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A Sustainable HazMat Logistic Network Design Considering Scale of Economy and Route Sensitivity and Solving with Hybrid GA-SA

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Abstract

Researchers have been investigating solutions to the Vehicle Routing Problem (VRP) as a practical means of tackling the rising transportation costs in businesses. The goal is to develop innovative methods that minimize shipping expenses and maximize profits. The transportation of Hazardous Materials (HazMat) is particularly complex and has attracted significant attention from scholars. When designing logistics networks for HazMat, factors such as time window constraints, uncertainties, vehicle capacity, and mileage capacity in sub-tours need to be considered to minimize overall transportation and pollution costs. This study presents a mathematical model for vehicle routing of HazMat from economic, route sensitivity, and uncertainty perspectives. An optimization approach using a hybrid Genetic and Simulated Annealing (SA) algorithm is then applied to solve the problem. The study includes numerous numerical examples and sensitivity analyses to demonstrate the model's efficacy. The results indicate that an increase in the route sensitivity coefficient leads to an increase in the objective function. Additionally, the effect of demand on the objective function generally increases, although there are instances where it decreases.

Keywords: Hazardous materials logistics, Scale of economy, Hybrid genetic simulated annealing algorithm, Vehicle routing problem.

1 | Introduction

Recently, the transportation of Hazardous Materials (HazMat), including radioactive and flammable materials, has become increasingly important due to the growth of industrial production. This transportation, especially

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to developing countries, has a significant national and international economic impact. As sustainable development encompasses economic, social, and environmental aspects, considering these factors in the location and routing of hazardous substances has become increasingly important in research. Furthermore, as the world's population grows and urbanization increases, effective management of waste, especially HazMat, is vital for community well-being and public health.

An essential concern in managing hazardous substances is minimizing pollution and the associated costs during transport. There are two main problems when planning routes for HazMat transportation: the Vehicle Routing Problem (VRP), where the load must be distributed below full capacity, and the shortcut route, where the load is distributed at full truck capacity. Vehicles travel through the HazMat distribution centers to address these challenges to collect items at each node. On specific routes, especially in densely populated areas, the sensitivity of the transshipment load increases, contributing to an increased transshipment risk. This concept is quantified as the path sensitivity coefficient. Furthermore, vehicles have a limited cargo capacity, and optimizing the load-to-capacity ratio is crucial, especially for HazMat.

In addition, specific time windows for collecting HazMat, varying environmental and traffic conditions, and the uncertainty of travel times further complicate the transportation process. These factors are particularly important when considering the sensitivity of the release of HazMat and the potential for contamination along the routes. Therefore, when planning collection routes and times, care should aim to reduce the uncertainty of time windows. Three key factors should be considered: the sensitivity of the collection path, economies of scale, and time uncertainties during the day. Accounting for these factors makes the research findings practically applicable in effectively managing HazMat.

This study attempts to introduce and optimize the routing of vehicles for the transportation of HazMat, considering route sensitivity, economies of scale, and time window uncertainties. The following sections of this paper include a literature review in Section 2, the problem definition and mathematical model in Section 3, the proposition of a hybrid genetic-Simulated Annealing (SA) approach in Section 4, the numerical analysis in Section 5, and finally, the conclusions and prospects for future research in Section 6.

2 | Literature Review

The field of vehicle routing is an essential area of study in transportation management that has brought significant advances in cost reduction and service facilitation for companies involved in physical goods distribution [1]. The problem of vehicle routing was initially introduced to design optimal routes for a fleet of vehicles serving customers in different geographical areas to minimize total operational costs [2]. In recent years, numerous researchers have attracted the interest of green vehicle routing due to its potential environmental and material benefits.

VRP involves specific methods to minimize carbon dioxide emissions from vehicles. [3], [4], [5] and [6] underwent research in the fields of hard and soft time windows, the effect of information traffic and the prevention of congestion in the vehicle navigation problem. In such an approach, time and speed are part of the requirements for calculating fuel consumption and greenhouse gas emissions. As a result of the development of these concepts, two main areas emerged: the first area is related to reverse logistics in loading and distribution of expired products and the second area is related to the simultaneous distribution and loading of second-hand products. Taking into account the internal costs in the general problem of vehicle routing [7] introduced the concept of routing-pollution problem. They identified important relations between several factors such as vehicle load, speed and cost, and suggested that the larger the vehicle routing problem, the more complex it becomes to solve. However, there are potential savings in the total cost. [8] conducted research on the minimization of vehicle costs and the efficiency of the green vehicle routing problem. Their research model sought to control pollution sources, optimize routing and have a positive effect on green routing. In addition, [9] proposed a green perspective on the issue of limited-capacity vehicle routing considering time windows. The model proposed by them was developed in a real-world configuration with different speed limits for time periods. [10], examined the state of the vehicle routing problem, which was considered as a semiconductor supply chain. In this research, two hybrid integer linear programming models were proposed to solve the green routing problem considering collection and delivery. [11] studied the problem of green vehicle routing with respect to time planning. They sought to minimize greenhouse gas emissions from vehicles in a logistics system while collecting and delivering products in that system. The effect of carbon emissions from transport integration on trucks, related to a specific situation of vehicle routing problem, was investigated by [12]. Thanks to the increase in public awareness regarding global warming and the harmful effects of greenhouse gas emissions, more research in recent years has been carried out with a focus on environmental factors related to vehicle routing optimization. Therefore [13] presented an environmental vehicle routing problem considering environmental effects of carbon emissions. From an economic point of view, logistics companies face rising operating costs due to long shipping distances or due to lack of available transportation resources provided by distribution network capacity [13]. In this regard, they presented a two-objective mathematical model consisting of economic and environmental functions. They also showed that assuming the validation of the model, a set of optimal answers can be provided by considering both economic and environmental indicators. [14] proposed a mathematical model for the location-routing problem with limited capacity, taking into account the environmental effects of the distribution system. Based on a two-objective integer linear programming problem, they showed that using more potential (active) vehicles would lead to more fuel storage in the long run and thus would lead to reduced emissions. According to their research, the higher the number of vehicles used in a short-distance distribution, the less the generated pollution, while the higher demand is in the higher priority. With the increase in human population and since stability leads to a balance between humans and their surroundings, the sustainability of planning and implementation of processes, both in production and in public services and also in territorial use would be of great importance. In a study conducted by [15], the concept of availability in order to optimize distribution processes, which was considered in the form of a vehicle routing problem, was investigated. Coverage was considered as part of a definitive global index.

