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3D fuzzy model for Sustainability of logistics system in dynamic vehicle routing problem with capacity constraint (DVCVRP)

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Due to the importance of vehicle routing for delivering a large number of orders with different restrictions in the world, various optimization methods have been studied in past researches. In this article, a number of researches of recent years have been discussed, then the proposed model is described in 3 phases with the penalty index. This model has the ability to assign orders, route vehicles and determine the number of active vehicles dynamically with the aim of minimizing the total cost of distribution. By examining valid metaheuristic models and using their strengths and weaknesses, and considering multiple limitations, a new model of "dynamic 3-phase optimization" has been designed. The main application of the proposed model is for vehicle routing problems with capacity constraints of fleet number and capacity constraints (maximum and minimum number of orders). Finally, with simulation, the outputs of the model have been analyzed in different conditions. Although the limitation of maximum and minimum capacity is added to the problem, by dynamically considering the number of vehicles and using star clustering (initiative of this research), three social, environmental and economic dimensions were improved. The time for orders to reach customers decreased by 19.3%, fuel consumption and air pollution by 14.9%, and logistics costs by 8.7%. To calculate the final value of system stability, a unique 3D fuzzy model has been used. With the sensitivity analysis, we came to the conclusion that the 3-phase dynamic optimization model has led to a 14.58% improvement in system stability.

Keywords: *sustainability, dynamic, optimization, routing, fuzzy, 3D*

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1. Introduction

One of the main challenges of company managers is deciding how to distribute goods. Distribution of goods includes all activities related to the transfer of economic goods between producers and consumers, which includes supply and distribution stages according to the type of items, volume, shipping method and delivery time. To effectively deploy and maximize the profitability of a company's supply chain system, both "effectiveness" and "efficiency" must be present. The factor "effectiveness" means providing a product or service in the right place, in the right quantity and under the right conditions. "Efficiency" means delivery at the right time and at the right cost. In researches, the condition to have practical results is to choose a correct and realistic sample that has different aspects. Finally, the modeling result in that case study should be quantitatively presented.

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1.1. The main issue

The main goal of this paper is to design and present a new model by incorporating real-world constraints (maximum and minimum number of orders that can be transferred per vehicle and limit on the number of vehicles). Considering that all the restrictions cannot be met simultaneously, the optimal solution is obtained by weighting and applying a penalty on the indicators. The problem of collections that will increase in the future due to the prediction of the increase in online orders is the limitation of the number and type of cars, the high covered space for order delivery, the high variety of food items, the lack of optimal control of delivery time and delivery costs. The final goal of this research is to optimize the route and minimize supply chain costs. If the specialized transport companies do not make such optimizations, in this competitive market, due to the high variety of goods, customer demand regarding the time and method of delivery, and the high costs of delivery, they will gradually lose their market share. In this research, the data of Bazargam startups, which are active in online sales of consumer items and door-to-door distribution in different cities of Iran, have been used. In recent months, Bazargam has been chosen by the government and the Ministry of Agricultural Jihad as a broadcasting network for market regulation items.

1.2. Literature Review

Naghshnilchi (2019), developed a high-performance algorithm for solving the capacity-constrained vehicle routing problem (CVRP), especially at large scales. This paper develops a new mathematical model for CVRP considering the satisfaction level of demand nodes. Then, the proposed model is validated using a numerical example and sensitivity analyzes implemented by the CPLEX/GAMS solver software. To solve the problem effectively, a genetic algorithm (GA) has been designed and implemented [1].

Tootooni et al (2020) proposed a type I and type II fuzzy programming approach for a new model of hub location problems (HLP). In their model, the flow level between the nodes is considered as a fuzzy parameter. In the fuzzy type I approach, a linear programming problem with fuzzy parameters is used, while for the fuzzy type II approach, interval calculus rules are developed to simplify the problem to the fuzzy type I state. Finally, they have applied their method on the transportation data of Calais Dairy Company as a case study and compared clear and fuzzy situations[2].

Using regular networks to develop models can omit key features needed to make sound decisions. Gabriel Policroniades and Idalia Flores (2021) presented a description of transportation models through the conceptualization of complex networks. By reconstructing the route and the cost matrix, it is possible to obtain practical routes. The purpose is to apply the proposed methods and models[14].

For an online retailer in China, it was found that experienced drivers can often find better routes instead of relying on computer tools using modern algorithms. The focus of Olivier Quirion-Blais and Lu Chen (2020) is to generate pathways based on experience. To do this, they have proposed an argument-based method. This method designs new routes to fulfill orders by retrieving and matching previously executed routes from a reservoir called base. They have developed a mechanism to maintain good quality routes in the database. Comparison with the Bone Route algorithm shows that the obtained solutions are on average 18.4% longer [15].

Traffic jams often lead to serious challenges for vehicle routing optimization. In order to effectively solve the routing problem of cash sections in transportation, Yuanzhi Jin et. al. (2021) conducted the vehicle routing problem in transportation with the aim of creating a new dual-objective model (including economic and environmental objectives and designing a new iterative local nearest neighbor search algorithm considering the specific region). The experimental results of their paper have shown that the developed algorithm helps decision makers to obtain high quality solutions compared to classical algorithms [16].

