Journal of Multidisciplinary Academic and Practice Studies (JoMAPS)
ISSN: 2656-2359, Vol 1, No 2, 2023, 129-142 https://doi.org/10.35912/jomaps.v1i2.1794

A mathematical model of routing problem for hazardous biomedical waste: A multi-objective particle swarm optimization solution approach

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Article History
Received on 11 May 2023
1st Revision on 22 May 2023
Accepted on 27 May 2023

Abstract

Purpose: This model aims to solve a Green Heterogeneous and Stochastic Capacitated Vehicle Routing Problem that considers risks and environmental hazards.

Research Methodology: Regarding an NP-hard and complex problem, and after confirming the accuracy of the problem-solving in smaller dimensions by GAMS software, the problem is solved by the metaheuristic algorithm of multi-objective particle swarm optimization (MOPSO) and its coding in MATLAB software.

Results: The results urge that using random sampling and probability The findings indicate that MOPSO effectively produces optimal or near-optimal solutions with significantly reduced computational time compared to GAMS. In small-scale cases, results matched the exact solutions, while larger-scale instances demonstrated the efficiency of the algorithm in handling complex routing problems. Sensitivity analyses revealed that prioritization of objectives—such as environmental impact, reliability, or routing cost—led to different but balanced routing strategies, confirming the model's adaptability.

Conclusions: The proposed model ensures reliable and environmentally conscious waste transportation by integrating cost, risk, and time-window considerations. It demonstrates strong performance in optimizing multi-objective routing problems under uncertainty.

Limitation: The proposed method is a routing problem and has been applied for the Green Heterogeneous and Stochastic Capacitated Vehicle Routing Problem. Future researchers may work on real data sets and hazardous biomedical waste data.

Contribution: Based on the results presented, the model derived in this study can support decisions such as routing, prioritization, and time to reach each node, so that the costs of routing, system reliability, environmental issues, and penalties for violation of the priority and maximum time elapsed for vehicles are considered.

Keywords: *Hospital Waste, Metaheuristic Algorithms, MOPSO, Nondeterministic Parameters, Vehicle Routing*

How to cite: Heydari, M., Torabi, H., & Jahromi, M. (2023). A mathematical model of routing problem for hazardous biomedical waste: A multi-objective particle swarm optimization solution approach. *Journal of Multidisciplinary Academic and Practice Studies*, 1(2), 129-142.

1. Introduction

Currently, due to the growing population of developed and developing countries, a significant amount of waste is generated annually. Over the past two decades, hospital waste has been recognized as an issue affecting human health and the environment. Moreover, in recent years, the production and disposal of hospital waste by Covid 19 patients has become a worldwide problem (Latunusa, Timuneno,

& Fanggidae, 2023). This study focuses on the infectious and hazardous waste that must be cleaned to render it of no risk to human health and the environment. On-site cleaning requires expensive equipment and can only be performed in large hospitals (Taghipour, Mohammadyarei, Asghari Jafarabadi, & Asl Hashemi, 2014). Therefore, waste should be collected from other centers and transported to a landfill or disposal site. It seems that the smaller the number of displacements and transfers, the lower the environmental risks. As a result, the issue of transportation routing and the selection of optimal vehicle routes will play an important role in this regard, and a simple advance in this area can have a significant impact on costs and reduce the risk associated with transporting such waste.

In this study, a mathematical model was developed to solve the problem of routing in a supply chain network related to the collection and transportation of infectious waste in hospitals, with a special focus on environmental issues (Muliyanto, Indrayani, Satriawan, Ngaliman, & Catrayasa, 2023). A metaheuristic method is used to find a solution close to the optimal solution according to the optimization criteria for the problem.

2. Literature review

Considering waste management combined with location, the issue of air pollution was investigated by (Emek & Kara, 2007). Considering pollution-related constraints, they minimized transportation costs using mixed-integer programming. Boyer, Sai Hong, Pedram, Mohd Yusuff, and Zulkifli (2013) conducted an interesting study to model waste management. Considering several multiple objective functions, they conducted comprehensive modeling of the economic discussions of the direct transfer of waste to landfills, in which the profit from the sale of recycled waste and transportation costs were examined. Regarding the risks posed by landfills, (Samanlioglu, 2013) examined direct routing for non-recyclable waste. Their work was later expanded by Ghezavati and Morakabatchian (2015), who introduced psychological factors influencing decision-making by integrating fuzzy logic into the system.

