The University of Tehran Press

**Interdisciplinary Journal of Management Studies (IJMS)**
Home Page: https://ijms.ut.ac.ir

Online ISSN: 2981-0795

# Providing a Robust Heterogeneous Vehicle Fleet Routing Model Based on Artificial Intelligence of Things (AIoT)

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## ARTICLE INFO

**Article type:**
Research Article

**Article History:**
Received 09 September 2023
Revised 23 January 2024
Accepted 02 February 2024
Published Online 18 September 2024

## Keywords:

*Vehicle routing,*
*Artificial intelligence of things,*
*Soft time window,*
*Green logistics,*
*Robust optimization method.*

## ABSTRACT

This paper introduces a novel bi-objective routing model based on Artificial Intelligence of Things (AIoT) principles. Our model not only aims to minimize vehicle transportation costs and prevent time window violations but also endeavors to mitigate environmental pollutants. This study addresses the complex challenge of optimizing routes for heterogeneous vehicle fleets usingAIoT technology. Analyzing the bi-objective model using AI tools (MOSCA and NSGA II), we unveil a fascinating trade-off: as energy consumption decreases, system costs increase. Employing robust optimization techniques, we validate the model's performance under pessimistic conditions characterized by rising uncertainty rates. Notably, heightened uncertainty correlates with increased objective function values. Through a series of diverse test cases, we observe that MOSCA demonstrates superior efficiency, notably outperforming in NP, MD, and T indices. Our findings offer valuable insights for practitioners, policymakers, and researchers in the domains of transportation optimization, AIoT, and environmental sustainability.

**Cite this article:** Ghaderi , A.; Ghahremani Nahr, J. & Safari, S. (2024). Providing a Robust Heterogeneous Vehicle Fleet Routing Model Based on Artificial Intelligence of Things (AIoT). *Interdisciplinary Journal of Management Studies* (*IJMS*), 17 (4), 1173-1188. DOI: http//doi.org/10.22059/ijms.2024.366021.676227

 **Publisher:** University of Tehran Press.
DOI: http//doi.org/10.22059/ijms.2024.366021.676227

## 1. Introduction

The economies of countries are based on production and these products must reach the consumer market; therefore, transportation is the main pillar in the economic cycle of a country. However, in addition to meeting the needs of access to its demand, the society needs a healthy environment to thrive. Concerns about how transportation is harming our environment are increasing, and according to studies, transportation is the largest source of pollution in logistics (Ghahremani-Nahr, Nozari et al., 2023). Transportation activities have many harmful effects on the environment, including pollution caused by greenhouse gas emissions from vehicles and traffic caused by them. The integration of green logistics and vehicle routing allows us to reduce the harmful environmental effects while achieving economic costs (Ahmad & Yousefikhoshbakht, 2023). On the other hand, for the area of vehicle routing problems with delivery time windows, there are many real-world applications that have the task of delivering and providing a service within a certain period of time. These services may cause increasingly irreparable damage to the environment due to the urgency to meet customer demands (Fadda et al., 2023). Pollution caused by transportation, such as carbon dioxide, which leads to the intensification of greenhouse gases, and carbon monoxide, which is combined in the blood and is harmful to human health , has increased the focus on green vehicle routing issues (Hemmelmayr et al., 2012).

Globalization has led production units to use different depots to distribute their products. The absence of a depot to distribute products can greatly increase transportation costs and is thus not economical (Stodola, 2020). As a result, in this type of problem, there is at least one depot, each serving a set of customers. The purpose of these types of issues is to determine the appropriate transportation route and provide services to customers assigned to the depot in alignment with the company's goals. This means, in what order and at what time the vehicle will serve the customers and then return to the depot (Ghahremani Nahr, Ghaderi, Kian, 2023). Failure to make appropriate strategic and tactical decisions, in addition to increasing network costs, leads to an increase in the amount of greenhouse gas emissions due to the increase in the length of the route. From social aspects, it can also lead to more congestion, traffic, and noise. Also, one of the important topics in this paper is the timely delivery of products to customers in a predefined time window. Therefore, in addition to determining the optimal route for the transfer of products, the model should not deliver its goods outside the time window; otherwise, a penalty will be added to the objective function.

With the emergence of new technologies such as the IoT and AI, the transportation industry has also been affected (Aliahmadi et al., 2022). The IoT means connecting everything to the Internet. Supply chain actors use IoT tools, such as electronic devices and software, sensors and actuators to reduce transportation and production costs, increase productivity, reduce product delivery time, etc. The simultaneous use of IoT and AI tools has created a new concept called Artificial Intelligence of Things (AIoT), which has improved the performance of the supply chain. This research investigates the location-dependent vehicle routing problem with soft time windows, considering its environmental effects under uncertainty based on artificial intelligence of objects. In this research, harmful environmental impacts are minimized by reducing the energy consumption of vehicles. This issue leads to the complexity of the problem by integrating robust optimization to control uncertain parameters of demand and transportation costs. Therefore, AI tools (NSGA II and MOSCA) have been used to solve the problem.