The stochastic and static vehicle routing problem with random requests describes realistic operational contexts where a fleet of vehicles must serve dynamic customer requests. Michael Saint-

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Guillain et. al. (2020) adopted a computational framework based on resource strategies to achieve the objectives of the random and static vehicle routing problem. The resulting models are applied in a real case study of the management of police units in Brussels, where the average expected response time is minimized. The results based on the simulation of this research, by providing a suitable solution method, have shown the high quality of the previously designed solutions, even compared to the solutions designed by field experts [18].

The best meta-heuristic in the capacity vehicle routing problem avoids getting stuck in local optimization (by placing special mechanisms such as diversity strategies in solution methods). Vinícius R.Máximo and MariáC.V.Nascimento (2021) have introduced a new adaptive version (of iterated local search) with path relation to the capacitated vehicle routing problem. The results of the experiments of this research with 100 samples show that the iterated local search with route association has better performance than the metaheuristics of the capacitated vehicle routing problem [19].

When environmental factors change, such as random client requests, routes must be adjusted for the new environment. Feng Wang et. al. (2021) have developed a multi-objective optimization model and proposed a new algorithm called EL-DMOEA. In their model, a collective learning method is investigated to improve the performance of the algorithm. In the proposed algorithm, in order to increase population diversity and accelerate convergence, three different strategies (population-based prediction strategy, migration strategy, and random strategy) have been used in the training process of three types of basic models [20].

Paweł Sitek et. al. (2020) considered the optimization of the capacitated vehicle routing problem with alternate delivery and time windows. The development of this problem is stimulated by the analysis of postal and courier delivery problems. The problem model is formulated in the form of binary integer programming. In addition, a hybrid approach integrating constraint programming, genetic algorithm, and mathematical programming is proposed for model implementation and optimization [21].

In a real-world vehicle routing problem, orders arrive at an online store dynamically throughout the day and must be delivered in a short time. The goal of Nikolaus Frohner et. al. (2021) is to predict the average time required to deliver an order for a given time and day. In this research, a white box linear regression model and a black box model based on neural network have been compared during three months. They have used an hourly data collection approach with sampling statistics to estimate the weighted mean square error as a loss function [22].

Reducing transportation risk and increasing traffic safety is also an important indicator for sustainable transportation. In the last four decades, several approaches to risk assessment and modeling have been proposed. Nikolai Holeczek (2021) has investigated the impact of different risk models on the results of the routing problem of hazardous materials vehicles. In this research, by comparing six different risk models, the effect of different path finding methods has been investigated as a basis. The sustainability aspect of the hazardous material vehicle routing problem has been investigated, with a special focus on the trade-off between social and environmental sustainability. As the basis of this model, considering the route generation between customer and warehouse nodes, the effect of fleet size has been investigated [23].

Isidoros Marampoutis et. al. (2022) has investigated a vehicle routing problem with time constraints and priority rules to avoid inventory saturation at collection points using integer linear programming. The presented model is based on a real application in the city of Lyon and its surrounding areas, including several objectives with specific assumptions. Numerical experiments have been performed on samples with different scales, which make it possible to model the current problem as well as its future evolution. These experiments have considered several examples using one vehicle among three types of vehicles (bicycle, car and van) and a network of 20 stores/customers [24].

The agricultural routing planning problem (a subset of the vehicle routing problem) focuses on agricultural operations and farm and vehicle configurations. Amalia Utamima and Arif Djunaidy (2022) have presented a short literature review on agricultural routing planning and various adaptations of the problem [25].

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Arit Thammano and Petcharat Rungwachira (2021) have developed a combination of three strategies: a modified ant system, a relocation algorithm, and a path relinking to solve the capacity vehicle routing optimization problem. Path relinking is used to construct a better solution (candidate) from a pair of guide and initial solutions. In their research, methods have been used to prevent solutions from getting trapped in a local minimum. The performance of the proposed algorithm of this research has been evaluated on three datasets, and this method has been competitive with advanced algorithms in terms of the total length of the path. They claim that the findings of this research can reduce the cost of transportation by reducing the travel distance and using the vehicle capacity effectively [26].

The global growth of e-commerce has created new challenges for logistics companies, such as fast and cheap delivery of products. Juan Camilo et. al. (2022) presented a heuristic for dynamically solving the last-mile path generation problem. This discovery is based on a multi-agent system integrated with trajectory data mining techniques. By extracting the regional patterns, they used them to solve the dynamic capacity vehicle routing problem with random customers. In this article, they have compared their proposal with benchmark algorithms and its performance has been evaluated under different scenarios. The results of the paper show that their approach is effective for scenarios with dynamic path [27].

Dynamic vehicle routing problems arise in several applications such as technician routing, food delivery, and package delivery. Jian Zhang et. al. (2022) considered the dynamic vehicle routing problem with random customer requests, where vehicles should be dynamically routed (with the aim of maximizing the number of requests submitted). They modeled their proposed problem as a multistage optimization problem. In this research, knapsack-based linear models have been used to accurately approximate the expected reward in any state of the random system. Computational experiments on very large samples based on a real street network have demonstrated the effectiveness of their proposed methods in prescribing high-quality offline route plans and online scheduling decisions [28].