Bula, Murat Afsar, González, Prodhon, and Velasco (2019) solved the problem of hazardous waste routing and disposal by using two opposite cost functions, one is the cost of waste transportation and the other is the risk of waste. In their method, a heterogeneous fleet of vehicles and statistical distribution of known input parameters were used. Several studies have been conducted in the field of green routing (Asghari & Mirzapour Al-e-hashem, 2021; Cao, Ye, Cheng, & Wang, 2022; Gupta, Govindan, Mehlawat, & Khaitan, 2022; Moghdani, Salimifard, Demir, & Benyettou, 2021). In such cases, the results of this paper can help decision-makers in the hospital waste supply chain (S. Liu, Zhang, Niu, Liu, & He, 2022). A vehicle routing problem refers to a set of problems in which a fleet consisting of several vehicles from one or more warehouses provides services to customers located in different geographical locations and does so in such a way that the cost of providing the service is minimal. Along these routes, customers are met once, unless one or several customers need to be served frequently. Usually, all the demands of these customers should be received by only one vehicle, which has a certain capacity for car routing problems. All routes start from a specific point (origin of loading), and after the vehicle has met several customers, it returns to the same starting point, and the path ends at the same place.

In the vehicle routing problem with time window constraints (VRPTW), service to each customer must be provided at a specific time interval, in which the objective is to serve the customer at a period usually determined by customers, and the timely presence of vehicles at designated stations increases customer satisfaction (Chen, Chen, & Leung, 2023). The time window is defined as $[e_i l_i]$, where ei is the earliest and l_i is the latest start time of the service, during which the service time (S_i) should be. The VRPTW can be divided into two main parts according to how the time window is applied:

1. The hard vehicle routing problem with time window (HVRPTW) states that the customer service start-up time must be within the period of each node and must not be before e_i or after l_i. Otherwise, the customer will not be allowed to use the service. Therefore, the service was returned.
2. The soft vehicle routing problem with time window (SVRPTW) differs from the previous type in that, in addition to the initial range for service time, another range is defined that includes the previous range and services that are before and after the range; are acceptable by imposing fines.

Another issue related to routing is that vehicles no longer need to return to the warehouse, which is called the open vehicle routing problem (Schrage, 1981). When time window constraints are added to the model, an open vehicle routing problem with a time window (OVRPTW) is encountered. To solve this problem, various heuristic algorithms, such as taboo search(Xia & Fu, 2019), neighborhood-based search (R. Liu, Tao, & Xie, 2019), particle swarm optimization(Islam, Gajpal, & ElMekkawy, 2021), ant colony optimization, and evolutionary calculations (Yuan Wang et al., 2020) have been used. During the development of this research, many new models and heuristic algorithms have emerged. Han et al. (2015) stated that atmospheric pollution has become severe owing to the sharp increase in the number of motor vehicles in recent years. The frequent occurrence of foggy days since 2012 provides good evidence for this trend.

Moreover, Demir et al. compared six fuel consumption models to assess greenhouse gas emissions (Demir, Bektaş, & Laporte, 2014). According to these models, fuel consumption depends on various factors, including the vehicle, driver, and traffic. Zhou and Lee (2017) proposed the pollution-routing problem as a model of greenhouse gas emissions for the vehicle routing problem. This model can convert all the energy consumed on each road directly into fuel emission. Among the first studies related to waste transportation routing modeling, Wu, Tao, and Yang (2020) can be mentioned. They solved a combined routing-location problem by considering only one type of waste. A similar study was conducted by (Fang et al., 2023), who incorporated several different types of waste to be transferred to waste disposal sites. Developing and introducing a stochastic mathematical model and using multi-objective functions, (Rabbani, Heidari, Farrokhi-Asl, & Rahimi, 2018) solved the problem of hazardous material and waste routing by considering three levels of decision-making and combining the problem with location and allocation problem for the construction of waste discharge ridges. In another study, by combining the problems of routing and location, (Rabbani, Nikoubin, & Farrokhi-Asl, 2021; Saeidi, Aghamohamadi-Bosjin, & Rabbani, 2021) developed a complex mathematical model in which different types of hazardous waste with potential environmental risks arising from the transport of these wastes and the proximity of discharge sites to high-risk areas were considered.