## 2. Literature Review

Breunig et al. (2019) introduced an algorithm for the two-level vehicle routing problem and examined its results with an exact algorithm. Yan et al. (2019) dealt with making strategic and tactical decisions in the two-level vehicle routing problem. Anderluh et al. (2020) presented an exact solution for the two-level vehicle routing problem where the problem parameters were under uncertainty. Ji et al. (2020) modeled an inventory routing problem for perishable products with a time window constraint. They used robust programming method to control uncertainty parameters. Vakili et al. (2021) investigated a green open location routing problem with simultaneous pickup and delivery to minimize public costs and improve the environmental index's desirability in terms of $CO_2$ emission costs and fuel consumption. Tirkolaee et al. (2021) investigated a multilevel vehicle location-routing problem under demand uncertainty. To do this, they presented a model to determine optimal locations for factories and warehouses. Liu and Jiang (2022) modeled a two-level vehicle routing problem with simultaneous pickup and delivery. In this case, the delivery of cargo from the depot to the customers is managed by transporting the cargo through intermediate satellites. Nozari et al. (2022) modeled a multi-warehouse routing model where demand and transportation costs were considered as fuzzy numbers. Jia et al. (2023) addressed the optimization of vehicle routing from multiple distribution centers referred to as depots. This issue included determining the appropriate transportation route from warehouses to satellites and delivery from satellites to final customers. Sutrisno and Yang (2023) investigated a bilevel routing-location problem with the objective of reducing total costs. In this context, in addition to routing mobile satellites to provide services to customers, the location of parking lots was also considered. Dumez et al. (2023) presented a different integer linear programming mathematical model for the bilevel vehicle routing problem focusing on the simultaneous collection and delivery of goods. Liu et al. (2023) presented a novel approach to the two-level vehicle routing problem for an electronic grocery delivery network. Their goal in presenting this approach was to simultaneously optimize the total costs and the amount of greenhouse gas emissions. Perwira Redi et al. (2023) developed a two-stage stochastic program for designing delivery networks under demand uncertainty that decomposed the problem into strategic and operational decisions. They used the sample average approximation (SAA) method to solve large-scale sample problems. Rahmanifar et al. (2023) proposed a two-echelon WMS to minimize operational costs and environmental impact by utilizing the industry 4.0 concept. Both models utilize modern traceability Internet of Things-based devices to compare real-time information of waste level in bins and separation centers with the threshold waste level (TWL) parameter. Tavana et al. (2023) designed Artificial Internet of Things (AIoT)-enabled sustainable supply chain network to increase network performance and create a secure and traceable environment. Wang et al. (2023) introduced the multi-compartment electric vehicle routing problem with time windows and temperature and humidity settings. In this paper, a hybrid adaptive large neighborhood search and tabu search heuristic is developed. Kuo et al. (2023) proposed a mathematical model for a multi-objective VRP with time windows, as well as an MOPSO algorithm to solve it. Based on the computational results, the improved MOPSO has the highest hypervolume and lowest spacing. Liu et al. (2023) modeled the time-dependent green vehicle routing problem with time windows, aiming to minimize carbon emissions. Accordingly, the first exact method based on a branch-cut-and-price (BCP) algorithm is proposed for solving the model. The results show the effectiveness of the proposed exact method in solving model instances involving up to 100 customers. Wu et al. (2024) proposed a neighborhood comprehensive learning particle swarm optimization to solve VRPTW. They introduced a new remove-reinsert neighborhood search mechanism, which consists of a removal operator and a reinsert operator. The results illustrated that the proposed algorithm outperforms or can compete with the majority of other three PSO variants, as well as other state-of-the-art algorithms. Lera-Romero et al. (2024) introduced a general version of the Time-Dependent Electric Vehicle Routing Problem with Time Windows, which incorporates the time-dependent nature of the transportation network in terms of both travel times and energy consumption. Based on extensive computational experiments, they showed that the approach is very effective in solving instances with up to 100 customers.

In Table (1), some of the most important papers published in this field have been reviewed.

Today, despite the dangers faced by mankind, the earth is becoming an uninhabitable place for humans. Therefore, for a peaceful and humanitarian life, environmental goals should also be included as a new responsibility in the main goals of economic enterprises. The routing models presented in the literature have paid little attention to this matter, and economic enterprises only intend to achieve their own goals. Therefore, the purpose of the upcoming research is to study and investigate the problem of vehicle routing based on artificial intelligence of objects, taking into account the time window and environmental considerations. In this paper, two objective functions are employed: minimizing total costs and minimizing the amount of energy consumed by the considered vehicles. A robust method is utilized to control the uncertainty parameters of demand and transportation cost.

**Table 1.** Review of the Most Important Papers on Vehicle Routing

| Author | Objective(s) | Location | Time Window | Model | Uncertainty Parameter | Control Method | AIoT | Solution Aprroach |
|---|---|---|---|---|---|---|---|---|
| Tirkolaee et al. (2021) | MCT | * | – | U | De | RP | - | Exact |
| Dellaert et al. (2021) | MCT | – | * | D | - | - | - | Meta |
| Huang et al. (2021) | MCT | * | – | D | - | - | - | Meta |
| Goli et al. (2022) | MCT | – | * | D | - | - | - | Meta |
| Zhou et al. (2022) | MCT | – | * | D | – | – | - | Meta |
| Nozari et al. (2022) | MCT, MPT | * | – | U | De-Tr | FP | - | Exact |
| Perwira Redi et al. (2023) | MTT | – | – | D | – | – | - | Exact |
| Du et al. (2023) | MCT | – | – | D | – | – | - | Heuristic |
| Akbay et al. (2023) | MCT | – | – | D | – | – | - | Meta-Exact |
| Sutrisno & Yang (2023) | MCT | * | – | D | – | – | - | Meta-Exact |
| Hajghani et al. (2023) | MCT, MPT, MST | * | – | U | Tr,Cp | RFP | - | Meta-Exact |
| Yan et al. (2023) | MCT | * | – | U | De | FP | - | Meta |
| Partovi et al. (2023) | MCT | * | – | U | De | SP | - | Exact |
| Khodashenas et al. (2023) | MCT, MPT, MWT | * | * | U | Dr, Tr | RFP | - | Meta |
| Ji et al. (2024) | MCT | - | * | D | - | - | - | Exact |
| Zhang, Chen et al. (2024) | MCT, MPT | * | * | U | Tr | SP | - | Meta |
| Zhang, Che & Liang (2024) | MCT | * | * | D | - | - | - | Meta |
| This Paper | MCT, MET | – | * | U | De ,Tr | RP | * | Meta-Exact |

Min Total Time (MTT); Min Total Cost (MCT); Min Total Co2 (MPT); Max Social Responsibility (MST); Min Work Time (MWT); Min Total Energy (MET); Uncertainty (U); Deterministic (D); Stochastic Programming (SP); Robust-Fuzzy programming (RFP); Fuzzy Programming (FP); Demand (D); Transportation Cost (Tr); Capacity (Cp); Robust Optimization (RP)

## 3. Problem Definition

In this section, a model for the location-dependent heterogeneous fleet vehicle routing problem with a soft time window is presented. The investigated problem, according to Figure (1), is a set of $N = \{0,1,\ldots,n,n+1\}$ nodes in an undirected graph $G = (N,A)$. Node 0 and n+1 represent the warehouse at the start and end of the tour, respectively, and the remaining nodes represent the customers' locations. The set of arcs $A = \{(i,j)|i,j \in N\}$ represents the possible trips between the warehouse and customers. In this problem, $K = \{1,\ldots,k\}$ represents the collection of heterogeneous vehicles with different capacities. Each customer in this graph can only be served by a subset of vehicles within a predefined time window. These limitations are referred to as compatibility or location-dependent constraints. This scenario will occur in real-world situations when customer demand requires a series of vehicles with special equipment for loading and unloading, or when large vehicles are not allowed to enter a series of places, such as roads or bridges.

