NSGA-II algorithm, has been used to select the solutions. The results of the comparison of two algorithms in solving the sample problem indicate that the proposed whale algorithm has a higher ability to produce solutions with more diversity and quality. Also, based on the designed structure of the proposed method, this method intelligently searches many points of the solution space in each iteration.

The innovation of the present article's model compared to previous researches is in considering the emission of pollutants, the amount of customer expectation, the radius of coverage and the dispersion principle for locating the collection points. In order to conduct future research, it is possible to consider vehicles of dual type (gasoline and electric fuel). It is also suggested to consider the VANET system as a transportation system for future research.

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Asian Journal of Basic Science & Research. Volume 4, Issue 2, Pages 01-31. (2022). http://doi.org/10.38177/AJBSR.2022.4201

Tables:

Table 1. Presentation of existing research gap

Authors	year	Last mile delivery	Pickup point	Location	Routing	Dispersion principle	Coverage radius	Customer wait time	Pollution	Mathematical Model	
										Single objective	Multi-objective
(7)	2010		√		√					√	
(10)	2013		√		√					√	
(8)	2014				√					√	
(9)	2015			√	√					√	
(12)	2014			√	√						√
(11)	2015			√	√						√
(13)	2016			√	√						√
(14)	2014	√	√								
(2)	2009	√	√								
(15)	2014	√	√								
(16)	2016	√	√								
(3)	2016	√	√								
(18)	2016	√	√	√	√					√	
(5)	2018	√	√	√						√	
(19)	2018	√	√	√						√	
(4)	2019	√	√	√	√					√	
(27)	2020	√	√	√							
(28)	2020	√	√								
(25)	2020	√	√								
(26)	2021	√	√								
(30)	2019	√	√	√	√				√		
(29)	2021		√	√							√
(22)	2022	√		√	√			√	√		√
(24)	2022	√	√		√		√	√			√
(23)	2022	√				√					√
(21)	2023	√	√		√			√	√		√
(20)	2023								√		√
This paper	2023	√	√	√	√	√	√	√	√		√

Table 2. Parameters of the mathematical model

parameter	Description	parameter	Description
q_v	Capacity of vehicle v	t_{ij}	Travel time between pickup points i and j
cap_i	Capacity of pickup point i	p_i	Service time in pickup point *i*
d_c	Demand for demand point c	vf	Volume of fuel (liters) consumption per unit of distance per unit of vehicle weight
fc_i	Cost of setting up candidate pickup point i	wc	Weight of pollutant gases emitted per liter of fuel consumption
fv_v	Fixed cost of using vehicle v	pc	The average price per unit of gas emitted
tc_{ij}	Cost of travel between pickup points i and j	R_{ic}	If the demand point *c* is within the coverage radius of point *i*, it is equal to 1; otherwise it is equal to 0
t_{ic}	Cost of travel between pickup point i and demand point c	dl_{ij}	Distance between pickup points *i* and *j*
pl_c	Penalty cost per minute of delay in vehicle arrival at pickup point c	DL	Minimum distance between set up pickup centers
l_c	Announced time to customers to pick up parcels from pickup point *c*		

Table 3. The value of model parameters

Parameter	Description	Parameter	Description
I	40 potential locations for Pickup points	C	10 demand points
V	3 types of vehicles	l_c	Respectively: 40,50,50,40,50,30,50,50,30,50
q_v	The capacity of vehicle type 1 is equal to 120, type 2 equals 60 and type 3 equals 100.	t_{ij}	20 minutes on average
cap_i	300	p_i	10 minutes on average
d_c	Delivery demand for demand points, respectively:32,25,29,35,30,18,19,28,30,22	vf	4.5 per kilometer
fc_i	10000	wc	105 grams per kilometer
fv_v	The cost of using different types of vehicles is 15, 5 and 10	pc	16000
tc_{ij}	5	R_{ic}	Determined based on information from the case study. If the distance from the demand point to the Pickup Point is less than 400, the value of the parameter is equal to 1.
t_{ic}	10	dl_{ij}	The distance between points i and j was determined using GIS.
pl_c	Respectively:10,12,10,10,12,10,12,12,10,12	DL	The minimum distance between the established harvest centers is equal to the average distance between the calculated points.