In terms of the number of objective functions, (Jozefowiez, Semet, & Talbi, 2008) stated that three types of objective functions are most applicable: cost minimization, maximum path length, and balance between path selection in terms of destination selection. Furthermore, to solve the multi-objective routing problem, they proposed two solution methods consisting of scalar methods (such as weighted aggregation) and evolutionary methods (such as genetic algorithms). (Labadie & Prodhon, 2014) confirmed the findings of (Jozefowiez et al., 2008). However, their study incorporated time windows. In the field of solution methods based on evolutionary algorithms, many studies have illustrated their importance and efficiency in solving vehicle routing problems have been done (Akbarpour, Salehi-Amiri, Hajiaghaei-Keshteli, & Oliva, 2021). Moreover, meta-heuristic methods such as ant colony (Rahmanishati, Dewi, & Kusumah, 2021), PSO (Salehi Sarbijan & Behnamian, 2022), and SA algorithm (Shang, Huang, Wang, Li, & Feng, 2022) have shown excellent performance.

Chao et al. believe that the high cost of transportation and the low quality of services are common weaknesses in various logistics networks, especially in food distribution. Owing to the perishability of food, its quality decreases during the delivery process. They proposed a two-step location-routing-inventory problem with time windows (2S-LRITW) for food products. In the first stage, the location routing inventory problem with time windows is addressed, and in the second stage, the transportation problem with limited vehicle capacity is considered. The problem is formulated as a complex-integer programming model. Then, a hybrid heuristic method is proposed in which the distance-based clustering approach, jump operation, and location retrieval exchange method are introduced to improve the performance of the algorithm. Finally, the hybrid heuristic method was tested with several cases, including small samples and one real case. The results show that the distance-based clustering approach can efficiently improve the response convergence speed, and the improved ant colony optimization (IACO) and location retrieval exchange methods can increase the search space. Accordingly, the hybrid heuristic method is suitable for solving applied problems on a larger scale. In addition, the results show that, according to the considered energy cost, the customer sequence has a significant impact (Yong Wang et al., 2022).

3. Research methodology

3.1 Mathematical Modeling

3.1.1 Problem description and Assumptions

This study aimed to determine the optimal routes for vehicles to collect infectious hospital waste. The objective function in the proposed model is multi-objective and aims to reduce routing costs by focusing on issues such as reducing environmental impact and increasing system reliability. The supply chain network includes vehicles, customers (hospitals), and waste-disposal sites. The main assumptions of this problem are as follows:

1. All types of waste are generated at specific nodes.
2. The total waste generated at each node does not exceed the permissible capacity of the vehicle intended for each type of waste.
3. Each vehicle has a maximum available time stochastic normal distribution.
4. Any type of waste in each node is inspected and serviced only once by a vehicle.
5. It is not allowed to collect waste incompletely from the nodes.
6. The vehicles designated for each specific type of waste vary in capacity.
7. Transportation costs were estimated based on the distance traveled.
8. The system reliability is calculated based on the failure rate.

3.1.2 Notations

Indices

N, I, J, P	a set of nodes (node 1 is the depot location)
K	set of vehicles

Parameters

dij_{ij}	The distance of node i from node j
QD_i	Node i demand
CK_k	Vehicle k capacity
$\bar{Q}_k$	The load carried at the beginning of the movement from the depot by the vehicle k
SS_i	Duration of service in node i
C_{ijk}	Cost of transportation from node i to j
$\tilde{T}T_k$	Maximum (stochastic) time available for each vehicle
$\bar{T}T_k$	The average maximum time available for a vehicle
σ_k	The standard deviation of the maximum time available for the vehicle
$1-\alpha$	Probability of meeting the maximum time constraint
P_ideal_i	Optimal priority for node i
env_{ijk}	*Environmental effects from node i to node j by vehicle k*
T_{ijk}	*The time elapsed between node i and node j by vehicle k*
w	*The importance of the various components of the objective function*

Decision variables

$$x_{ijk} \quad \begin{cases} 1 & \text{if the path between node } i \text{ and node } j \text{ is traveled by vehicle } k. \\ 0 & \text{otherwise} \end{cases}$$

at_i *Time to reach node i*

$MM1_{ik}$ *Auxiliary variable to eliminate sub-net*

atx_{ijk} *Auxiliary variable for linearizing nonlinear expressions*

pp_i *Priority achieved in practice for node i*

ppx_{ijk} *Auxiliary variable for linearizing nonlinear expressions*

vvp_i *Auxiliary variable for linearizing nonlinear expressions*

$vvat$ *Auxiliary variable for linearizing nonlinear expressions*

qq_i *The amount of load remaining up to node i*

3.1.3 Objective function and constraints

Based on the objective function of the problem, the first to fifth expressions are the costs of routing, system reliability, environmental impacts, fines for violating node priorities, and fines for the maximum time elapsed for each vehicle, respectively. The proposed model is as follows