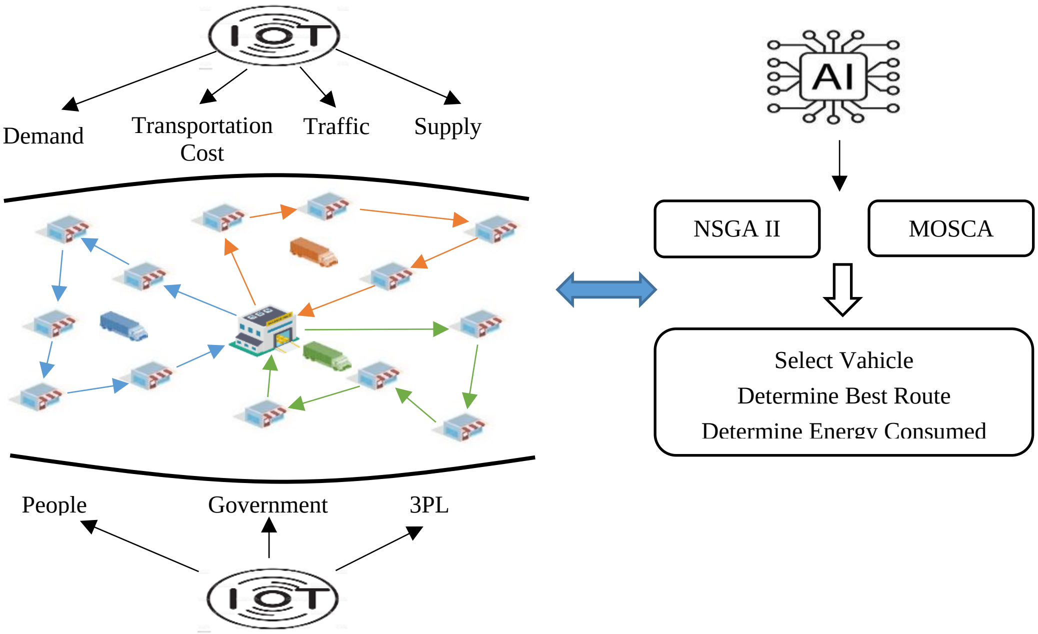


**Fig. 1.** A Robust Heterogeneous Fleet Vehicle Routing Problem Based on AIoT

The main purpose of the presented model is to determine tours to provide services to a set of customers within a specific time window. To establish these tours, two objective functions have been considered: minimization of total costs (transfer costs, vehicle setup costs, and late and early delivery costs of customer requests) and minimization of the energy required for vehicle operations.

The following symbols are designed to provide a location-dependent robust heterogeneous fleet vehicle routing model with a soft time window:

**Parameters**

| | |
|---|---|
| $Q_k$ | The capacity of the vehicle $k$ |
| $f_k$ | The fixed cost of using the vehicle $k$ |
| $\tilde{q}_i$ | Demad of customer $i$ |
| $\tilde{c}_{ij}^k$ | Travel cost in arc $(i,j)$ by vehicle $k$ |
| $s_i$ | The service time for customer $i$ |
| $[e_i, l_i]$ | The service time window for customer $i$ |
| $r_i$ | Penalty for arriving early to the customer $i$ |
| $h_i$ | Penalty for arriving late to the customer $i$ |
| $A_j$ | Type of vehicles allowed to serve the customer $i$ |
| $d_{ij}$ | Distance in arc $(i,j)$ |
| $w_k$ | The empty mass of the kth vehicle $k$ |
| $l_k^r$ | Minimum speed level $r$ of vehicle $k$ |
| $u_k^r$ | Maximum speed level $r$ of vehicle $k$ |
| $a$ | Acceleration of vehicles |
| $c_r$ | Coefficient of rotational resistance |
| $c_d^k$ | The traction coefficient of the vehicle $k$ |
| $ar^k$ | The area of the front surface of the vehicle $k$ |
| $\rho$ | air density |
| $g$ | Gravitational constant |
| $\theta_{ij}$ | arc angle arc angle $(i,j)$ |
| $\tau_q, \tau_c$ | Uncertainty rate |

**Decision Variables**

| | |
|---|---|
| $X_{ij}^k$ | 1; If the vehicle $k$ travels on the arc $(i,j)$<br>0; otherwise |
| $Z_{ij}^{kr}$ | 1; If the vehicle $k$ travels on the arc $(i,j)$ with the speed level $r$<br>0; otherwise |
| $F_{ij}^k$ | The amount of load transferred on the arc $(i,j)$ by the vehicle $k$ |
| $Y_i^k$ | The arrival time to customer $i$ by vehicle $k$ |
| $E_i^k - L_i^k$ | The amount of time to exceed the time window customer $i$ by vehicle $k$ |
| $U_{ik}$ | The variable related to the removal of subtour |
| $P_{ij}^k$ | The energy required to move on arc $(i,j)$ by vehicle $k$ |
| $\alpha_{ij}$ | special constant of arc $(i,j)$ |
| $\beta_k$ | specific constant of vehicle $k$ |
| $\bar{v}_k^r$ | Average speed level $r$ of the vehicle $k$ |

Based on the defined symbols, the location-dependent heterogeneous robust fleet vehicle routing problem with soft time window is as follows.

$$MinZ_1 = \sum_{k=1}^{K}\sum_{i=0}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n+1} \tilde{c}_{ij}^k X_{ij}^k + \sum_{k=1}^{K}\sum_{j=1}^{n} f_k X_{0j}^k + \sum_{k=1}^{K}\sum_{i=1}^{n}\left(r_i E_i^k + h_i L_i^k\right) \tag{1}$$

$$MinZ_2 = \sum_{k=1}^{K}\sum_{i=0}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n+1}\left(\alpha_{ij} d_{ij}\left(w_k X_{ij}^k + F_{ij}^k\right) + \beta_k d_{ij}\sum_{r=1}^{R}\left(\bar{v}_k^r\right)^2 Z_{ij}^{kr}\right) \tag{2}$$

$s.t:$

$$\sum_{k\in A_j}\sum_{\substack{i=0\\ j\neq i}}^{n} X_{ij}^{k}=1,\quad \forall j\in N/\{0,n+1\} \tag{3}$$

$$\sum_{i=p}^{n} X_{ip}^{k}-\sum_{j=1}^{n+1} X_{pj}^{k}=0,\quad \forall p\in N/\{0,n+1\},k\in A_p \tag{4}$$

$$\sum_{k\notin A_j}\sum_{\substack{i=0\\ j\neq i}}^{n} X_{ij}^{k}=0,\quad \forall j\in N/\{0,n+1\} \tag{5}$$

$$U_{ik}-U_{jk}+|P|X_{ij}^{k}\leq|P|-1,\quad \forall\, i,j,P\in N/\{0,n+1\},k\in K \tag{6}$$

$$Y_i^{k}+s_i+Y_j^{k}-\sum_{r=1}^{R}\left(\frac{d_{ij}}{\bar{v}_k^{r}}\right)Z_{ij}^{kr}\leq M\left(1-X_{ij}^{k}\right),\quad \forall k\in K,i\in N/\{n+1\},j\in N/\{0\},i\neq j \tag{7}$$