One of the most important issues in vehicle routing is hazardous materials routing. In this regard, a hazardous substance can include any type of chemical, radiological or biological substances that can lead to a wide range of risks to human health, including body tissue inflammation, allergies and cancer. Hazardous materials can also cause physical problems such as ignition, rust and over-reactivity. Therefore, specific instructions for transporting hazardous materials should be proposed [16]. [17] worked on the issue of vehicle transportation (VRP) to serve the HazMat demand. The aim of their study was to minimize the exposure of people to hazardous substances by solving the VRP problem. In addition to the economic aspects of transporting hazardous materials, human and environmental indicators must also be considered in order to transport such materials. However, in the event of any accident, irreparable damage is done to the environment and humans [18]. [19] presented a two-step model that minimizes the risk of transporting hazardous materials and optimizes the length of route. [20] investigated a multi-objective transportation model of hazardous substances, used the epsilon constraint method and presented a rapid meta-heuristic in multi-objective mode. [21] provided a systematic framework for developing a hazardous materials transportation model where potential hazards are reduced at designated levels. In a study conducted by [22], a genetic algorithm was used to solve a two-objective stochastic model for the transportation, location and allocation of hazardous substances. The model used in this research was developed based on the delivery of a product to the customer and was defined only in a period of time in which each customer and each facility was allocated to only one landfill (for hazardous materials). The results showed that the management of hazardous materials transportation and proper location of waste centers for this category of materials can significantly reduce the risk of accidents and upcoming social aspects. Particular attention should be paid to reducing hazardous effects, especially those affecting the environment and safety, when it comes to management of hazardous materials. [23] developed a two-objective model for the VRP problem for transporting hazardous substances. In their model, they introduced new decision variables to describe the sequence of customers. In addition, the risk measurement of their model took into account the change in load due to the nature of the transport of hazardous materials. [24] presented a three-tier supply chain model with hazardous inventory and transportation between suppliers, factories and consumers. The aim of their research was to balance risk and cost by assuming the fuzziness of consumer demand. [25] presented a study entitled optimization of lane planning and vehicle scheduling for the distribution of hazardous substances. Their model had two general stages. In the first step, a two-level optimization algorithm was provided to design the route planning. In the first level, a set of dominant answers was obtained from the routes of distribution centers and destinations of each one, and in the next level, a multi-objective optimization method based on the NSGA-II algorithm of transportation routes was obtained. [26] defined a multi-objective function for risk-based vehicle routing for hazardous materials. They also defined an independent startup time by considering the time window in their proposed model. Finally, the model used in their research was defined as a problem of routing a vehicle with limited capacity and considering the time windows and dynamic travel times based on the phenomenon of congestion.

In addition to the above factors, considering uncertainty at different times of the day can reduce uncertainty in the management of hazardous materials transportation. [1] presented a multi-objective problem for vehicle routing with flexible time windows based on the ant colony hybrid algorithm. Flexible time windows are the windows in which customers can receive service before the earliest service time or after the latest service time, within a specified time period. [27] proposed a two-objective mathematical model for routing vehicles to transport hazardous materials. The first goal is to reduce routing costs, and the second goal is to reduce the routing risk. To solve this problem, the variable neighborhood search algorithm is used, and the results are compared with the Epsilon constraint method, which indicates the efficiency of the variable neighborhood search algorithm. [28] designed a drug logistics network as a problem of transportation of hazardous substances. In this study, a soft time window was used for drug delivery. Two meta-algorithms have been used to solve this problem, namely variable neighborhood and large neighborhood searches. The results of this research indicate the high quality of the proposed solution methods. [29] proposed a mathematical model for routing hazardous materials using GPS. In this research, first, different regions were clustered using the FCM method, then the paths of each device were obtained by optimizing the designed model. The results showed that this method could reduce transportation costs up to 82%. [30] combined the problem of equipment location and design of hazardous materials transportation network. In this study, the two-level game theory approach has been used and the amount of greenhouse gas emissions from this transportation system has been considered as uncertain. A robust optimization approach has been used to solve the model in uncertain conditions. The results of this research show the efficiency of the robust optimization method. [31] Evaluated the effective factors on green supply chain management using statistical methods and SWARA approach. Table 1 is presented to indicate the contribution of this paper clearly. Based on the review of the literature in this section, it can be stated that in the field of optimization of transportation, and especially hazardous materials, a study that is simultaneously from three perspectives of economic, route sensitivity and factors causing uncertainty in the collection time and delivery of hazardous materials has not been investigated based on available knowledge. Thus, for the first time in the literature, the issue of vehicle routing problem (particularly concerning hazardous materials) is raised with respect to the concept of route sensitivity, economies of scale and time window uncertainty. The hybrid genetic- simulated annealing algorithm is also used to solve the problem. [32] presented a new variable service rate queue model for hub median problem. [33] proposed a new method to predict the quality of umbilical cord blood units based on maternal and neonatal factors and collection techniques. [34] designied an agile sustainable closed-loop supply chain network with different sales channels.

Table 1. A comparative assessment of the previous literature.

Paper	Solution Method	Uncertainty	Capacity Constraint	Multi-Objective	Homogeneous Shipping	Non-Linear	Linear	Scale of Economy	Routing
[20]	ϵ-constraint method			√	√				√
[4]	Exact method		√		√		√		√
[21]	Field study		√	√	√				√
[7]	Exact method				√		√		√
[8]	Exact method		√				√		√
[22]	GA			√			√		√
[6]	Exact method					√			√
[11]	Exact method		√				√		√
[9]	Heuristic method		√		√		√		√
[26]	Exact method		√	√			√		√
[1]	Ant Colony		√				√		√
[27]	VNS		√	√		√			√
[28]	VNS		√				√		√
[29]	Exact method				√		√		√
[30]	Robust optimization	√	√	√		√			√
This paper	Hybrid GA-SA	√	√	√			√	√	√

3 | Mathematical Modeling

In this section, following the description of the HazMat transportation problem, we present the mathematical model considering route sensitivity and scale effects.

3.1 | Problem Description

The HazMat transportation problem involves a set of nodes representing points of hazardous material generation and disposal, each acting as a landfill for hazardous waste. To meet the demand at these points, vehicles are deployed from the landfill to collect HazMat at each node. Routes in urban areas vary depending on population density, the presence of schools, accident-prone roads, and other factors, which has led to the introduction a route sensitivity coefficient. This coefficient considers the increased sensitivity of the transported load and, consequently, the transportation costs along specific routes. Routes with a higher probability of accidents result in higher coefficients, contributing to higher transportation costs for HazMat. Factors such as the harshness of the route, the type of material being transported, and the need for special equipment or professional drivers impact sustainable transportation and insurance costs.