Objective function:

$$zz = \sum_{i,j,k} c_{ijk}x_{ijk} + w_1\sum_{i,j,k}\Delta_k dij_{ij}x_{ijk} + w_2\sum_{i,j,k} env_{ijk}x_{ijk} + w_3\sum_{j\geq 2} penp_j vvp_j$$

$$+w_4\sum_k vvat_k penat \tag{1}$$

s.t

$$\sum_i\sum_k x_{ijk} = 1 \quad \forall j \in J \tag{2}$$

$$\sum_j\sum_v x_{ijv} = 1 \quad \forall i \in I \tag{3}$$

$$\sum_i x_{ipv} = \sum_i x_{pjv} \quad p \in P \quad k \in K \tag{4}$$

$$\sum_{i,j} SS_i x_{ijk} + \sum_{i,j} T_{ijk} x_{ijk} \leq \tilde{T}T_k \quad k \in K \tag{5}$$

$$\tag{6}$$

$$MM1_{ik} - MM1_{jk} + (|N|-1)x_{ijk} \leq (|N|-2) \quad \forall i \in I, \forall j \in J, \forall k \in K, i \geq 2\ j \geq 2 \tag{7}$$

$$at_j = \sum_i\sum_k at_i x_{ijk} + \sum_i\sum_k (ss_i + T_{ijk})x_{ijk} \quad \forall j \in J, j \geq 2 \tag{8}$$

$$at_1 = 0 \tag{9}$$

$$at_j = \sum_i\sum_k atx_{ijk} + \sum_i\sum_k (ss_i + T_{ijk})x_{ijk} \quad \forall j \in J, j \geq 2 \tag{10}$$

$$atx_{ijk} \leq at_i \quad \forall i \in I, \forall j \in J, \forall k \in K,\ j \geq 2 \tag{11}$$

$$atx_{ijk} \leq Mbig\ x_{ijk} \quad \forall i \in I, \forall j \in J, \forall k \in K,\ j \geq 2 \tag{12}$$

$$at_i - Mbig(1 - x_{ijk}) \leq atx_{ijk} \quad \forall i \in I, \forall j \in J, \forall k \in K,\ j \geq 2 \tag{13}$$

$$QQ_j = \sum_i \sum_k QQ_i x_{ijk} + \sum_i \sum_k QD_j x_{ijk} \qquad \forall j \in J, j \geq 2 \tag{14}$$

$$QQ_1 = 0 \tag{15}$$

$$QQ_j = \sum_i \sum_k QQx_{ijk} + \sum_i \sum_k QD_j x_{ijk} \qquad \forall j \in J, j \geq 2 \tag{16}$$

$$QQx_{ijk} \leq QQ_i \quad \forall i \in I, \forall j \in J, \forall k \in K, \ j \geq 2 \tag{17}$$

$$QQx_{ijk} \leq Mbig \ x_{ijk} \quad \forall i \in I, \forall j \in J, \forall k \in K, i \geq 2 \ j \geq 2 \tag{18}$$

$$QQ_i - Mbig\left(1 - x_{ijk}\right) \leq QQx_{ijk} \quad \forall i \in I, \forall j \in J, \forall k \in K, i \geq 2 \ j \geq 2 \tag{19}$$

$$pp_j = \sum_i \sum_k pp_i x_{ijk} + \sum_i \sum_k x_{ijk} \qquad \forall j \in J, j \geq 2 \tag{20}$$

$$pp_1 = 0 \tag{21}$$

$$pp_j = \sum_i \sum_k ppx_{ijk} + \sum_i \sum_k x_{ijk} \qquad \forall j \in J, j \geq 2 \tag{22}$$

$$ppx_{ijk} \leq pp_i \quad \forall i \in I, \forall j \in J, \forall k \in K, \ j \geq 2 \tag{23}$$

$$ppx_{ijk} \leq Mbig \ x_{ijk} \quad \forall i \in I, \forall j \in J, \forall k \in K, i \geq 2 \ j \geq 2 \tag{24}$$

$$pp_i - Mbig\left(1 - x_{ijk}\right) \leq ppx_{ijk} \quad \forall i \in I, \forall j \in J, \forall k \in K, i \geq 2 \ j \geq 2 \tag{25}$$

$$MVVP_j = \max_j \left\{0, pp_j - P\_ideal_i\right\} \qquad \forall j \in J, j \geq 2 \tag{26}$$

$$pp_j - P\_ideal_i \leq vvp_j \qquad \forall j \in J, j \geq 2 \tag{27}$$

$$MVVat = \max_j \left\{at_j\right\} \qquad \forall j \in J, j \geq 2 \tag{28}$$

$$at_j \leq vvat \qquad \forall j \in J, j \geq 2 \tag{29}$$

$$\sum_{i \neq 1} \sum_k QD_i x_{ijk} \leq CK_k \qquad \forall k \in K \tag{30}$$