To provide heterogeneous services in mass transit routing problems, the assumption of similarity of vehicles is questioned considering different start/end locations, capacities, and also changes in time window type. In this regard, Abu-Monshar and Al-Bazi (2022) proposed a new agent-based meta-heuristic architecture to capture the uniqueness of vehicles by modeling them as agents. Their goal is to create near-optimal routes by minimizing the number of vehicles used, the total distance traveled, and the total waiting time. Their innovative architecture incorporates three distinct core modules into a flexible meta-heuristic implementation. The problem is initially modeled by an agent-based module, which includes components in displaying, evaluating, and changing solutions. A second meta-heuristic module is designed and integrated. This is followed by the introduction of a multi-objective module to sort the solutions generated by the meta-heuristic module based on Pareto, resulting in an average reduction of 21.2 units of expected time [29].

E-commerce, like all sectors, must consider social sustainability. Pilati and Tronconi (2022) proposed a mathematical model for the socially and economically sustainable vehicle routing problem to integrate these themes into the logistics of e-commerce platforms. Their proposed model optimizes drivers' energy consumption along with delivery costs. The model is solved through simulated annealing and validated with a realistic case study for an e-commerce platform. The results of their research show that by assigning a small weight to the dimension of social sustainability, the platform can improve this aspect by 20% and the economic performance decreases by only 4% [30].

The transportation sector has destructive effects on the economy, the environment, and the quality of life of citizens. In recent years, some key performance indicators have been proposed to quantify these negative effects on the economic, environmental and social dimensions of the concept of sustainability. Abdullahi et. al. (2020) considered the problem of stable vehicle routing with the above dimensions. They proposed a multi-objective optimization model to combine economic, environmental and social dimensions as well as a stochastic iterative greedy algorithm to solve the integrated problem. In this paper, a series of experiments and sensitivity analysis have been carried out to measure the

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impact of each sustainability dimension and examine the trade-offs between them with newly produced samples [31].

Jelen et. al. (2022) presented a multi-agent system for electric vehicle routing that provides a tool for cost-effective planning and resource utilization in urban operations. Their multi-agent system consists of three main parts: model, routing algorithms and platform. In the case study, the cleaning of urban areas in the city of Split with electric cleaners has been used to evaluate the multi-agent system. Their model consists of three main entities: electric vehicle, charging station and warehouse. Multi-agent system routing algorithms are defined with artificial intelligence usage models. Using these algorithms, the multi-agent system for the case study has shown a 5.6% improvement in urban cleaning operations and an 18.5% improvement in car charging at charging stations [32].

In the past years, attention has been paid to the problem of sustainable vehicle routing with economic, environmental and social concerns. Dündar et. al. (2021) reviewed the domains, objectives, methodology of solutions, and types of data in the articles. In their paper, they analyzed the indicators used in the proposed quantitative models and how they relate to sustainability and green criteria in the field of vehicle routing. These criteria emphasize economic, environmental and social dimensions. One of the key findings of their research is the high importance of the economic dimension among the three pillars of sustainability, and researchers pay less attention to environmental and social dimensions [33].

With increasing fuel prices and stricter emission regulations, electric vehicles have been used in various logistics distribution activities. Most studies have focused on the routing problem of electric vehicles under a deterministic environment and ignore the effects of uncertain factors in practical logistics distribution. Therefore, a new fuzzy electric vehicle routing problem with time windows and charging stations (FEVRPTW) has been investigated in the research of Zhang et al. (2019) and they developed a fuzzy optimization model based on credit theory for this problem. In their presented model, fuzzy numbers are used to represent the uncertainties of service time, battery energy consumption and travel time. In their research, an adaptive large neighborhood search (ALNS) algorithm with fuzzy simulation method is proposed to solve the model. In the proposed ALNS algorithm, four new deletion algorithms are designed and integrated to address FEVRPTW [34].

There are several vehicle routing problems with uncertain capacity whose costs and delivery demands cannot be estimated using deterministic/statistical methods due to the lack of available or reliable data. To overcome this lack of data, third-party information obtained from experts can be used to represent those uncertain costs/demands as fuzzy numbers. The method proposed by Figueroa–García and colleagues (2022) used two covariates α and λ and the cumulative membership function of a fuzzy set to obtain real-valued costs and demands [35].

1.3. research gap

In total, the results obtained from the research of recent years related to this article can be seen in Table 1. One way to find a suitable route is to use clustering. In many of these researches, clustering has been done using the genetic algorithm. The results showed that the use of the genetic algorithm led to the classification of cars into acceptable groups and the most appropriate cars of each category were selected as the group leader. In this method, the genetic algorithm acts as a function and takes the non-optimal cluster network as input. Finally, it returns a network with a number of distinct and optimal clusters.