Regarding social and environmental sustainability, efforts are being made to reduce accidents and minimize the population's exposure to HazMat. Economic savings in freight transfer are introduced as a concept to capture the benefits resulting from increased cargo amounts, allowing the sharing of fixed costs and leading to potential economic savings. However, the cargo capacity of vehicles is limited. In addition, certain time windows, environmental conditions, and traffic fluctuations lead to uncertainties in journey times, especially when considering sensitivities to releasing HazMat and the contamination they can cause along routes. The design of collection routes and times aims to improve the resilience of the HazMat collection and transportation process to the uncertainties of time windows. HazMat transportation network planners must devise routes between recycling and generation centers that minimize overall transportation and pollution costs while considering the constraints of time windows, uncertainties, vehicle capacities, and mileage capacities in sub-tours.

3.2 | Model Assumptions

It seems like the assumptions used in the model for HazMat transportation are as follows:

I. There are multiple nodes (customers) with varying amounts of HazMat (demand), and this demand is fulfilled from HazMat depots.

II. There are a limited number of vehicles with specific capacity constraints.

III. Vehicles commence their routes from the depot, visit the nodes to collect HazMat, and then return to the depot.

IV. The model considers a single type of hazardous material with fixed value and volume.

V. Transportation costs are dependent on the distance traveled.

VI. Each vehicle incurs a specific unit cost for the pollution produced while transporting HazMat between nodes, reflecting social or environmental impacts.

It's essential to consider these assumptions when formulating the mathematical model for addressing the problem of HazMat transportation. These assumptions will be critical in determining the model's variables, constraints, and objective function.

3.3 | Notations

Indexes

i and j: customer index (i = 1, 2,…, N).

k: Index of vehicles (k = 1, 2,…, V).

d: depot index (d = 1, 2,…, D).

Parameters

N: number of customers.

V: number of vehicles available.

D: number of depots.

tr_{ij}: route traveling time (i, j).

S_j: customer service time j.

C_{ij}: route traveling cost (i, j).

CE_{ijk}: cost of environmental pollution produced by vehicle k, resulting from HazMat transportation between customers (HazMat producers) i and j.

CE_{idk}: cost of environmental pollution produced by vehicle k, resulting from HazMat transportation between customer i and depot d.

C'_{di}: cost of traveling the route (i, d) or route (d, i) between customer i and depot d.

d_i: amount of customer demand (produced hazardous material) i.

Q_k: vehicle capacity k.

M: very large positive number.

$\tilde{e}_i$: the earliest time customer service i can be started, that follows a normal distribution with mean μe_i and standard deviation σe_i.

$\tilde{l}_i$: the latest time customer service i can be started, which follows a normal distribution with mean μl_i and standard deviation σl_i.

ρ_i: penalty for violating the time window for the customer i.

γ: profit from balancing in different routes.

τ_{ij}: sensitivity coefficient of route (i, j).

τ_{id}: sensitivity coefficient of route (i, d).

Decision variables

X_{ijk}: if vehicle k crosses the path (i, j), it is equal to 1, and otherwise, it is equal to 0.

Y_{dik}: if vehicle k k crosses the path (d, i), it is equal to 1, and otherwise, it is equal to 0.

Z_{idk} : if vehicle k crosses path (i, d), it is equal to 1, and otherwise, it is equal to 0.

Δa_{ik}: the rush time of starting service for node i.

Δb_{ik}: the delay time of starting service for node i.

T_{ik}: time to reach node i with vehicle k (Service start time for node i).

β: the minimum ratio of the total transported load to the vehicle capacity between the total routes formed.

3.4 | Mathematical Model

$$\text{Min} \sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N}\sum_{k=1}^{V} \tau_{ij}X_{ijk}(C_{ij}+CE_{ijk}) + \sum_{d=1}^{D}\sum_{i=1}^{N}\sum_{k=1}^{V} Y_{dik}C'_{di} + \sum_{i=1}^{N}\sum_{d=1}^{D}\sum_{k=1}^{V} \tau_{id}Z_{idk}(C'_{di}+CE_{idk}) + \sum_{i=1}^{N}\sum_{k=1}^{V}\rho_i(\Delta a_{ik}+\Delta b_{ik}) - \gamma\beta. \quad (1)$$

$$\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} X_{ijk}d_j + \sum_{d=1}^{D}\sum_{i=1}^{N} Y_{dik}d_i}{Q_k} \geq \beta, \text{for all k.} \quad (2)$$

$$\sum_{d=1}^{D}\sum_{k=1}^{V} Y_{dik} + \sum_{\substack{j=1\\ j\neq i}}^{N}\sum_{k=1}^{V} X_{jik} = 1, \text{for all i.} \quad (3)$$

$$\sum_{\substack{j=1\\ j\neq i}}^{N}\sum_{k=1}^{V} X_{ijk} + \sum_{d=1}^{D}\sum_{k=1}^{V} Z_{idk} = 1, \text{for all i.} \quad (4)$$

$$\sum_{d=1}^{D}\sum_{i=1}^{N} Y_{dik} - \sum_{j=1}^{N}\sum_{d=1}^{D} Z_{jdk} = 0, \text{for all k.} \quad (5)$$

$$\sum_{d=1}^{D}\sum_{i=1}^{N} Y_{dik}\, d_i + \sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N} X_{ijk}\, d_j \leq Q_k, \text{for all k.} \quad (6)$$

$$\sum_{d=1}^{D} Y_{dik} + \sum_{\substack{j=1\\ j\neq i}}^{N} X_{jik} - \sum_{\substack{j=1\\ j\neq i}}^{N} X_{ijk} - \sum_{d=1}^{D} Z_{idk} = 0, \text{i for all k.} \quad (7)$$

$$\sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N} X_{ijk} \leq \left(\sum_{d=1}^{D}\sum_{i=1}^{N} Y_{dik}\right) * M, \text{for all k.} \quad (8)$$

$$T_{ik} + S_i + tr_{ij} \leq T_{jk} + M(1 - x_{ijk}), \text{for all i, j, k.} \quad (9)$$

$$\Delta a_{ik} \geq \tilde{e}_i - T_{ik}, \text{for all i, k.} \quad (10)$$

$$\Delta b_{ik} \geq T_{ik} - \tilde{l}_i, \text{for all i, k.} \quad (11)$$

$$X_{ijk} \in \{0,1\}, \text{for all i, k} \quad i \neq j. \quad (12)$$

$$Y_{dik} \in \{0,1\}, \text{for all i, k, d.} \quad (13)$$

$$z_{idk} \in \{0,1\}, \text{for all i, k, d.} \quad (14)$$

$$\Delta a_{ik}, \Delta b_{ik}, \beta, T_{ik} \geq 0, \text{for all i, k.} \quad (15)$$

Eq. (1) captures the multifaceted objective function of the model. It includes the following elements:

I. The cost of transporting HazMat and the associated pollution between customers.

II. The cost of traveling between the depot and the first customers after the move.

III. Costs associated with journeys between the last customers and the depots, including the environmental costs of transporting HazMat on these journeys.