$$\sum_i \sum_j \sum_k soc_{ij} x_{ijk} \leq SOW \tag{31}$$

$$x_{ijk} \ ww_i \in \{0,1\} \tag{32}$$

$$\begin{array}{l} lt_i \ ato_i \ at_i \ MM1_{ik} \ pp_i \\ QQx_{ijk} \ ppx_{ijk} \ vvp_i \ vvdd \ vvat \qquad \in R^+ \\ MVVP_i \ MVVat \end{array} \tag{33}$$

$$zz \in R \tag{34}$$

Term (1) expresses the objective function. According to this, the first to fifth terms represent routing costs, system reliability, environmental issues, penalty for violation of priority for nodes, and penalty for maximum time elapsed for vehicles, respectively. Given that we intend to maximize the reliability of the system, the reliability is calculated as in (2).

To maximize the reliability obtained from term (2), the value $\sum_{i,j,k} \Delta_k dij_{ij} x_{ijk}$ is minimized. This value is observed in the objective function. Constraints (3) and (4) ensure that each node is serviced by a single vehicle. Constraint (5) shows that if a vehicle reaches a node, it must leave there, in which case the continuity of the route will be maintained. Constraint (6) is related to the maximum time available for each vehicle to complete its route. This maximum time is stochastic and has a normal distribution with mean $\bar{T}T_k$ and deviation σ_k. Equation (7) prevents the creation of subnetworks in routes. Constraint (8) indicates that the time to reach a node is equal to the sum of the time to reach the previous node, service time per node, and carrying time between the two nodes. Constraint (14) indicates that the load accumulated in each node is equal to the load accumulated up to the previous node plus the current node's load. Constraint (20) states that the priority of each node is equal to the sum of the priorities of the previous and latter nodes. Based on constraint (26), the violation of the priority in each node is equal to the maximum of zero and the difference between the priority in each node and the ideal priority. Constraint (28) indicates that the maximum time for each node is equal to the maximum time for all nodes. The load capacity limit of each vehicle is mentioned in Constraint (30), which states that the total load of each vehicle must be less than the capacity of that vehicle. Moreover, Constraints (31), (32), (33), and (34) indicate the social adverse effects, binary, positive, and free variables of the problem, respectively.

Notably, the time to reach node 1 (depot node), load accumulated in node 1, and priority in node 1 are all equal to zero.

Linearization of model constraints

In Equations (8), (14), and (20), a binary variable is multiplied by a continuous variable, which creates a nonlinear term. To linearize the above terms, Equations (10), (16), and (22) were replaced, and Constraints (11) to (13), (17) to (19), and (23) to (25) were added to the model, respectively. Constraints (26) and (28) are nonlinear relations owing to the existence of a max operator, which becomes linear in the form of constraints (27) and (29).

3.1.4 Dealing with uncertainty in the problem

In the aforementioned model, the parameter of the maximum time available to the vehicle was considered stochastically. Uncertainty in the above parameters can be caused by factors such as traffic, weather conditions, driver skills, vehicle type, and driver skills. The chance-constrained method is an important approach for solving optimization problems under various uncertainties. This method limits the available space such that the level of reliability of the solution is high. Using the concept of the chance-constrained method, the stochastic constraint, and inequation 6, the model mentioned above is deterministically presented as follows: The CDF of any normal random variable can be written in terms of the Φ function, so the Φ function is widely used in probability (the constraints 38 to 40). If the inverse of the Φ function is taken, the next steps are straightforward, as shown in Equations 41–43.

$$pr\left\{\sum_{i,j} SS_i x_{ijk} + \sum_{i,j} T_{ijk} x_{ijk} \leq \tilde{T}T_k\right\} \geq 1-\alpha \quad k \in K \tag{35}$$

The terms 36 to 37 illustrate how to convert the variable to a standard normal one.