Table1: Summary of some past studies related to the current research

researcher	Year	Model type	Model conditions	Broadcast network type	Tools used
Zhang et al	2018	Genetic algorithm	Artificial Intelligence QoS	Routing	NS-2 simulation software
Hamza Toulni and Benayad Nsiri	2015	Using ontology and traffic information	Routing protocol	Hybrid routing	Simulation software

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J.M. García-Campos et al	2016	A method for performing reliable simulations	Routing protocol	Adrenal Routing Protocol (AODV)	Simulation software
Omar Sami Oubbati et al	2017	Ad hoc networks	Two different routing methods	Routing	Use of UVAR-G and UVAR-S
Saifullah Khan et al	2018	Advertising networks	Routing protocol	New routing called TASR	Calculation of Expected Connection Degree (ECD)
Mazzuco et al	2018	Transportation planning and vehicle routing	Routing protocol	Vehicle Routing	Optimizing the delivery of goods and choosing the best route
N.V. Dharani Kumari, B.S. Shylaja	2019	Based on AHP	Multimeter for urban environment	Geographic routing protocol	Multiple routing features
Merve Keskin et al	2020	Based on two-stage simulation	Random waiting time	with time window (VRPTW)	Adaptive Large Neighborhood Search (ALNS) - Penalty for timing violations
Binbin Pan et al	2020	Combined meta-heuristic algorithm	with limited capacity (CVRP)	with time window (VRPTW)	Adaptive Large Neighborhood Search (ALNS)
Wenli Li et al	2021	Development of adaptive large neighborhood search algorithm	with limited capacity (CVRP)	with time window (VRPTW)	Simultaneous routing of goods and services
Duygu Taş	2020	Column generation algorithm	Penalty fees for delay	Flexible time windows	integer programming problem
Yong Wang et al	2021	3D customer clustering algorithm with discrete load strategies	multi-campus	with time window (VRPTW)	Genetic algorithm and forbidden search algorithm
Feng Wang et al	2021	A new multi-objective evolutionary algorithm called EL-DMOEA	Random customer requests	with time window (VRPTW)	Dynamic vehicle routing with time window
Juan Camilo Fonseca-Galindo et al	2022	Multi-agent system	Dynamic capacity	Random customers	Using route data mining
Jian Zhang et al	2022	Multi-stage optimization	Dynamic vehicles	random requests (DVRPSR)	Backpack based linear models
Anees Abu-Monshar , Ammar Al-Bazi	2022	Multi-objective centralized agent-based optimization	Unique vehicles	with time window (VRPTW)	Innovative architecture with three separate main modules

The research gap that has been investigated is the lack of simultaneous focus on the limits of the number of vehicles and the limits of their maximum and minimum capacity. In this research, the number of dynamic vehicles is considered simultaneously with the capacity limit. For the simultaneous application of restrictions, the proposed model has been solved in 3 phases and by applying fines, it has moved towards the real world and optimization in 3 social, environmental and economic dimensions. Finally, to calculate the sustainability of the system, a unique three-dimensional fuzzy model has been designed and implemented.

2. Concepts and theoretical foundations

Capillary distribution or intensive and mass distribution system is known today as a successful method of distributing products. In general, one of the elements of the marketing mix that plays a decisive role in the success of manufacturers in industrial markets is the distribution system. Due to globalization and more competitive industries, the need for integrated and coordinated broadcast system is felt more than before. Today, producers' attention has been drawn to the variables affecting the broadcast channel structure, and accordingly they modify, update and design a new broadcast system of their company. Capillary distribution companies play an essential role in distributing goods throughout the country. Considering the remarkable success of capillary diffusion in the distribution of

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goods, especially in the food and drug sector, a more scientific investigation is needed to decide on the choice of such a distribution system.

Sustainable transportation is a part of global sustainability that meets the current needs of communities without reducing the power of future generations. The concept of sustainable transportation can be obtained from the general concept of sustainability that includes all aspects of human life. Urban transportation can play an important role in urban development and efficiency when the movement of goods, services and people is done with minimum time, investment and operating costs. Routing and scheduling of urban transport, while reducing time and costs, seeks a balance between social, environmental and economic sustainability criteria. Definitions about sustainable transportation are conceptually different and are mostly descriptive and output-oriented rather than analytical and process-oriented. In order to achieve more practicality in the definition of sustainable transportation, more evaluations and investigations should be done regarding the quantification of the various elements of the sustainable transportation system. Finally, in this research, numerical values are obtained for social, environmental and economic aspects.

2.1. Explaining and expressing the subject

In the classic routing problem, a homogeneous (similar) fleet is used to serve customers. Each vehicle is defined by the limitation of weight capacity, width, length and height, which are the same for all vehicles in the classic routing problem.

In this paper, two main and practical problems of vehicle routing are combined:

1- Capacity-constrained vehicle routing problem (CVRP)
2- Dynamic vehicle routing problem (DVVRP)

The scientific term is the Dynamic Vehicle Routing Problem with Capacity Constraint (DVCVRP).

Despite the applicability of such a problem, there is still not enough research in this field, the main reason of which is the possible contradiction between the limitations and the distance from optimality.