IV. Cost accrued from not providing on-time service to customers.

V. Economic benefits derived from balancing route loads based on route sensitivities.

Eq. (2) calculates the minimum ratio of the total load carried to the vehicle's capacity over all routes. The variable β indicates the minimum value of this ratio.

The model's objective function is for this index to reach its maximum value. *Constraints (3)* and *(4)* ensure that each customer is visited only once in each period. They determine the sequence of customer visits to ensure that all customers are served. *Constraint (5)* relates to the start and end of each route, ensuring that each route starts and ends at a designated depot. The capacity of each vehicle is addressed by *constraint* (6), which ensures that the total demand of customers on a route by each vehicle does not exceed the vehicle's capacity. *Constraint (7)* requires the input and output to each customer to be equal for each vehicle, with each customer being served by only one route. *Constraint (8)* ensures that a vehicle can cross an edge if it has started its journey from a depot. *Constraint (9)* relates to the time vehicles take to reach each point, preventing sub-tours and establishing an efficient route based on time considerations. *Constraints (10)* and *(11)* are associated with time windows for service provision, ensuring that service is provided within specified time intervals. *Constraints (12)-(15)* relate to the allowable values for the decision variables. These constraints allow uncertainty in the time windows to be taken into account by following a normal distribution with a specified confidence level, as indicated by the replacement of *constraints (10)* and *(11)* by *constraints (16)* and *(17)* at the confidence level.

Together, these equations and constraints form a robust mathematical modeling framework to address the complex requirements and considerations of transporting dangerous goods, considering economic, logistical, and time-sensitive factors. If you have specific aspects of the equations or constraints you would like to discuss further, please provide additional details.

$$\Delta b_{ik} \geq \mu e_i + Z_\alpha \sigma e_i - T_{ik}, \text{ for all } i, k. \quad \textbf{(16)}$$

$$\Delta b_{ik} \geq T_{ik} - \mu l_i - Z_\alpha \sigma l_i, \text{ for all } i, k. \quad \textbf{(17)}$$

4 | Hybrid Genetic-Simulated Annealing Algorithm

It appears that you have a well-defined hybrid algorithm that combines Genetic Algorithm (GA) and Simulated Annealing (SA) to optimize the proposed mathematical model for transporting dangerous goods. The algorithm initially uses a GA approach by generating a set of random solutions and then applying crossover and mutation operators at each iteration. However, if the best solution found in the last 10 generations does not change, indicating a lack of improvement, the algorithm switches to SA. At this stage, the best solution found by the GA becomes the input to the SA algorithm, and a neighborhood is created from it based on the characteristics of the SA algorithm. This hybrid approach combines the exploration capabilities of GA s with the local search and optimization properties of SA, resulting in a more robust and adaptive optimization process. If you require further assistance with specific steps to implement this proposed algorithm, such as details on the GA operators, the SA process, or the integration of the two methods, please feel free to share more details, and I can provide further guidance.

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Step 0. Determine a method for presenting the solution appropriate to the problem at hand.

Step 1. Generate an initial set of random responses (called the initial population).

Step 2. Repeat the following steps until the maximum number of iterations is reached.

Step 3. Execute the crossover operator as described in Section 4.2.

Step 4. Run the mutation operator as described in Section 4.3.

Step 5. Proceed to *Step 6* if there has been no improvement in the crossover and mutation operators in the last 10 iterations; otherwise, return to *Step 3*.

Step 6. Use the SA algorithm to produce a solution that is close to the best solution found. The steps to do this are outlined in Section 4.1.

Step 7. Present the best solution obtained by the hybrid algorithm.

Representing each valid solution to the problem as a numerical vector is essential. In this study, each solution to the problem consists of a vector representing the path of each machine. In addition, a cell with the value 0 is inserted between the paths to mark their differences. For example, in the scenario with 4 customers and 2 depots, the depots are represented by numbers 1 and 2, while the customers are represented by numbers 3 to 6. An illustration of a solution to this problem is shown in *Table 2*.

Table 2. An example of a problem-solving string.

1	4	5	2	0	2	3	6	2

According to *Table 2*, the path created for the first vehicle is 1-4-5-2, and for the second vehicle, it is 2-3-6-2. It should be noted that if the capacity limit is exceeded, a penalty is applied to the objective function (penalty method in the development of meta-heuristic algorithms).

4.1 | Creating a Neighborhood based on the Process of Simulated Annealing Algorithm

The purpose of this phase is to make a sudden change to the existing response. For this purpose, 3 methods are considered. In the first method, a point from one path changes completely and randomly with a point in another path. The second method uses two points. In the third method, two points of one path are exchanged with two points of the other.

4.2 | Crossover Operator in Genetic Algorithm

In this crossover method, it is assumed that the grid is defined as $j \in \{1, \dots, i, i+1, \dots, j, j+1, \dots, n\}$. By removing two edges $(i, i+1), (j, j+1)$ and adding two edges $(i, j), (i+1, j+1)$, this algorithm creates a neighborhood for the current grid. This method examines the possible values of i and j, $j, i \in \{1,2, \dots, n-2\}$ and $j \in \{i+2, \dots, n\}$, and selects the best change in the objective function respective. *Fig. 1* shows an example of this operator.

4.3 | Mutation Operator in Genetic Algorithm

Two network points are selected in this mutation method, and their positions on the visited points' paths are exchanged. An example of this operator is shown in *Fig. 2*.