$$pr\left\{\frac{\sum_{i,j} SS_i x_{ijk} + \sum_{i,j} T_{ijk} x_{ijk} - \bar{T}T_k}{\sigma_k} \leq \frac{\tilde{T}T_k - \bar{T}T}{\sigma_k}\right\} \geq 1-\alpha \quad k \in K \tag{36}$$

$$pr\left\{\frac{\sum_{i,j} SS_i x_{ijk} + \sum_{i,j} T_{ijk} x_{ijk} - \bar{T}T_k}{\sigma_k} \leq z\right\} \geq 1-\alpha \quad k \in K \tag{37}$$

$$1-\phi\left(\frac{\sum_{i,j} SS_i x_{ijk} + \sum_{i,j} T_{ijk} x_{ijk} - \bar{T}T_k}{\sigma_k}\right) \geq 1-\alpha \quad k \in K \tag{38}$$

$$-\phi\left(\frac{\sum_{i,j} SS_i x_{ijk} + \sum_{i,j} T_{ijk} x_{ijk} - \bar{T}T_k}{\sigma_k}\right) \geq -\alpha \quad k \in K \tag{39}$$

$$\phi\left(\frac{\sum_{i,j} SS_i x_{ijk} + \sum_{i,j} T_{ijk} x_{ijk} - \bar{T}T_k}{\sigma_k}\right) \leq \alpha \quad k \in K \tag{40}$$

$$\frac{\sum_{i,j} SS_i x_{ijk} + \sum_{i,j} T_{ijk} x_{ijk} - \bar{T}T_k}{\sigma_k} \leq \phi^{-1}(\alpha) \quad k \in K \tag{41}$$

$$\sum_{i,j} SS_i x_{ijk} + \sum_{i,j} T_{ijk} x_{ijk} - \bar{T}T_k \leq \phi^{-1}(\alpha)\ \sigma_k \quad k \in K \tag{42}$$

$$\sum_{i,j} SS_i x_{ijk} + \sum_{i,j} T_{ijk} x_{ijk} \leq \phi^{-1}(\alpha)\ \sigma_k + \bar{T}T_k \quad k \in K \tag{43}$$

4. Results and discussions

4.1 Computational Results

The performance of the proposed meta-heuristic algorithms is compared with that of the GAMS software in this section. The related results, including the objective function, solution time, and difference between the software report and meta-heuristic algorithms, are summarized in Table 1. It should be noted that the difference between the objective function obtained from GAMS and the meta-heuristic algorithms is calculated as follows:

$$Gap(\%) = \frac{TC_{ME} - TC_{GAMS}}{TC_{ME}} \times 100 \tag{44}$$

Where TC_{GAMS} and TC_{ME} are objective functions derived from GAMS software and meta-heuristic algorithms, respectively. As the results illustrated in Table 1, for Instances 1 and 2, the difference between the outputs of the meta-heuristic algorithm and the GAMS software is zero. This indicates that the proposed algorithm can provide an optimal answer. Therefore, it can be concluded that the meta-heuristic algorithm can obtain the optimal and near-optimal answer at a very good time, whereas the time related to the GAMS exponentially increases.

The results of the model, including the objective function, solution time, and the difference between GAMS software and the MOPSO meta-heuristic algorithm in MATLAB software, are shown in Table 1. The results of the sensitivity analysis in different states illustrate that when one of the states is more important, the solutions generated by the MOPSO meta-heuristic algorithm (Table 2) show a significant reduction in the desired index as well as the maximum time fluctuation to reach the nodes.

Table 1. The objective function, solution time, and the difference between the GAMS software and the MOPSO

Instance size	Instance	Number of customers	Number of vehicles	Cost			Time (in seconds)		
				GAMS	MOPSO	The difference in Objective function (%) (Based on the equation 44)	GAMS	MOPSO	Difference (MOPSO- GAMS)
Small	1	2	2	87.63	87.63	0	0.2	0.2	0
	2	3	2	141.3	141.3	0	5.663	0.82	-4.843
	3	4	3	187.562	189.17	1.608	81.633	3.33	-78.303
	4	5	3	195.648	196.92	1.272	263.745	4.42	-259.325

	5	6	4	227.614	231.08	3.466	1432.23	5.6	-1426.63
Medium	6	7	4	263.448	267.30	3.852	21007.515	7.127	-21000.388
	7	8	5	295.948	300.63	4.682	182049.8	9.368	-182040.432
	8	9	5	328.449	333.95	5.501	1577632.013	10.214	- 1577621.799
	9	10	6	360.950	367.28	6.33	13671658.9	12.454	- 13671646.45
	10	11	6	393.451	400.61	7.159	118477728.4	13.300	- 118477715.1
Large	11	12	7	425.951	433.94	7.989	1026720475	15.541	-1026720459
	12	13	7	458.452	467.27	8.818	8897494478	16.386	-8897494462
	13	14	8	490.953	500.60	9.647	77105122481	18.627	- 77105122462
	14	15	8	523.453	533.92	10.467	-	19.473	-
	15	16	9	555.954	567.25	11.296	-	21.713	-

Figure (1) and the first row of Table (2) show the computational results when the components of the objective function are of equal importance and weight. Based on this, the routing costs, system reliability penalties, environmental issues, priority violation penalties, and maximum time-out penalties were calculated. After checking the arrival time of vehicles at different nodes, it was found that the maximum arrival time was 16.95 units.