In this research, in order to balance the contradiction between the limitations, the proposed model is solved in 3 phases. For the objective function, there is also a penalty for crossing the limits. Finally, for the sustainability of the logistics system, the percentage of improvement in 3 social, environmental and economic dimensions is obtained.

2.2. Society and statistical sample

Society is a group or class of people, objects, variables, concepts or phenomena that have at least one feature in common. In some cases, all the members of the society are studied, which is called a census. In this article, the statistical population includes all broadcasting companies and online stores, and even stores that have home delivery in their programs.

The statistical population may be large or small in terms of the number of people or cases to be observed. In order to save manpower, cost, time and observe other executive considerations, instead of studying all the members of the society, a sample of the members of the society can be selected and investigated. In this article, the data and information of Bazargam startup is selected as a sample for checking and solving the model due to the high volume and variety of orders and the extent of the areas covered in Iran as well as the high number of active vehicles in the country.

2.3. Work innovation

In this research, in order to innovate the work and move forward in the real world, it is considered to optimize several constraints simultaneously, which have been studied only in a separate way in the world's articles so far. The dynamic number of vehicles is more compatible and applicable to the real world, because for many reasons, the number of vehicles may be more or less available than the forecast. Dynamically considering the number of vehicles in different time intervals can reduce the number of active vehicles and thus lead to a significant reduction in the fixed costs of companies.

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Another innovation of this research is considering the maximum and minimum capacity of vehicles at the same time. The limitation of the maximum capacity makes the results of the model usable in the real world. The minimum capacity constraint is a dynamic complement to consider the number of vehicles to reduce the final cost of sending orders.

Another innovation of this research is to quantitatively consider the sustainability of the logistics system in three social, environmental and economic dimensions. Finally, the output of the work is a new algorithm called "Dynamic 3-Phase Optimization" which optimally optimizes routing problems with 2 main constraints of fleet capacity and dynamic vehicle number. The proposed model will have more applications in the real world than many previous models.

Another innovation of this fuzzy research is to consider 3 social, environmental and economic dimensions, which has been designed and modeled as 3-dimensional fuzzy for the first time.

3. Research methodology

In order to reach the proposed mathematical model, the parameters, multiple objective functions and limitations considered in the meta-heuristic model proposed in this article are described below.

3.1. parameters

V Total number of main and auxiliary vehicles
V^1 number of main vehicles
CP_{v_i} vehicle capacity penalty i
Y_{v_i} variable zero and one for active or inactive vehicle i
C_1 The transfer cost of each order above the original capacity
C_2 The cost of using any auxiliary vehicle
Q_{v_i} the number of delivery orders for vehicle i
Q_v^2 is the number of orders above which a separate fee (penalty) must be paid
Q_v^1 minimum number of delivery orders per vehicle
EV Number of auxiliary vehicles available

3.2. Objective functions

In the objective function (1), we minimize the amount of crimes of exceeding the capacity of the determined number of orders and the number of the main vehicle. In the objective function (2), we seek to minimize the number of active vehicles in that delivery period to reduce the company's costs.

$$\min \sum_{i=1}^{V} CP_{v_i} + \sum_{i=1}^{V} VP_{v_i} \qquad (1)$$
$$\min \sum_{i=1}^{V} Y_{v_i} \qquad (2)$$

3.3. Limitations

In constraint (3), the formula for calculating the amount of the penalty for exceeding the capacity of vehicle i is given. In constraint (4), we do not allow the number of delivery orders of each vehicle to be less than the specified value, so that less number of vehicles will be used in the end. In constraint (5), the amount of the penalty for using an auxiliary vehicle is calculated. In constraint (6), the sum of main and auxiliary vehicles is determined by parameter V.

$$CP_{v_i} = C_1 \left(\sum_{i=1}^{V} MAX\left(0, Q_{v_i} - Q_v^2\right)\right) \qquad (3)$$
$$Q_{v_i} \geq Q_v^1 \qquad (4)$$
$$VP_{v_i} = C_2 \left(\sum_{i=1}^{V} MAX\left(0, \left(\sum_{i=1}^{V} Y_{v_i}\right) - V^1\right)\right) \qquad (5)$$
$$V = V^1 + EV \qquad (6)$$

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3.4. Model solution method

Optimization algorithms can be used in the models, which are divided into two categories: exact and approximate algorithms. Exact algorithms are not efficient enough for complex optimization problems because, naturally, an exact answer cannot be obtained in a short period of time. The execution time of exact algorithms increases exponentially according to the dimensions of the problems. Approximate algorithms are able to find near-optimal solutions in a short solution time, which are divided into heuristic and meta-heuristic algorithms. Considering the two main problems of heuristic algorithms (getting stuck in local optimal points and early convergence to these points), meta-heuristic algorithms have been used to solve the proposed model of this research, which can be genetic algorithms, Tabu Search algorithm, Simulated Annealing algorithm, Ant colony algorithm and particle swarm optimization. Finally, in this article, a new meta-heuristic algorithm called "Dynamic 3 Phase Optimization" is proposed with the integration of other algorithms. The proposed model has been implemented and implemented with Python programming.