Table 4. Values of the objective functions of the Pareto frontier of the whale optimization algorithm

Solution number	Value of first objective	Value of second objective
1	2.208×10^{11}	440
2	2.993×10^{11}	410
3	3.111×10^{11}	380
4	3.780×10^{11}	320
5	4.001×10^{11}	300
6	4.314×10^{11}	240
7	5.881×10^{11}	100

Table 5. Values of the objective functions of the Pareto frontier of the NSGA-II algorithm

Solution number	Value of first objective	Value of second objective
1	3.552×10^{11}	580
2	4.773×10^{11}	423
3	5.021×10^{11}	390
4	5.992×10^{11}	370
5	6.012×10^{11}	345
6	6.880×10^{11}	310
7	7.221×10^{11}	280
8	7.994×10^{11}	250

Table 6. Comparison of solution algorithms based on different metrics

NSGA-II					WOA					Prob
MID	NOS	Diversity metric	Spacing metric	Quality metric	MID	NOS	Diversity metric	Spacing metric	Quality metric	p/m/c/l
1834.7	7	885.1	0.73	0	1067.21	6	1396.4	0.99	100	

Table 7. Allocation of demand points to localized pickup points

DP/PP	DP1	DP2	DP3	DP4	DP5	DP6	DP7	DP8	DP9	DP10
PP7		1	1							
PP14						1		1		
PP15				1			1			
PP18	1				1					
PP26									1	1

Table 8. Time of arrival of vehicles at the collection points

DP/PP	a_i
PP7	20
PP14	20
PP15	50
PP18	20
PP26	50

Table 9. Delivery delay of parcels to the demand point

DP	DP1	DP2	DP3	DP4	DP5	DP6	DP7	DP8	DP9	DP10
Due date	50	30	50	50	30	50	40	50	50	40
Ready time	20	20	20	50	20	20	50	20	50	50
Yl_c	0	0	0	0	0	0	10	0	0	10

Figures:

Figure 1. WOA flowchart [4]
Figure 2. Comparison of the Pareto frontier resulting from the algorithms
Figure 3. Routing of vehicles and the amount of transported parcels

Figure. 2. WOA flowchart [31]