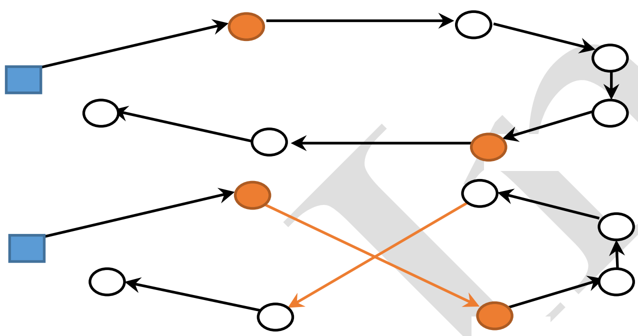

Fig. 1. Example of the crossover operator.

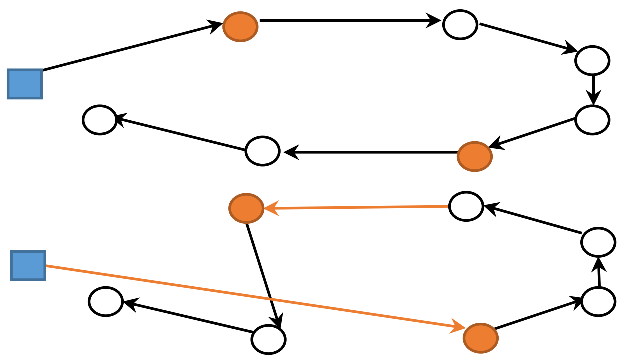

Fig. 2. Example of the mutation operator.

5 | Numerical Analysis and Sensitivity Analysis

To validate the mathematical model, we present the numerical results obtained by optimizing the model and carrying out a sensitivity analysis on the main model parameters. First, a problem was generated under the following conditions: A transport network consists of a depot and 6 customers to be visited. In addition, 2 vehicles with a capacity of 40 units are assigned to collect HazMat from these 6 customers. It is assumed that each customer has a demand of 10 units. The cost of pollution from customers to depots is assumed to be zero. The average lower and upper bounds of each customer's time window are 1 and 100, respectively, with a standard deviation of 0.5-time units. The service duration at each customer location is estimated to be 0.5 time units. For other parameters, both lower and upper limits are defined. Based on these limits, different values are generated and treated as the final value of the parameter. The range of values generated is shown in *Table 3* for reference.

Table 3. Model inputs in the validation example.

Parameter	Upper Line	Lower Line
Duration of travel	4	2
Travel expenses between customers	7	3
Travel costs from depot to customers	6	4
Cost of environmental pollution between customers	3.5	0.5
Path sensitivity	2.5	1

After entering this information as model inputs into the GAMS optimizer software, the optimal model response is obtained after 12 iterations, and the final solution is 48.054053. *Fig. 3* shows the paths generated in the network.

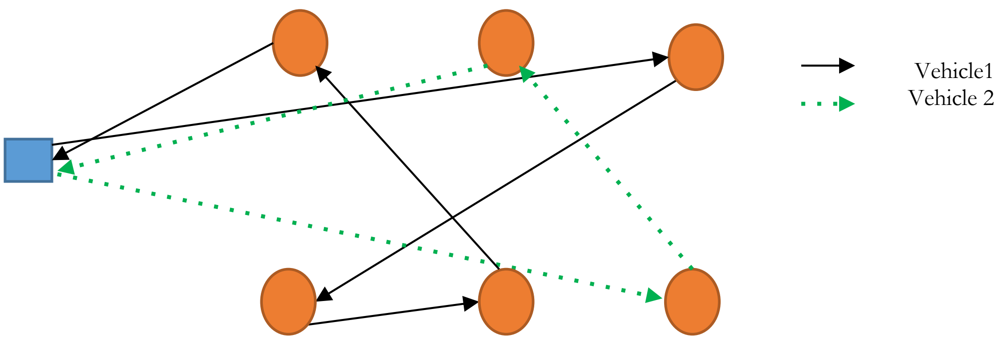

Fig. 3. Routes formed in the optimal answer.

Fig. 3 shows that the first vehicle starts its route from the depot, visits customers 3, 6, 5, and 1 in that order, and then returns to the depot. Meanwhile, the second vehicle starts its route from the depot, visits customers 4 and 2, and then returns to the depot. Vehicle 1 uses its full capacity of 40 units, while vehicle 2 uses only 20 units of its capacity. As a result, the vehicle's capacity limit is not exceeded. The generated routes are meticulously determined and logically sound, with no sub-networks created. These results underline the accuracy of the proposed mathematical model. After validating the mathematical model, evaluating the effectiveness of the solution methods is essential. In this study, the exact solution of the mathematical model is obtained using the GAMS environment, while the GA-SA algorithm in the Matlab environment serves as an approximate solution method. For this purpose, 20 instances are generated with different dimensions and data values consistent with the validation example, as detailed in *Table 4*. These 20 instances are subjected to an implementation using both the GAMS software and the GA-SA algorithm. The corresponding results are shown in *Table 5*. In particular, given the operational nature of the routing problem, each solution method is expected to deliver its objective function value within a reasonable time frame. Therefore, a time constraint of 1 hour is enforced for both methods.

Table 4. Dimensions of generated examples.

Example number	N	D	V
P1	6	1	2
P2	8	2	2
P3	10	2	3
P4	12	4	4
P5	14	4	5
P6	16	6	6
P7	18	6	7
P8	20	8	8
P9	22	8	9
P10	24	10	10
P11	26	10	11
P12	28	12	12
P13	30	12	13
P14	32	14	14
P15	34	14	15
P16	36	16	16
P17	38	16	17
P18	40	18	18
P19	45	18	19
P20	50	20	20

In *Table 4*, N is the number of points, D is the number of depots, and V is the number of vehicles. In *Table 5*, Z is the value of the objective function, Time is the solution time of the desired method in seconds, and GAP is the relative error of the GA-SA algorithm, which is calculated as follows:

$$\mathrm{GAP} = \frac{Z_{\mathrm{GA-SA}} - Z_{\mathrm{GAMS}}}{Z_{\mathrm{GAMS}}} \times 100. \tag{18}$$

Table 5. Results of implementing examples produced by two solution methods.