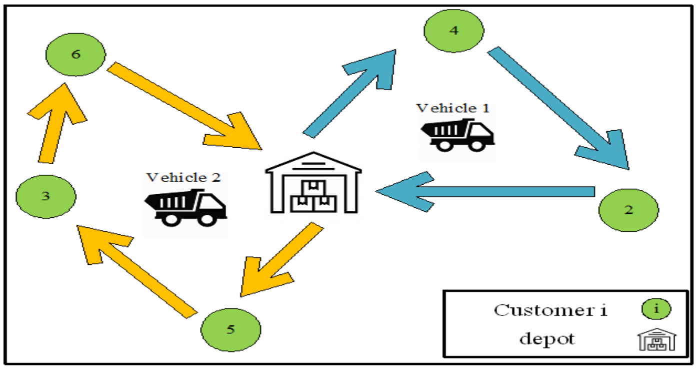

Figure 1. Routing when the components of the objective function are of equal importance

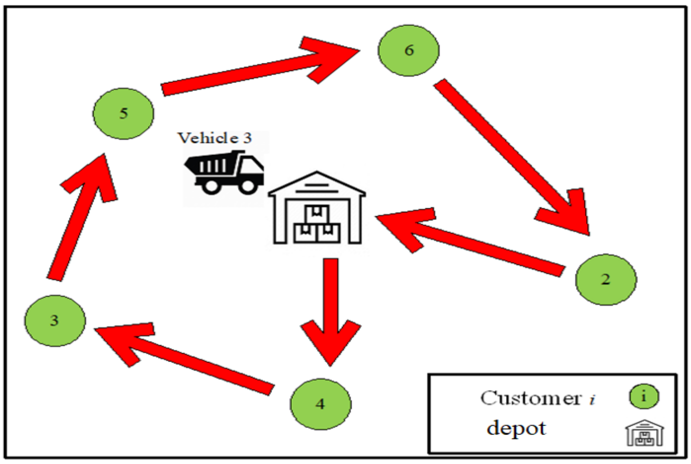

Figure 2. Routing shaped when routing costs are more important

Figure 3 and the third row of Table 2 show the computational results when the system reliability is more important. The results show a reduction in the penalty for system reliability compared with previous states. The system reliability penalty is 39,533 units, and the maximum time to reach the nodes in this case is 36,173 units.

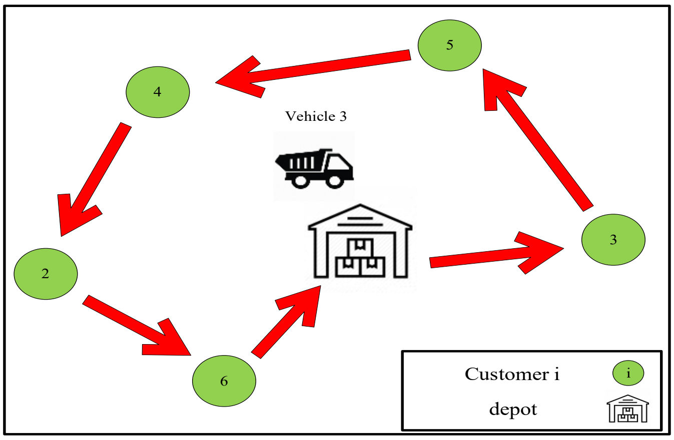

Figure 3. Routing shaped when system reliability is more important

Figure 4 and the fourth row of Table 2 show the computational results when environmental issues were more important. When the environmental impacts caused by the vehicles are of higher weights, the routing according to Figure 4 is performed using the minimum number of vehicles. The value of this component of the objective function was reduced compared to the previous states and was equal to 35,592 units. The maximum time to reach the nodes is 34,929 units, which seems reasonable considering the number of vehicles allocated, as shown in Figure (4).