4. Case study

In this research, Bazargam startup has been selected for case study and model implementation. Bazargam has started to operate in the field of selling and distributing fast food items in several cities of Tehran, Isfahan, Yazd, Kerman and Karaj and now it has covered other provincial centers of Iran. In this research, the data of Tehran metropolitan city of this startup was used, which is naturally wider and with more restrictions than other cities. In larger and more complex projects, optimizations can be seen in higher and more impressive figures. The number of primary vehicles in each order delivery time frame and the minimum and maximum number of orders that each vehicle must deliver are determined in each separate time frame based on the total orders.

4.1. Simulation and analysis of model outputs

Simulation has the ability to compress time and expand time. Sometimes it is necessary to stop the time to study the results obtained up to that moment or to change only the values of some of the parameters in each of the repetitions in order to get their effect on the system behavior and the results. According to the advantages of simulation, in this research, simulation has been used to observe the results of allocations and routing. In this article, using Python programming, the final goal is to propose a structure and a model that plans information on the time and place of the trip, the duration of the trip, the stations and the time range of the activity in the city and the transportation network.

In this article, in order to analyze the information and aggregate the broadcast network data from the allocation-routing model by using the proposed algorithm "dynamic 3-phase optimization" and using Python programming, the results and outputs of the model have been analyzed.

5. Discussion

The proposed algorithm of this article is designed in 3 phases, which is discussed on a case-by-case basis, based on the data of an entrepreneurial startup, along with the description of the phases.

5.1. The first phase

The total area covered by the orders (the criteria for the location of the orders is the delivery time interval) is divided by the number of the initial vehicle of that interval (initial variable data). For this purpose, an innovative method called "star clustering" has been used. After obtaining the center of the orders, we go to the farthest order in each step and form a cluster. Again, we go from the center of that cluster to the farthest unclustered order and repeat the process.

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- We do the initial allocation without considering the restrictions. (The following maps show 3 models with 5, 10 and 20 vehicles and 2 thousand orders)

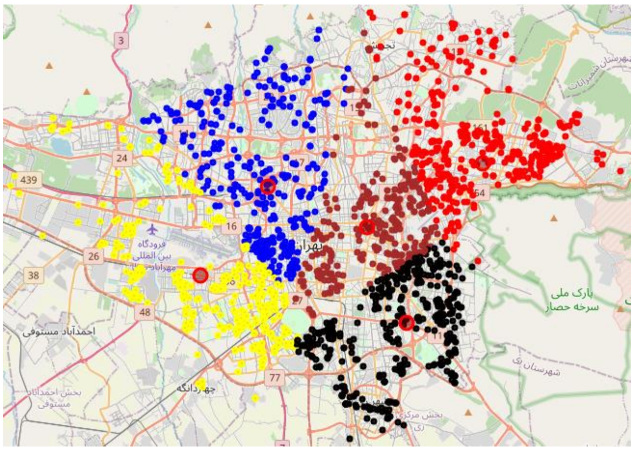

Figure 1: Initial allocation of 2 thousand orders to 5 vehicles with the innovative star method

The number of allocated orders for each vehicle: [425, 412, 369, 477, 317]
As a result, the maximum order of each device is 477 orders and the minimum order is 317 orders without restrictions and only with star clustering.

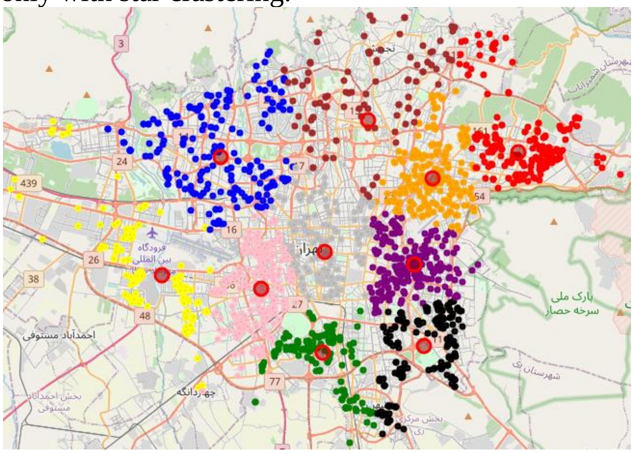

Figure 2: Initial allocation of 2 thousand orders to 10 vehicles with the innovative star method

Number of allocated orders for each vehicle: [147, 195, 208, 196, 108, 169, 253, 303, 263, 158]
As a result, the maximum order of each device is 303 orders and the minimum order is 108 orders without restrictions and only with star clustering.