GA-SA			GAMS		Example Number
GAP	Time	Z	Time	Z	
0.00%	0.96	48.05	0.74	48.05	1
0.00%	1.23	50.88	1.79	50.88	2
0.00%	1.96	63.71	12.54	63.71	3
0.00%	2.16	83.97	21.68	83.97	4
0.00%	2.45	115.18	58.61	115.18	5
1.21%	2.88	162.28	79.33	160.34	6
1.28%	3.26	175.89	113.42	173.66	7
1.86%	3.64	221.39	254.85	217.35	8
2.35%	4.72	351.51	347.68	343.44	9
1.83%	5.19	476.93	482.51	468.36	10
2.95%	6.92	673.57	599.87	654.27	11
2.73%	8.07	708.38	750.13	689.56	12
3.56%	8.19	691.30	904.63	667.53	13
2.88%	9.73	899.74	1132.11	874.55	14
3.80%	10.28	1102.99	1924.87	1062.61	15
3.70%	11.45	1288.51	2684.14	1242.54	16
4.19%	12.86	1640.59	3600	1574.61	17
3.69%	15.12	2144.97	3600	2068.63	18
4.19%	17.55	2451.37	-	-	19
4.93%	20.71	3114.92	-	-	20
2.26%	7.4665	823.3066866	920.494	586.6253876	Average

The results show that the GA-SA algorithm had an average error of about 2.26%. The highest error rate recorded for this algorithm is 4.93%. While the average GA-SA solution time is about 7.46 seconds, the GAMS software has an average time of 920.494 seconds. To better understand this issue, *Fig. 4* compares the solution times of the two methods, and *Fig. 5* shows the value of the objective function of the two methods on different examples.

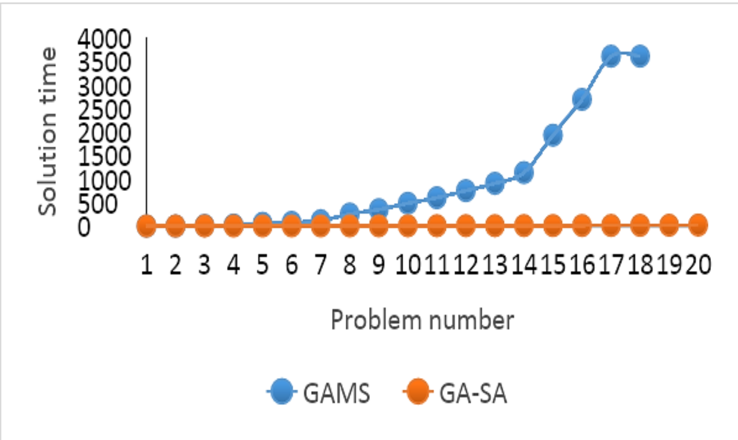

Fig. 4. Comparing the solution time of the two methods.

As shown in *Fig. 4*, the solution time of GAMS shows an exponential increase. This characteristic is attributed to routing problems belonging to the NP-HARD category. In such problem domains, solution times increase dramatically as the problem dimensions increase. Consequently, GAMS is not an efficient method for solving large mathematical models. Conversely, the GA-SA algorithm shows a remarkably short solution time, with a very low slope in increasing its solution time. It emphasizes the algorithm's effectiveness in providing fast solutions, especially compared to GAMS for handling larger mathematical models.

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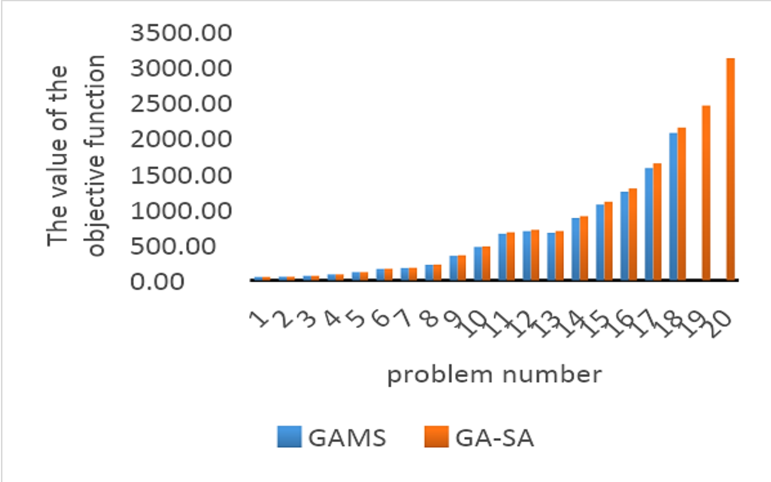

Fig. 5. Comparing the value of the objective function of the two methods.

Fig. 5 shows that the GAMS software failed to solve the last 2 problems within the 1-hour time limit. In addition, the GA-SA algorithm showed zero error in the first 5 examples and minimal error in the remaining instances. Therefore, the GA-SA algorithm shows high efficiency in quickly providing solutions that are very close to the optimal solution, indicating exceptional performance speed and solution quality. Sensitivity analysis aims to explore the influence of a parameter on the value of the objective function. This study selected two critical parameters, namely demand and route sensitivity coefficient, for sensitivity analysis. The default value of each parameter varied between -30 and +30, and the resulting objective function values were documented. The results of the demand sensitivity analysis are presented in *Table 6* and *Fig. 6*, while the results of the sensitivity analysis of the route sensitivity coefficient parameter are presented in *Table 7* and *Fig. 7*.

Table 6. Demand sensitivity analysis.

Percentage of demand fluctuations	**-30**	**-20**	**-10**	**0**	**10**	**20**	**30**
The value of the objective function	48.04	48.06	48.08	48.05	48.54	48.48	49.49

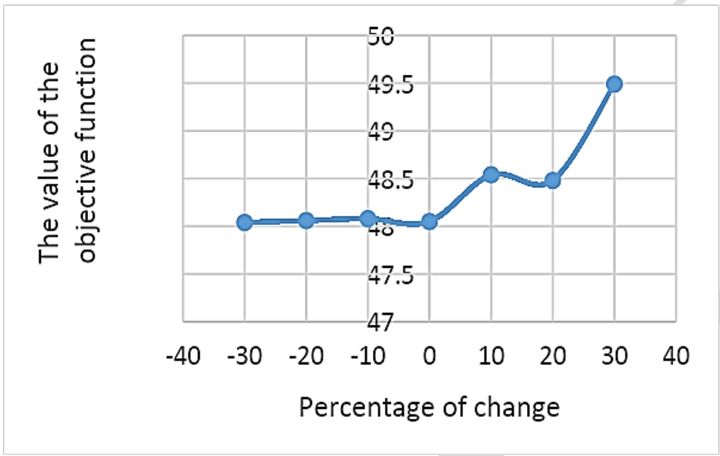

Fig. 6. Demand sensitivity analysis chart.

The non-linear effect of demand on the value of the objective function is shown in *Fig. 6*. While the overall trend is upward, there are instances where it is downward. This behavior is due to the fact that an increase in demand leads to an increase in costs but, at the same time, increases revenue through offsetting. If the additional revenue exceeds the additional costs, a downward trend is observed; conversely, if the costs exceed the additional revenue, an upward trend is observed. *Fig. 6* shows that the additional revenue exceeds the additional costs only with a 20% increase in demand.