$$\sum_{j=0}^{n} X_{0j}^{k}\leq 1,\quad \forall k\in K \tag{8}$$

$$\sum_{j=1}^{n}\sum_{i=0}^{n}\tilde{q}_j X_{ij}^{k}\leq Q_j,\quad \forall k\in K \tag{9}$$

$$E_i^{k}\geq e_i\sum_{j=1}^{n+1} X_{ij}^{k}-Y_i^{k},\quad \forall i\in N/\{0,n+1\},k\in K \tag{10}$$

$$L_i^{k}\geq Y_i^{k}-l_i,\quad \forall i\in N/\{0,n+1\},k\in K \tag{11}$$

$$\sum_{k=1}^{K}\left(X_{ii}^{k}+X_{i0}^{k}+X_{(n+1)i}^{k}+X_{0(n+1)}^{k}\right)=0,\quad \forall i\in N \tag{12}$$

$$\sum_{k=1}^{K} Y_0^{k}=0 \tag{13}$$

$$\sum_{r=1}^{R} Z_{ij}^{kr}=X_{ij}^{k},\quad \forall k\in K,i,j\in N \tag{14}$$

$$\sum_{i=1}^{n} X_{i(n+1)}^{k}\leq 1,\quad \forall k\in K \tag{15}$$

$$\sum_{k\in A_p}\sum_{i=0}^{n} F_{ip}^{k}-\sum_{k\in A_p}\sum_{j=1}^{n+1} F_{pj}^{k}=\tilde{q}_i,\quad \forall p\in N/\{0,n+1\} \tag{16}$$

$$P_{ij}^{k}\cong\alpha_{ij}d_{ij}\left(w_k+F_{ij}^{k}\right)+\beta_k d_{ij}\sum_{r=1}^{R}\left(\bar{v}_k^{r}\right)^2,\quad \forall i,j\in N,k\in K,r\in R \tag{17}$$

$$\alpha_{ij}=a+g\,sin\theta_{ij}+g\,c_r\,cos\theta_{ij},\quad \forall i,j\in N \tag{18}$$

$$\beta_k=\frac{\rho c_d^{k} ar^{k}}{2},\quad \forall k\in K \tag{19}$$

$$\bar{v}_k^{r}=\frac{l_k^{r}+u_k^{r}}{2},\quad \forall i,j\in N,k\in K \tag{20}$$

$$X_{ij}^{k},Z_{ij}^{kr}\in\{0,1\} \tag{21}$$

$$F_{ij}^{k},Y_i^{k},E_i^{k},L_i^{k},\alpha_{ij},\beta_k\geq 0 \tag{22}$$

Equation (1) minimizes the total costs of the vehicle routing problem. Equation (2) minimizes the energy required for vehicle travel to meet customers' needs. Equation (3) guarantees that the demand of each customer is provided by one of the authorized vehicles. Equation (4) shows the flow balance associated with the vehicles that each vehicle leaves after serving the customer. Equation (5) shows that it is not possible to visit customers with unauthorized vehicles. Equation (6) shows the sub-tour elimination. Equation (7) shows the vehicle arrival time to each customer. Equation (8) allows vehicles to remain in storage, when they are not needed. Equation (9) ensures that the load capacity of each vehicle does not exceed its maximum capacity. Equations (10) and (11) show the value of exceeding the time window. Equations (12) and (13) start the tour starting time with zero value. Equation (14) states that if a vehicle moves, it must consider a speed level to move in each arc. Equation (15) ensures that the vehicles return to the depot after serving the last customer. Equation (16) expresses the flow balance of the amount of goods imported to and exported from each customer. Specifically, the customer's demand is equal to the amount of goods that are exported to other nodes and the amount of goods that are imported to that node.

In this model, in order to reduce environmental pollutants, the amount of fuel needed by the transport fleet will be minimized. Obviously, doing this automatically leads to the reduction of pollutants. As can be seen, the second objective function consists of two components related to the bow and the vehicle. The first reflects road engineering specifications, and the second part pertains to the vehicle itself. The energy required for transmission in each arc of the transportation network is obtained according to Equation (17) (Bektaş & Laporte, 2011). Equations (18) and (19) also show the special constants of the bow and the vehicle. According to the different speeds of the vehicle along the route, the average speed of the vehicle is obtained according to Equation (20). Equations (21) and (22) show the types of decision variables.

Therefore, by reducing the energy needed to travel the fleet of vehicles and meet the needs of customers, it is possible to simultaneously minimize the pollution caused by transportation, including $CO_2$ gas. On the other hand, due to the uncertainty in demand and transportation costs, a robust method has been used to control uncertain parameters. In this method, by considering the penalty coefficients for the objective function, it is possible to addressthe problem under uncertain conditions (Ghahermani-Nahr et al., 2023). Considering this issue, the robust model of the heterogeneous fleet vehicle routing problem is as follows:

$$MinZ_1 = \sum_{k=1}^{K}\sum_{i=0}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n+1}\left(c_{ij}^{k} X_{ij}^{k} + \eta_c\right) + \sum_{k=1}^{K}\sum_{j=1}^{n} f_k X_{0j}^{k} + \sum_{k=1}^{K}\sum_{i=1}^{n}\left(r_i E_i^{k} + h_i L_i^{k}\right) \tag{23}$$

$$MinZ_2 = \sum_{k=1}^{K}\sum_{i=0}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n+1}\left(\alpha_{ij} d_{ij}\left(w_k X_{ij}^{k} + F_{ij}^{k}\right) + \beta_k d_{ij}\sum_{r=1}^{R}\left(\bar{v}_k^{r}\right)^2 Z_{ij}^{kr}\right) \tag{24}$$

$s.t:$

$$\sum_{j=1}^{n}\sum_{i=0}^{n}\left(\bar{q}_j + \tau_q \bar{q}_j\right) X_{ij}^{k} \leq Q_j, \quad \forall k \in K \tag{25}$$

$$\sum_{k\in A_p}\sum_{i=0}^{n} F_{ip}^{k} - \sum_{k\in A_p}\sum_{j=1}^{n+1} F_{pj}^{k} = \left(\bar{q}_j + \tau_q \bar{q}_j\right), \quad \forall p \in N / \{0, n+1\} \tag{26}$$

$$\tau_c c_{ij}^{k} X_{ij}^{k} \leq \eta_c, \quad \forall i, j \in N, k \in K \tag{27}$$

$$\tau_c c_{ij}^{k} X_{ij}^{k} \geq -\eta_c, \quad \forall i, j \in N, k \in K \tag{28}$$

$$Eqs.(3-8),(10-15),(17-22) \tag{29}$$

## 4. Solution Method

In the mathematical programming of multi-objective optimization, there is no solution that can simultaneously optimize all the objective functions. In these cases, the concept of Pareto optimality replaces the concept of optimality. There are different classical methods for solving multi-objective optimization problems. The methods of weighted sum, ideal planning, achieving the ideal and turning into an adverb are among these methods. In this paper, three different approaches are used to solve the two-objective problem. The improved epsilon constraint approach has been used to solve the problem in small scale, and the AI tool (NSGA II and MOSCA) has been used to solve the problem in large scale.