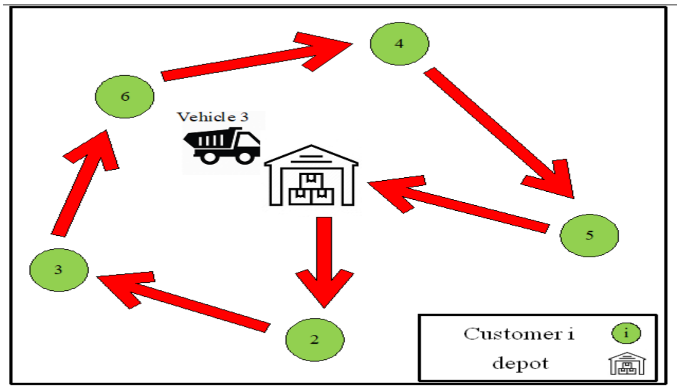

Figure 4. Routing shaped when environmental issues are more important

In the state where the priorities and maximum time penalty are important, according to Figure (5), almost all vehicles are activated to perform the necessary service with less priority and time. In these two states, the penalty for violating the priorities and the maximum elapsed time is reduced, and the latter is at its lowest value, that is, 13,975 units.

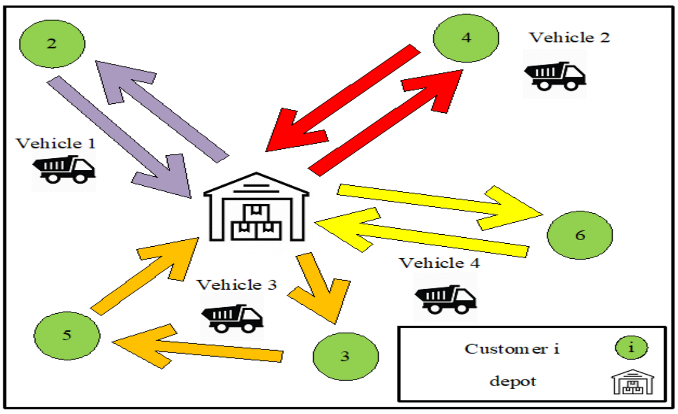

Figure 5. Routing shaped when priorities are more important in the objective function

Table 2. The results of the components of the objective function in different states

Objective function component / Sensitivity analysis	Routing costs ($\sum_{ijk} c_{ijk}x_{ijk}$)	Environmental Issue ($\sum_{ijk} env_{ijk}x_{ij}$	penalty for maximum time elapsed ($\sum_k vvat_k pena$)	penalty for System reliability ($\sum_{ijk} \Delta_k dij_{ij}x_{ij}$)	Penalty for violation of priorities ($\sum_{j\geq 2} penp_j vvp$)	Maximum time to reach the nodes
When the components of the objective function are of equal importance	46.515	45.728	74.144	46.81	14.41	16.955
When routing costs are more important	35.937	44.791	140.264	47.964	36.79	32.075
When system reliability is more important	39.463	44.569	158.185	39.533	36.153	36.173
When environmental issues are more important	48.438	35.592	152.745	68.506	29.721	34.929
When the priorities are more important	66.283	63.334	61.113	96.618	2.45	13.975
When the penalty for maximum time elapsed is more important	66.283	63.334	61.113	96.618	2.45	13.975

5. Conclusion

Utilizing the meta-heuristic particle swarm optimization algorithm and considering the uncertainty conditions, in this study, a multi-objective supply chain optimization model was developed. This model aims to solve a Green Heterogeneous and Stochastic Capacitated Vehicle Routing Problem that considers risks and environmental hazards. The reliability of the system along the route was also considered to increase the reliability of the problem. Therefore, it is ensured that any kind of waste reaches the desired and appropriate sites. Finally, in this study, a particle swarm optimization algorithm is used, through which the proposed model can be solved more efficiently. The results indicate that using random sampling and probability distribution, non-deterministic parameters were converted into deterministic ones, and high-quality solutions were obtained. Examples were used to evaluate the usefulness of the proposed method. In the first two examples, the difference between the meta-heuristic algorithm and GAMS was zero. This means that the proposed particle swarm optimization algorithm was able to obtain the optimal solution. The sensitivity of the model parameters was also examined. For this purpose, depots, customers, and means of transportation were considered. Based on the results presented, the model derived in this study can support decisions such as routing, prioritization, and time to reach each node, so that the costs of routing, system reliability, environmental issues, and penalties for violation of the priority and maximum time elapsed for vehicles are considered. It was concluded that for all the sensitivities analyzed, the model made the optimal decision, and the computational results demonstrated the efficiency of the proposed model and solution method using the proposed meta-heuristic algorithm. Moreover, those interested in the subject of this research may focus on the following aspects:

1. Comparison of the results of other meta-heuristic algorithms with MOPSO in solving the problem raised in this research
2. Considering the issue of recycling into the issue at hand

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