Table 7. Percentage of fluctuation of route sensitivity coefficient.

Percentage of Oscillation of Path Sensitivity	-30	-20	-10	0	10	20	30
The value of the objective function	42.93	44.69	46.72	48.05	50.53	52.79	53.19

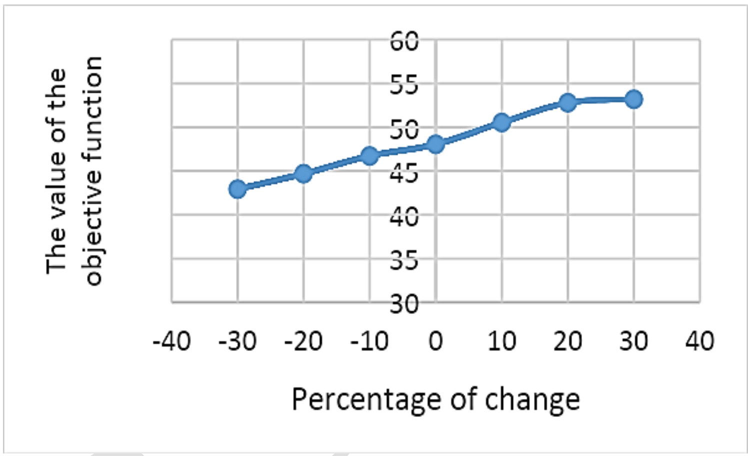

Fig. 7. Route sensitivity coefficient sensitivity analysis chart.

In *Fig. 7*, it is observed that as the route sensitivity coefficient increases, the value of the objective function also increases. According to the mathematical model, an increase in route sensitivity results in a higher variable amount of routing costs, leading to the incremental behavior observed in the value of the objective function.

6 | Conclusion

This study has undertaken a review of the most recent and cutting-edge literature in the field of vehicle routing. The review revealed that a significant research gap in this area is the incorporation of route sensitivity, economies of scale, and time window uncertainty in transporting HazMat. As a result, a new mathematical model for the routing of HazMat was developed with key assumptions. The objective was to determine the optimal route for a fleet of transports across multiple depots with limited capacity, considering path sensitivity and economies of scale in the model parameters and constraints. In addition, the aspect of time window uncertainty, characterized by a specific mean and variance, required adjustments to certain elements of the mathematical model. Subsequently, to optimize this model, the exact solution was computed using the GAMS software, while an approximate solution was derived in the Matlab environment using the GA-SA algorithm. Due to its robust local search capabilities, this algorithm skillfully explores the solution space and ultimately identifies the best possible solution. In presenting the numerical results, the model was first validated, demonstrating the structural integrity and rationality of the model relationships and the reliability of its results. Subsequently, 20 different instances were generated in various dimensions, and the responses obtained by GAMS and the GA-SA algorithm were compared. The results underlined the ability of the GA-SA algorithm to provide the most accurate solution in the shortest time.

To advance this research, the following suggestions are made:

I. Include the objective function of minimizing pollution as an independent metric.

II. Introducing the objective function of increasing employment opportunities in transporting HazMat.

III. Use precise solution methods such as branch and bound and branch and cut algorithms.

IV. Incorporating intermittent uncertainty and using a robust optimization approach

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Conflicts of Interest

The researchers certify that the work submitted is original and is not under consideration for publication elsewhere, indicating that there are no conflicts of interest.

References

[1] Zhang, H., Zhang, Q., Ma, L., Zhang, Z., & Liu, Y. (2019). A hybrid ant colony optimization algorithm for a multi-objective vehicle routing problem with flexible time windows. *Information sciences*, *490*, 166–190. https://www.sciencedirect.com/science/article/pii/S002002551632120X

[2] Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem. *Management science*, *6*(1), 80–91. https://doi.org/10.1287/mnsc.6.1.80

[3] Sbihi, A., & W. Eglese, R. (2007). *The relationship between vehicle routing & scheduling and green logistics - a literature survey*. (**In Persian**). https://hal.science/hal-00644133

[4] Pokharel, S., & Mutha, A. (2009). Perspectives in reverse logistics: a review. *Resources, conservation and recycling*, *53*(4), 175–182. https://www.sciencedirect.com/science/article/pii/S0921344908002024

[5] Govindan, K., Jafarian, A., & Nourbakhsh, V. (2015). Bi-objective integrating sustainable order allocation and sustainable supply chain network strategic design with stochastic demand using a novel robust hybrid multi-objective metaheuristic. *Computers & operations research*, *62*, 112–130. https://www.sciencedirect.com/science/article/pii/S030505481500009X

[6] Govindan, K., Soleimani, H., & Kannan, D. (2015). Reverse logistics and closed-loop supply chain: a comprehensive review to explore the future. *European journal of operational research*, *240*(3), 603–626. https://www.sciencedirect.com/science/article/pii/S0377221714005633

[7] Bektaş, T., & Laporte, G. (2011). The pollution-routing problem. *Transportation research part b: methodological*, *45*(8), 1232–1250. https://www.sciencedirect.com/science/article/pii/S019126151100018X

[8] Xiao, Y., Zhao, Q., Kaku, I., & Xu, Y. (2012). Development of a fuel consumption optimization model for the capacitated vehicle routing problem. *Computers & operations research*, *39*(7), 1419–1431. https://www.sciencedirect.com/science/article/pii/S0305054811002450

[9] Kazemian, I., & Aref, S. (2017). A green perspective on capacitated time-dependent vehicle routing problem with time windows. *International journal of supply chain and inventory management*, *2*(1), 20–38. https://www.inderscienceonline.com/doi/abs/10.1504/IJSCIM.2017.086372

[10] Madankumar, S., & Rajendran, C. (2018). Mathematical models for green vehicle routing problems with pickup and delivery: a case of semiconductor supply chain. *Computers & operations research*, *89*, 183–192. https://www.sciencedirect.com/science/article/pii/S0305054816300636

[11] Xiao, Y., & Konak, A. (2016). The heterogeneous green vehicle routing and scheduling problem with time-varying traffic congestion. *Transportation research part E: logistics and transportation review*, *88*, 146–166. https://www.sciencedirect.com/science/article/pii/S1366554516000193

[12] Turkensteen, M., & Hasle, G. (2017). Combining pickups and deliveries in vehicle routing – an assessment of carbon emission effects. *Transportation research part C: emerging technologies*, *80*, 117–132. https://www.sciencedirect.com/science/article/pii/S0968090X17301122