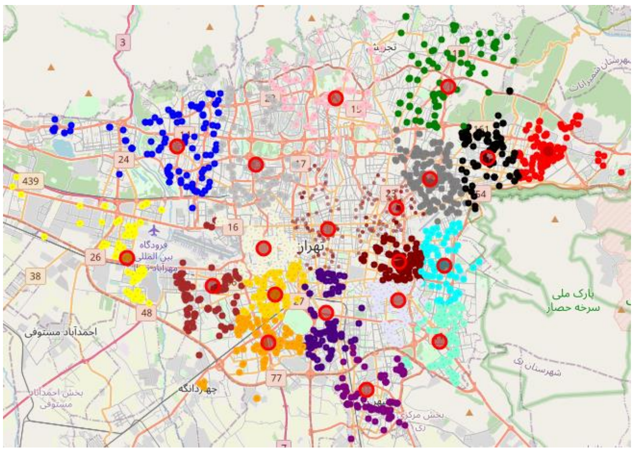

Figure 3: Initial allocation of 2 thousand orders to 20 vehicles with the innovative star method

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Number of allocated orders for each vehicle: [83, 102, 109, 98, 91, 86, 111, 77, 101, 93, 98, 127, 96, 101, 152, 113, 101, 83, 78, 100]
As a result, the maximum order of each device is 152 orders and the minimum order is 77 orders without restrictions and only with star clustering.

5.2. The second phase

-We consider the longitude and latitude of the center of each region.

-The two-by-two distance between the centers of the regions is calculated by air with all the orders and placed in the table.

-For each order, we calculate the penalty for not being allocated to the nearest region (difference between the nearest region and the second region).

-We start allocating from the highest fine until all orders are allocated.

-Whenever the number of orders in each region reaches the maximum capacity, it will no longer be allocated to that region.

-Due to the fact that the limit of the maximum capacity of orders that can be sent by each vehicle cannot be exceeded, if this limit is not reached, by adding a vehicle and applying a fine (overhead cost of a vehicle), we will go to the beginning of the first phase.

- Secondary allocation is done by taking into account the penalties and the maximum capacity limit.

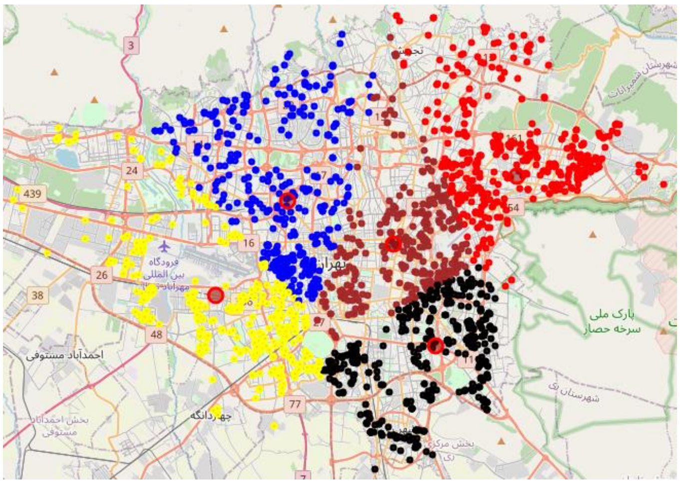

Figure 4: Secondary allocation of 2 thousand orders with 5 vehicles and a maximum capacity of 450

The number of allocated orders for each vehicle: [429, 414, 369, 450, 338]
As a result, in this case, the vehicle allocation of 27 orders has been moved between the active vehicles.

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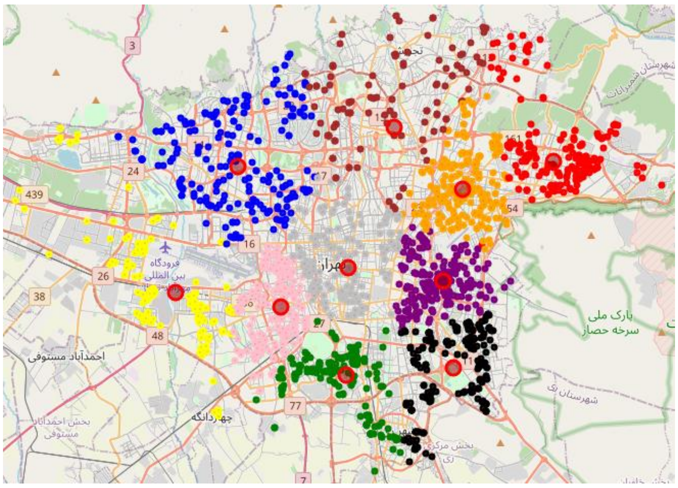

Figure 5: Secondary allocation of 2 thousand orders with 10 vehicles and a maximum capacity of 250

Number of allocated orders for each vehicle: [153, 196, 210, 204, 113, 185, 250, 250, 250, 189]
As a result, in this case, the vehicle allocation of 71 orders has been moved between active vehicles.

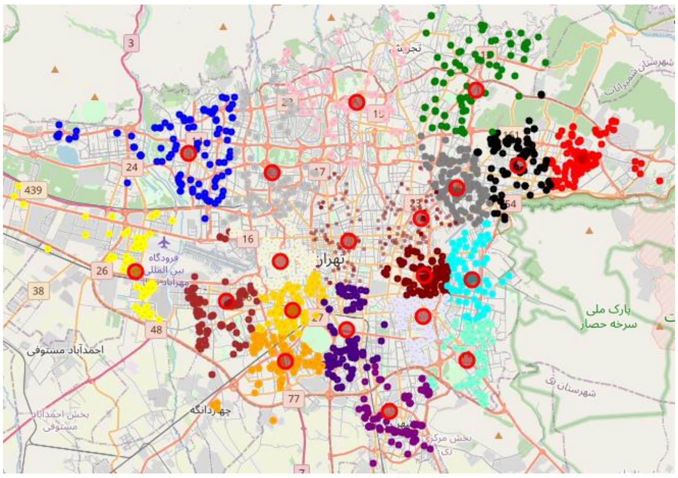

Figure 6: Secondary allocation of 2 thousand orders with 20 vehicles and a maximum capacity of 125

Allocated order number of each vehicle: [83, 102, 109, 106, 91, 86, 111, 77, 101, 93, 98, 125, 99, 103, 125, 113, 117, 83, 78, 100]
As a result, in this case, the vehicle allocation of 29 orders has been moved between active vehicles.