For the proposed model, a representation of length $|K|+|N|-1$ is considered and a random number is assigned to each of its cells in the first part from real numbers in the range $[0,1]$. It should be noted that there is an allocation space for all types of vehicles; if a city is allocated to a vehicle that is not allowed in that city, a penalty will be applied, resulting in a significantly large and unacceptable value for the objective function. To separate paths from each other, between chromosome strings, numbers with a numerical value greater than the number of customers are considered as separators. Since the number of vehicles is not known in advance, the display of the answer is created for the maximum number of vehicles, the vehicles are numbered in order, and in cases where a vehicle is not used, the corresponding cell in the route for that vehicle becomes zero. In fact, if two separators are consecutive in the first part of the solution representation, it means that the vehicle is left unused.

Figure (2) shows the initial solution of the problem for a numerical example with 5 customers and two vehicles. Therefore, there are 6 cells; That is, the paths formed by each active vehicle will be placed before, after, or between two separating genes. In Figure (2), two paths 2-4-3 and 1-5 are formed after sorting for vehicle one and vehicle two, respectively. It should be noted that if the first gene is a seperator, vehicle 1 will not be activated.

| | | | | | | |
|---|---|---|---|---|---|---|
| Rand | 0.21 | 0.40 | 0.15 | 0.78 | 0.45 | 0.12 |
| Visit tour | 3 | 4 | 2 | 6 | 5 | 1 |

**Fig. 2.** Showing the Initial Solution of the Problem

Now, the next part of the solution representation is related to determining the speed of the vehicle. This structure is first created for all potential routes, then the speed of the routes formed in the previous part of this structure is determined. Figure (3) is considered as a numerical example with 5 customers and 2 vehicles. The lowest case for the number of edges is when one vehicle serves all customers, as illustrated in the figure on the left, where the number of edges is equal to the number of customers plus one. The maximum state for the number of edges arises when both vehicles serve customers; in this case, according to the figure on the right, the number of edges formed is equal to the number of customer nodes plus the number of vehicles. Therefore, the speed-determining chromosome length is equal to the maximum number of edges, that is, the number of customer nodes plus the number of vehicles. If the number of edges formed in the previous part of the solution is less than the maximum, the additional part of the chromosome will remain empty and unused.

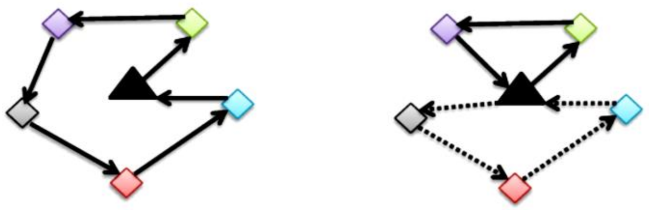

**Fig. 3.** The Structure of All Potential Paths for the Initial Solution

Now if it is assumed that there are 4 speed levels; the maximum number of chromosomes, for example, is equal to 7 cells. In each cell, random numbers are created in the range $[0,1]$ and then it is converted to the specified speed with the following relationship. If $rand \in [i-1, i]$ then the selected speed level is equal to $i$. In this relationship, $i-1$ and $i$ is equal to the speed number.

## 5. Results

### 5.1. Analysis of a Sample Problems

In this section, a sample problem is considered in order to validate the mathematical model and also analyze the sensitivity of the problem. The size of the proposed model is highly dependent on the size of the network consisting of the number of nodes, the number of vehicles and the number of speed levels. Since the problem is difficult to solve for medium and large-sized samples, a small-scale sample problem was solved using the IEPC approach. In this example, a network with 10 nodes consisting of 9 customer nodes and one warehouse node is considered, where four vehicles are located in the warehouse to serve customers. In order to assign a numerical value to the parameters of this example, the uniform distribution function, according to Table (2), has been used.

After designing the sample problem, in order to check the validity of the mathematical model, three different approaches have been used to solve the problem. Therefore, Figure (4) shows the Pareto front created by solving the sample problem with different solution approaches.

**Table 2.** Interval Limits of Problem Parameters

| Parameter | Value | Unit |
|---|---|---|
| $Q_k$ | $\sim U(5500{,}38000)$ | $kg$ |
| $f_k$ | $\sim U(40000{,}60000)$ | $ |
| $\tilde{q}_i$ | $\sim U(1200{,}1900)$ | $kg$ |
| $\tilde{c}_{ij}^k$ | $\sim U(200{,}2000)$ | $ |
| $s_i$ | $\sim U(10{,}20) * 60$ | $s$ |
| $[e_i, l_i]$ | $\sim U(10{,}200) * 60$ | $s$ |
| $r_i$ | $\sim U(10{,}50)$ | $ |
| $h_i$ | $\sim U(10{,}60)$ | $ |
| $A_j$ | $matrix\ of\ zeros\ and\ ones\ (K * N)$ | |
| $d_{ij}$ | $\sim U(5{,}50) * 1000$ | $m$ |
| $w_k$ | $\sim U(5000{,}9000)$ | $kg$ |
| $[l_k^r, u_k^r]$ | $\sim U(11{,}20)$ | $m/s$ |
| $a$ | 2 | $m/s^2$ |
| $C_r$ | $\sim U(1.01{,}1.015)$ | |
| $c_d^k$ | $\sim U(0.7{,}0.86)$ | |
| $ar^k$ | $\sim U(5{,}8)$ | $m^2$ |
| $\rho$ | $1.2041\ (at\ 20\ °C)$ | $kg/m^3$ |
| $g$ | 9.81 | $m/s^2$ |
| $\theta_{ij}$ | $\sim U(-15{,}15)$ | $degree$ |
| $\tau_q, \tau_c$ | 0.5 | |