[13] Wang, Y., Zhang, S., Assogba, K., Fan, J., Xu, M., & Wang, Y. (2018). Economic and environmental evaluations in the two-echelon collaborative multiple centers vehicle routing optimization. *Journal of cleaner production*, *197*, 443–461. https://www.sciencedirect.com/science/article/pii/S0959652618318584

[14] Toro, E. M., Franco, J. F., Echeverri, M. G., & Guimarães, F. G. (2017). A multi-objective model for the green capacitated location-routing problem considering environmental impact. *Computers & industrial engineering*, *110*, 114–125. https://www.sciencedirect.com/science/article/pii/S0360835217302176

[15] Ibarra-Rojas, O. J., Hernandez, L., & Ozuna, L. (2018). The accessibility vehicle routing problem. *Journal of cleaner production*, *172*, 1514–1528. https://www.sciencedirect.com/science/article/pii/S0959652617325532

[16] Pamučar, D., Ljubojević, S., Kostadinović, D., & Đorović, B. (2016). Cost and risk aggregation in multi-objective route planning for hazardous materials transportation—a neuro-fuzzy and artificial bee colony

approach. *Expert systems with applications*, *65*, 1–15. https://www.sciencedirect.com/science/article/pii/S0957417416304183

[17] Tarantilis, C. D., & Kiranoudis, C. T. (2001). Using the vehicle routing problem for the transportation of hazardous materials. *Operational research*, *1*(1), 67–78. https://doi.org/10.1007/BF02936400

[18] Zografos, K. G., & Androutsopoulos, K. N. (2004). A heuristic algorithm for solving hazardous materials distribution problems. *European journal of operational research*, *152*(2), 507–519. https://www.sciencedirect.com/science/article/pii/S0377221703000419

[19] Kara, B. Y., & Verter, V. (2004). Designing a road network for hazardous materials transportation. *Transportation science*, *38*(2), 188–196. https://doi.org/10.1287/trsc.1030.0065

[20] Bérubé, J. F., Gendreau, M., & Potvin, J. Y. (2009). An exact ϵ-constraint method for bi-objective combinatorial optimization problems: application to the traveling salesman problem with profits. *European journal of operational research*, *194*(1), 39–50. https://www.sciencedirect.com/science/article/pii/S0377221707012106

[21] Kazantzi, V., Kazantzis, N., & Gerogiannis, V. C. (2011). Risk informed optimization of a hazardous material multi-periodic transportation model. *Journal of loss prevention in the process industries*, *24*(6), 767–773. https://www.sciencedirect.com/science/article/pii/S0950423011000751

[22] E rdjmand, E., Weckman, G., Park, N., Taherkhani, P., & Singh, M. (2015). Applying genetic algorithm to a new location and routing model of hazardous materials. I*nternational journal of production research*, *53*(3), 916–928. https://doi.org/10.1080/00207543.2014.942010

[23] Yuan, W., Wang, J., Li, J., Yan, B., & Wu, J. (2018). Two-stage heuristic algorithm for a new model of hazardous material multi-depot vehicle routing problem. *Advances in computational intelligence systems* (pp. 362–366). Springer. https://doi.org/10.1007/978-3-319-66939-7_32

[24] Hu, H., Li, J., & Li, X. (2018). A credibilistic goal programming model for inventory routing problem with hazardous materials. *Soft computing*, *22*(17), 5803–5816. https://doi.org/10.1007/s00500-017-2663-y

[25] Chai, H., He, R., Ma, C., Dai, C., & Zhou, K. (2017). Path planning and vehicle scheduling optimization for logistic distribution of hazardous materials in full container load. *Discrete dynamics in nature and society*, *2017*, 9685125. https://doi.org/10.1155/2017/9685125

[26] Cuneo, V., Nigro, M., Carrese, S., Ardito, C. F., & Corman, F. (2018). Risk based, multi objective vehicle routing problem for hazardous materials: a test case in downstream fuel logistics. *Transportation research procedia*, *30*, 43–52. https://www.sciencedirect.com/science/article/pii/S2352146518300772

[27] Bula, G. A., Murat Afsar, H., González, F. A., Prodhon, C., & Velasco, N. (2019). Bi-objective vehicle routing problem for hazardous materials transportation. *Journal of cleaner production*, *206*, 976–986. https://www.sciencedirect.com/science/article/pii/S0959652618329615

[28] Bouziyane, B., Dkhissi, B., & Cherkaoui, M. (2020). Multiobjective optimization in delivering pharmaceutical products with disrupted vehicle routing problem. *International journal of industrial engineering computations*, *11*(2), 299–316. http://growingscience.com/beta/ijiec/3543-multiobjective-optimization-in-delivering-pharmaceutical-products-with-disrupted-vehicle-routing-problem.html

[29] Zhao, H., Qian, D., Lv, Y., Zhang, B., & Liang, R. (2020). Development of a global positioning system data-based trip-purpose inference method for hazardous materials transportation management. *Journal of intelligent transportation systems*, *24*(1), 24–39. https://doi.org/10.1080/15472450.2019.1615487

[30] Liu, X., & Kwon, C. (2020). Exact robust solutions for the combined facility location and network design problem in hazardous materials transportation. *IISE transactions*, *52*(10), 1156–1172. https://doi.org/10.1080/24725854.2019.1697017

[31] Nasiri, A., Mansory, A., & Mohammadi, N. (2022). Evaluating of effective factors on green supply chain management using statistical methods and SWARA approach. *International journal of research in industrial engineering*, *11*(2), 165–187. https://www.riejournal.com/article_144942.html

[32] Saeedi, S., Poursabzi, O., Ardalan, Z., & Karimi, S. (2023). A variable service rate queue model for hub median problem. *Journal of applied research on industrial engineering*, *10*(2), 155–166. DOI:10.22105/jarie.2021.301634.1372

[33] Jamshidi, R., Rajabpour Sanati, S., & Zarrabi, M. (2023). A new method to predict the quality of umbilical cord blood units based on maternal and neonatal factors and collection techniques. *Journal of applied research on industrial engineering*, *10*(2), 218–237. https://www.journal-aprie.com/article_138375.html

[34] Tajani, E. K., Kanafi, A. G., Daneshmand-Mehr, M., & Hosseinzadeh, A. A. (2022). Robust design of an agile sustainable closed-loop supply chain network with different sales channels. *Journal of decisions & operations research*, *7*(1).