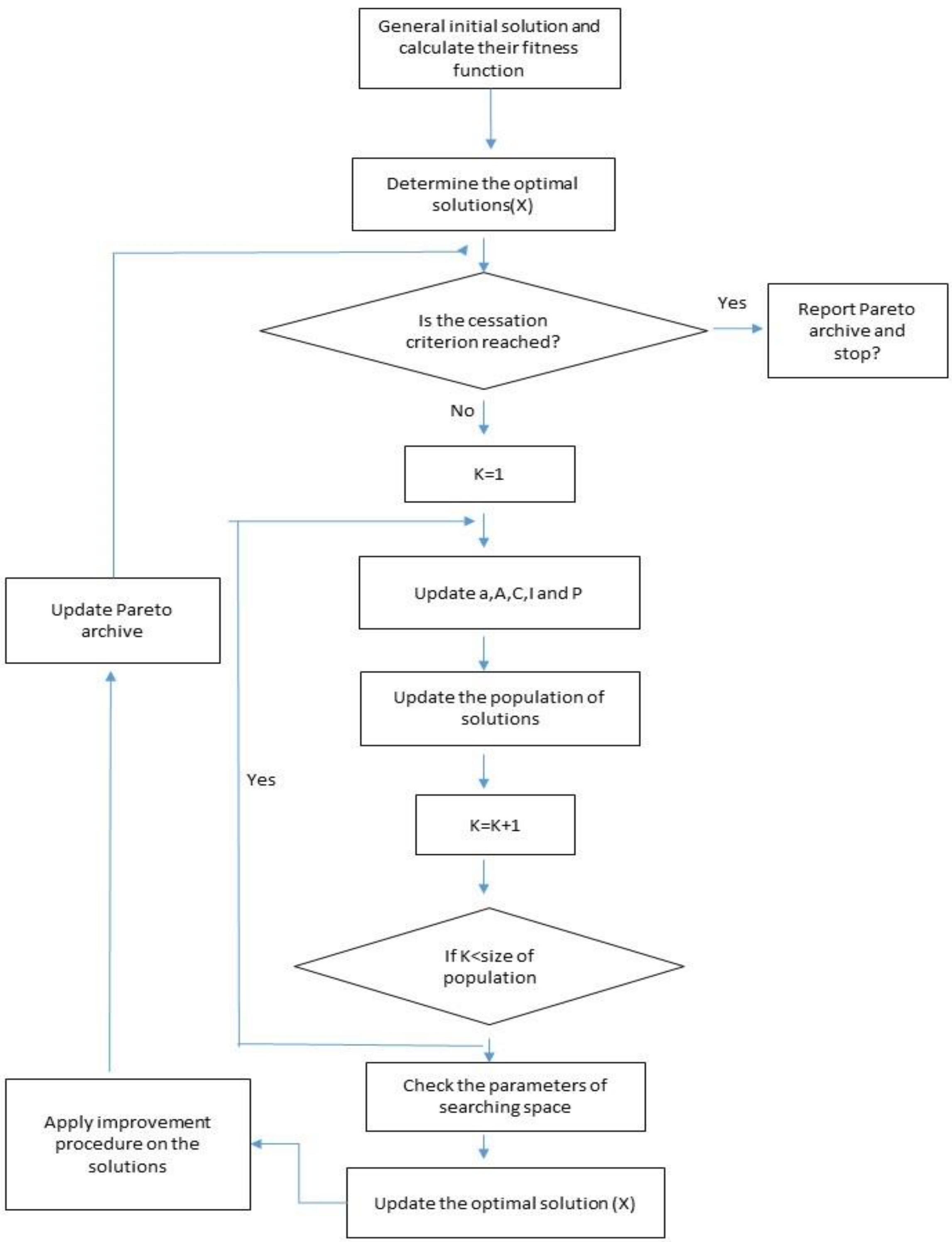


Figure 2. Comparison of the Pareto frontier resulting from the algorithms

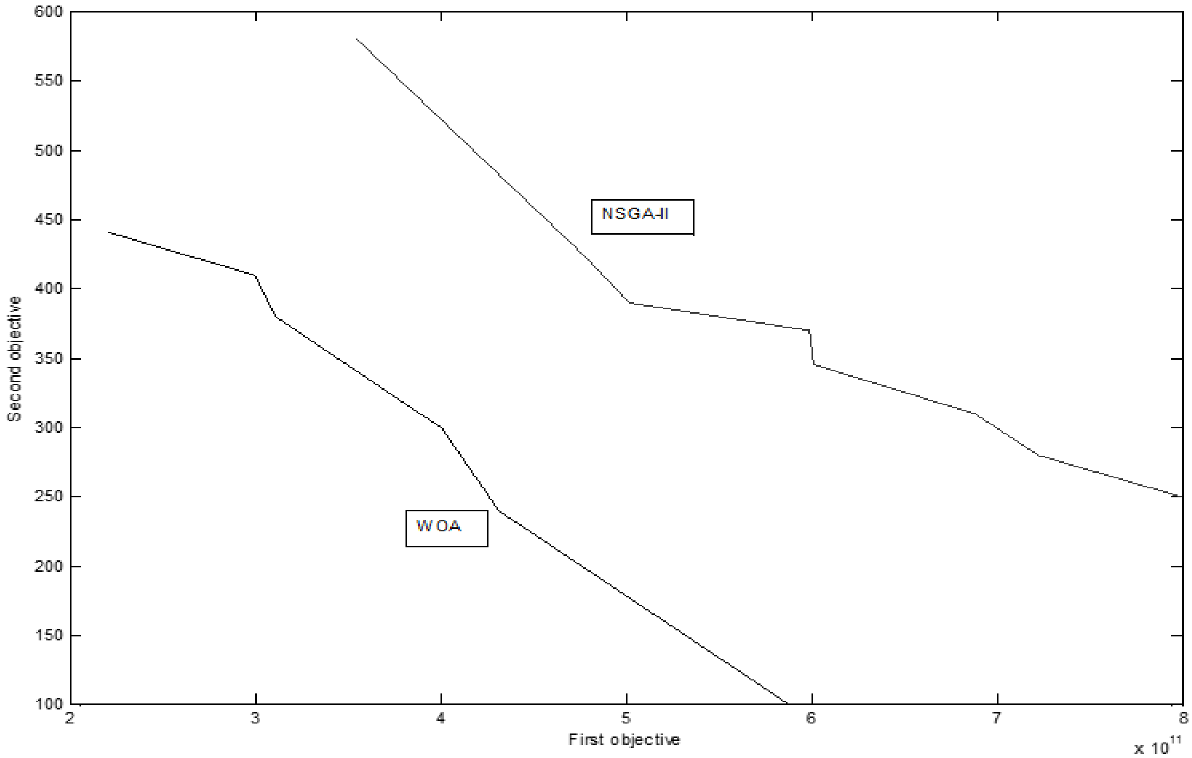
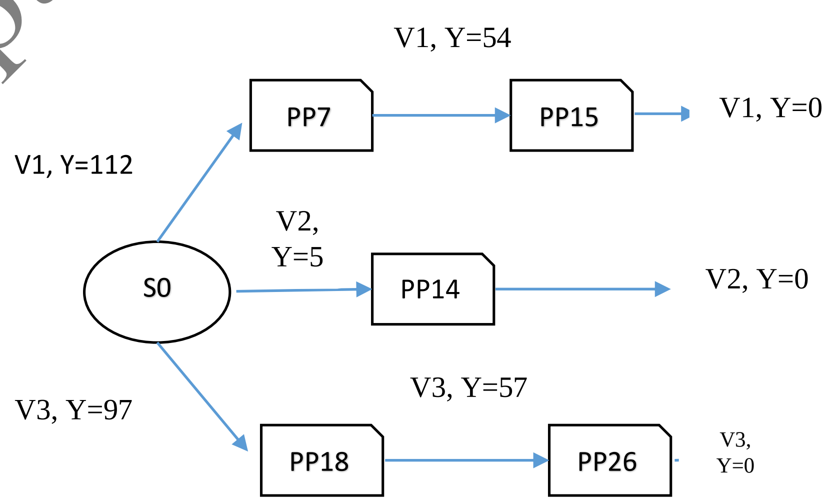


Figure 3. Routing of vehicles and the amount of transported parcels



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