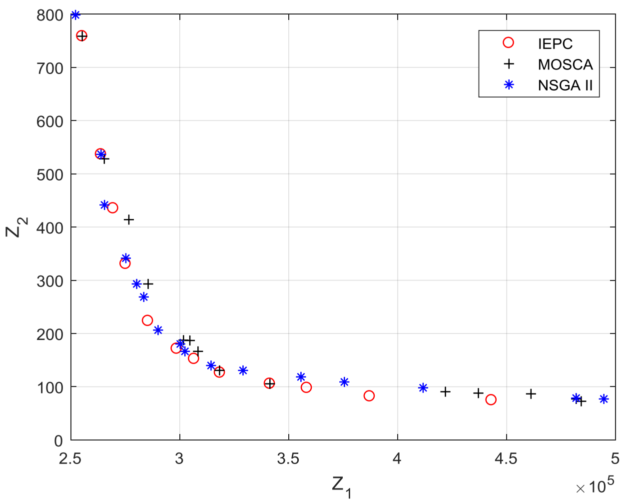


**Fig. 4.** Pareto Front Created from Solving the Sample Problems

The set of efficient solutions obtained from solving the sample problem shows that by reducing the amount of energy required for the transport fleet in order to reduce the harmful environmental effects, the costs related to the selection of the fleet and also the routing of the vehicle have increased. Therefore, as the mathematical model seeks to improve the second objective function of the problem, the value of the first objective function of the problem deviates from the optimal value. Examining the Pareto front also shows that the IEPC approach has obtained 12 efficient solutions, the NSGA II has obtained 16 efficient solutions, and the MOSCA has obtained 14 efficient solutions.

The first efficient solution of the IEPC approach was investigated in order to check the output variables of the mathematical model. It is assumed that vehicles 1 and 2 are not able to serve customer 8 due to the difficult route, and vehicles 3 and 4 are not allowed to serve customer 4 due to their weight. Figures (5) and (6) respectively show the best solution from the first and second objective function solutions, and Figure (5) shows the first efficient solution obtained from the IEPC approach. The numbers written on the service tracks of the vehicles indicate the speed level of the vehicle. Here, four speed levels are considered; speed level 1 represents the lowest speed, and as the number increases, the speed level also increases.

According to Figure (6), two vehicles, namely No. 1 and No. 3 have been used to provide services to customers, and in order to reduce the costs, the speed of the vehicles has been set at the fourth level. At this level, the amount of energy consumed by vehicles is at its highest.

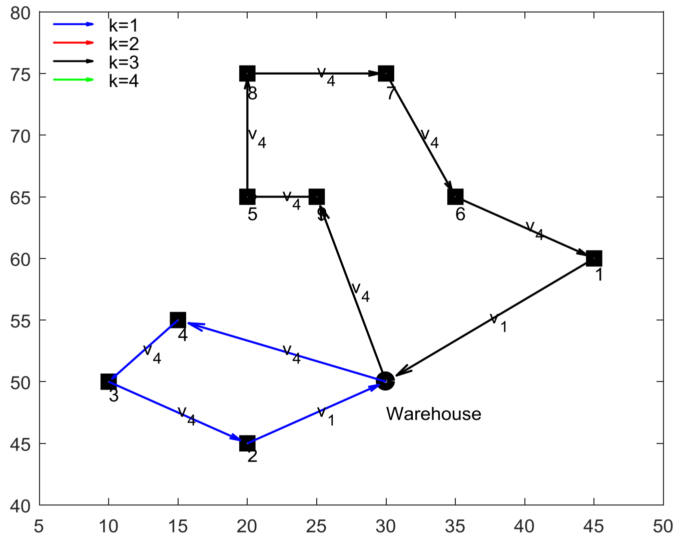


**Fig. 5.** Vehicle Routing in the Optimization of the First Objective Function

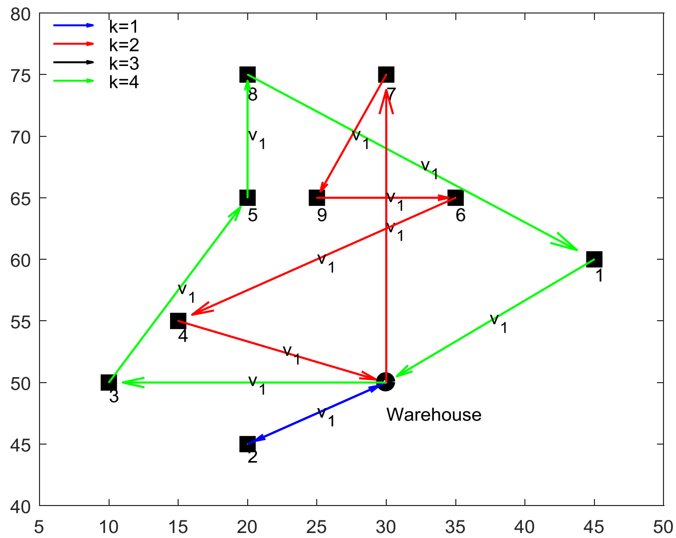


**Fig. 6.** Vehicle Routing in the Optimization of the Second Objective Function

Contrary to the results of Figure (5), it can be seen in Figure (6) that in order to reduce the energy consumed by vehicles, 3 vehicles with minimum speed were used. In this case, the cost of using the transport fleet, as well as the cost of routing the vehicle takes the highest amount. In this case, three vehicles, namely No. 1, 2 and 4 have been used to provide services to customers.

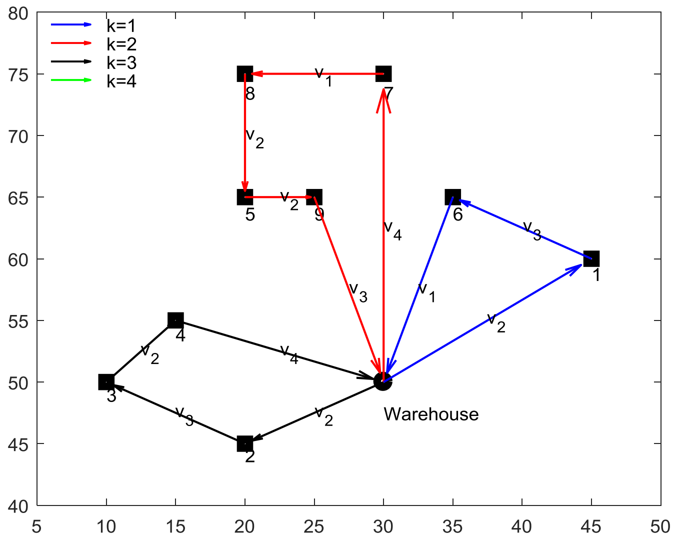


**Fig. 7.** Vehicle Routing in the Optimization of the both Objective Functions

Figure (7) shows vehicle routing in conditions of simultaneous optimization of two objective functions. In this case, it can be seen that the vehicle routing, as well as the speed level of the vehicles are not optimal. In this effective solution, 3 vehicles, namely No. 1, 2 and 3 have been selected to provide services to customers and the speed of vehicles in different routes has taken different values.

Due to the uncertainty of customer demand parameters, as well as travel costs, the robust optimization method has been used to control the uncertainty model. Therefore, in Table (3), the changes in the objective functions values at different uncertainty rates have been investigated. In this analysis, the amount of uncertainty rate in travel costs and also customer demand between 0 (optimistic model) and 1 (pessimistic model) is considered for the first effective solution.

**Table 3.** The Objective Functions Values in Different Uncertainty Rates

| $\tau_q, \tau_c$ | State | Mean | | Std | |
|---|---|---|---|---|---|
| | | $Z_1$ | $Z_2$ | $Z_1$ | $Z_2$ |
| **0** | **Deterministic** | **384891.26** | **60.48** | **924.15** | **5.15** |
| 0.1 | Robust | 404139.36 | 65.66 | 1039.48 | 7.18 |
| 0.3 | Robust | 421568.49 | 70.48 | 1255.68 | 9.86 |
| 0.5 | Robust | 443061.47 | 74.57 | 1687.68 | 11.35 |
| 0.7 | Robust | 450215.94 | 77.12 | 2035.99 | 15.68 |
| 0.9 | Robust | 463581.48 | 80.67 | 2788.68 | 19.72 |

In Table (3), for each uncertainty rate, three random data point in the considered range, according to Table (2), are presented, including production, average, and standard deviation. Based on this analysis, it can be seen that with the increase of the uncertainty rate in the network, the costs related to the robustness of the model also rises. As a result, if the model faces excessive demand, it is possible to meet the demand with higher costs. Moreover, the standard deviation of costs, as well as the amount of energy spent in pessimistic conditions is significantly higher. Figure (8) shows the changes in the objective functions values at different uncertainty rates.

Analysis of different solution approaches show that NSGA II has the highest number of efficient solutions among other solution approaches. The comparison of problem-solving approaches was made based on the number of Pareto solution (NP), maximum distance (MD), spasic metric (SM) and CPU time (T), and its results for the designed sample problem are shown in Table (4).

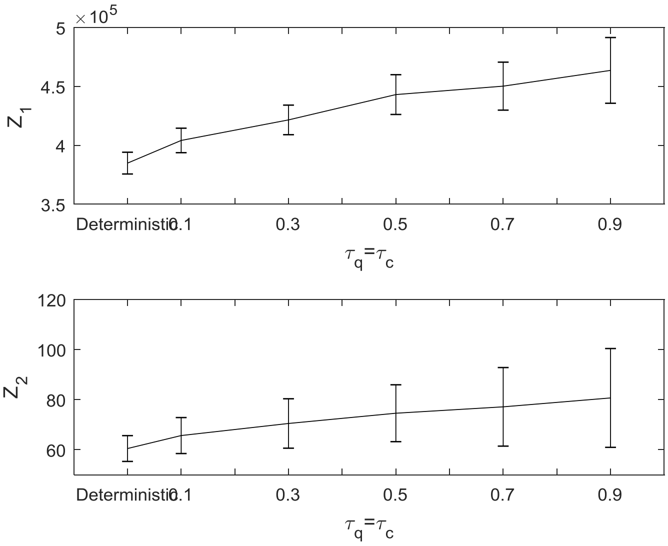


**Fig. 8.** Changes in the Objective Functions Values in Uncertainty Rates

**Table 4.** The Results of the Comparison Indices for the Sample Problem

| Solution Approach | SM | MD | NP | T |
|---|---|---|---|---|
| IEPC | 0.485 | 32586.48 | 12 | 424.15 |
| NSGA II | 0.726 | 57418.52 | 16 | 97.48 |
| MOSCA | 0.633 | 63487.66 | 14 | 56.99 |

The results of Table (4) show the high efficiency of NSGA II in producing the Pareto solution. Moreover, the IEPC method has the appropriate uniformity of answers compared to other methods. In this analysis, MOSCA has obtained the highest index of expansion of answers in the shortest processing time. In order to better investigate the efficiency of the solution approaches, several sample problems have been designed in large scales.

### 5.2. Analysis of Sample Problems in Different Scales

The efficiency of different solution approaches in solving the proposed model has been measured based on 15 sample problems, according to Table (5). As a result, the efficiency of problem-solving approaches can be evaluated based on this analysis. Also, the range limits of the parameters for each of the sample problems are provided in Table (2).

In order to examine the problem more precisely, the average comparison indices of each sample problem in three consecutive implementations have been considered. Therefore, Table (6) shows the average comparison indices among different solution approaches in the mentioned sample problems.

The results of Table (6) show that the IEPC approach has only been able to solve 5 sample problems in a small size. While NSGA II and MOSCA solved the sample problem in a shorter time than IECP. The results show that the maximum processing time by NSGA II is 464.74 seconds and the maximum processing time by MOSCA is 297.70 seconds. Figure (9) shows the average comparison indices in different sample problems among the solution approaches.

**Table 5.** Large Scale Sample Problems

| Sample Problem | Small | | | Sample Problem | Medium | | | Sample Problem | Large | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***I*** | ***R*** | ***K*** | | ***I*** | ***R*** | ***K*** | | ***I*** | ***R*** | ***K*** |
| 1 | 10 | 4 | 4 | 6 | 20 | 8 | 8 | 11 | 50 | 15 | 18 |
| 2 | 11 | 4 | 4 | 7 | 25 | 8 | 10 | 12 | 60 | 18 | 18 |
| 3 | 12 | 5 | 5 | 8 | 30 | 10 | 10 | 13 | 70 | 20 | 20 |
| 4 | 13 | 5 | 6 | 9 | 35 | 10 | 12 | 14 | 80 | 22 | 23 |
| 5 | 15 | 6 | 6 | 10 | 40 | 12 | 14 | 15 | 90 | 25 | 25 |

**Table 6.** The Average Comparison Indices among Different Solution Approaches

| Sample | IEPC | | | | NSGA II | | | | MOSCA | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Problem** | **NP** | **MD** | **SM** | **T** | **NP** | **MD** | **SM** | **T** | **NP** | **MD** | **SM** | **T** |
| 1 | 11 | 25265.5 | 0.44 | 529.18 | 14 | 27215.7 | 0.56 | 28.49 | 13 | 26510.0 | 0.67 | 26.33 |
| 2 | 17 | 32954.2 | 0.61 | 1268.1 | 29 | 30361.3 | 0.38 | 40.66 | 34 | 40068.2 | 0.54 | 27.33 |
| 3 | 18 | 34359.7 | 0.50 | 1692.2 | 26 | 25750.1 | 0.31 | 50.80 | 13 | 37162.9 | 0.50 | 32.54 |
| 4 | 19 | 25681.6 | 0.45 | 2563.9 | 34 | 37585.0 | 0.37 | 60.63 | 35 | 33258.4 | 0.50 | 38.84 |
| 5 | 16 | 37535.4 | 0.33 | 3263.9 | 24 | 29952.4 | 0.42 | 71.87 | 28 | 27657.6 | 0.52 | 46.04 |
| 6 | | | | | 27 | 23499.0 | 0.53 | 86.82 | 16 | 27678.2 | 0.68 | 55.61 |
| 7 | | | | | 18 | 29568.3 | 0.41 | 102.33 | 22 | 33178.1 | 0.33 | 65.55 |
| 8 | | | | | 22 | 37185.4 | 0.47 | 123.91 | 31 | 37842.7 | 0.59 | 79.37 |
| 9 | | | | | 15 | 27300.0 | 0.33 | 151.45 | 22 | 29896.1 | 0.69 | 97.01 |
| 10 | | | | | 18 | 21160.4 | 0.48 | 185.89 | 26 | 25068.9 | 0.49 | 119.07 |
| 11 | | | | | 13 | 26841.9 | 0.31 | 221.91 | 35 | 35241.3 | 0.57 | 142.15 |
| 12 | | | | | 17 | 26265.0 | 0.60 | 271.27 | 16 | 26035.5 | 0.69 | 173.76 |
| 13 | | | | | 25 | 33718.8 | 0.61 | 333.34 | 24 | 35348.6 | 0.42 | 213.53 |
| 14 | | | | | 34 | 32164.9 | 0.48 | 400.39 | 13 | 35439.3 | 0.36 | 256.48 |
| 15 | | | | | 15 | 25841.0 | 0.57 | 464.74 | 19 | 37848.1 | 0.34 | 297.70 |

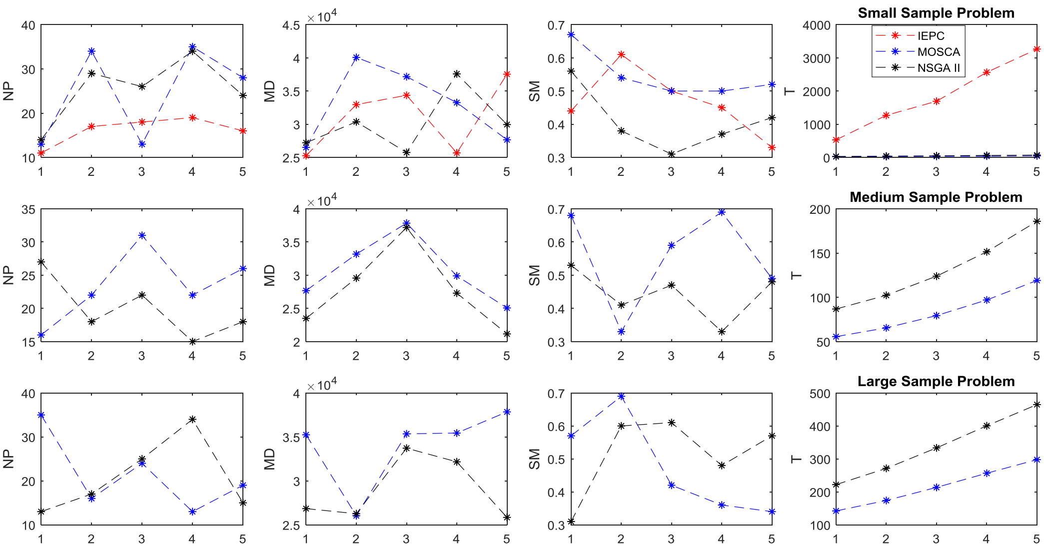


**Fig. 9.** Comparison of Indicators in Different Sample Problems

By comparing the indices between NSGA II and MOSCA, it can be seen that NSGA II was only successful in obtaining the SM index, and MOSCA obtained the highest NP and MD in the lowest T. These results show that MOSCA is a more efficient AI tool than NSGA II for solving the problem.

## 6. Conclusion

In this paper, a vehicle routing problem with time window and biological considerations based on AIoT was studied in order to reduce the costs caused by the transportation sector on the one hand, and to minimize the harmful effects of the transportation industry on the environment based on reducing energy consumption on the other hand. The problem, presented in two objective functions, tries to reduce energy consumption and simultaneously minimize harmful emissions while minimizing the transportation costs of economic enterprises to estimate the needs of customers in the time windows of their desired service in conditions of uncertainty. Due to the uncertainty in the amount of demand and travel costs, the robust optimization method was used to control these parameters. The results of the analysis of the mathematical model with the IEPC approach showed that by reducing the amount of energy consumption due to the increase in the number of vehicles, the total costs of the model will increase. Also, the studies showed that the increase in the uncertainty rate in the demand has led to its increase in the system and the transportation costs; therefore the amount of energy consumption has also increased. Due to NP-Hardness of the presented model, NSGA II and MOSCA were also used.

The analysis of the sample problem in a small scale showed that the problem-solving time by AI tools is shorter, and NP is higher than IEPC, so that IEPC was unable to solve sample problems greater than No. (6). On the other hand, by comparing the indices of two AI tools, it was found that MOSCA has a better efficiency than NSGA II due to obtaining more indices. The results of this research help the managers to make the best decision in choosing the transport fleet in order to reduce the energy consumed and the costs incurred. Also, due to the use of the robust optimization method in controlling uncertainty parameters, managers can estimate the total expenses incurred on their transportation problem along with the energy required for the transportation fleet.

The analysis results of this article regarding the impact of uncertainty on total costs, greenhouse gas emissions and location-routing decisions are similar to the results obtained in the articles of Khodashanas et al. (2012), Hajghani et al. (2012), Nozari et al. (2022) and Tirkolaee et al. (2021). By examining the type of use of uncertainty control methods, it was also observed that the use of a strong method to deal with uncertainty yields better results than those obtained using the fuzzy programming method, as used in the papers of Nozari et al. (2022) and Yan et al. (2023).

Also, the results of this paper help managers to know how to use IoT tools to optimize vehicle routing for the distribution of goods and to use AI tools to speed up decision-making. Using the IoT system leads to cost reduction and systematization of the transportation network, while AI tools facilitate quick and accurate decision-making in this field.

In order to further study the problem, topics, such as modeling the problem by considering the rail and road transport fleet, modeling the problem in a multi-level way, presenting other heuristic and meta-heuristic algorithms and using the time-dependent version of the problem, especially on busy and congested roads with traffic should be considered. The fact that vehicles often have a speed of less than 40 km/h, and frequent acceleration and stopping causes a lot of greenhouse gas emissions, can be taken into consideration by researchers in this field.

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