5.3. The third phase

-The minimum order limit for each vehicle is checked.

-If the minimum order limit is not met, we will reduce one vehicle. By nature, one area will decrease. Then we go to the beginning of the first phase and repeat the algorithm.

- After the limits of the orders are met and the fines are added, the final allocation orders are given.

Some of the checked modes for analyzing the model outputs are as follows:

- 5vehicles, 2000 orders, maximum capacity 450 and minimum capacity 350

The number of allocated orders for each vehicle: impossible (with 5 vehicles, the minimum capacity limit of 350 orders cannot be met. By reducing one vehicle, the maximum capacity limit cannot be met. If we allocate 450 orders to all 4 vehicles, 200 orders will not be fulfilled. allocation remains(

As a result, in this mode of vehicle allocation, we have to modify the maximum or minimum capacity.

- 10devices, 2000 orders, maximum capacity 250 and minimum capacity 150

Allocated order number of each vehicle: [250, 250, 250, 250, 250, 250, 250, 250[

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As a result, in this case, the vehicle allocation of 252 orders has been moved. The optimal number of vehicles will be 8 (the cost of 2 vehicles will decrease.(

- 10devices, 2000 orders, maximum capacity 250 and minimum capacity 120

Allocated order number of each vehicle: [178, 213, 236, 227, 150, 246, 250, 250, 250[
As a result, in this case, the vehicle allocation of 140 orders has been moved. The optimal number of vehicles will be 9 (the cost of one vehicle will decrease.(

- 20vehicles, 2000 orders, maximum capacity 125 and minimum capacity 75

Allocated order number of each vehicle: [83, 102, 109, 106, 91, 86, 111, 77, 101, 93, 98, 125, 99, 103, 125, 113, 117, 83, 78, 100[
As a result, in this case, given that the minimum capacity is less than the minimum number of orders, the second allocation is approved without change.

5.4. Comparison of system sustainability

To measure the sustainability of the system, we compare 2 models:

1) Fixed zoning and division of orders between fixed number of vehicles
2) Dynamic zoning and division of orders between the number of dynamic vehicles

To reach quantitative values, the entire area covered by past data analysis is divided into 8 regions with latitude and longitude according to Table 2.

Table 2: Suggested length and width for 8 areas in Tehran

Region	x	y
1	51.4396285	35.803613
2	51.4476082	35.7618831
3	51.5100427	35.7318271
4	51.4399957	35.7166553
5	51.3810374	35.7694224
7	51.3686976	35.7286007
7	51.3056439	35.7515952
8	51.3690278	35.6857595

The two-by-two distance between the centers of the regions with all the orders was calculated by air and placed in a table. For each order, the penalty of non-allocation to the nearest area was calculated, which is shown in Table 3, the example of allocation of 20 orders to 8 vehicles.

Table 3: The distance of the orders to the centers and the penalty for not allocating to the nearest area

Order	latitude	Longitude	Nearest area	for not Penalty allocating to the nearest area
1	35.7622	51.29249	7	0.066389364
2	35.755454	51.30567	7	0.064650815
3	35.748394	51.305017	7	0.063424352
4	35.765562	51.299736	7	0.063077069
5	35.76532	51.30264	7	0.061527521
6	35.73085	51.28844	7	0.053338464
7	35.694369	51.445639	4	0.044552997

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8	**35.700081**	**51.446594**	**4**	**0.043971007**
9	**35.782783**	**51.383266**	**5**	**0.042561529**
10	**35.81138**	**51.44082**	**1**	**0.042102352**
11	**35.81178**	**51.4351**	**1**	**0.042102318**
12	**35.75973**	**51.32028**	**7**	**0.040816387**
13	**35.699481**	**51.453602**	**4**	**0.040778327**
14	**35.68168**	**51.36349**	**8**	**0.04033061**
15	**35.7192**	**51.43748**	**4**	**0.040289995**
16	**35.68293**	**51.37405**	**8**	**0.040218847**
17	**35.784834**	**51.374016**	**5**	**0.039548602**
18	**35.78465**	**51.37188**	**5**	**0.038370562**
19	**35.813036**	**51.448847**	**1**	**0.037985888**
20	**35.80971**	**51.42679**	**1**	**0.037948695**

It started to be allocated from the highest fine. Whenever the number of orders in each region reached the maximum capacity, no more vehicles were allocated to that region. The minimum order limit of each vehicle is checked. If the limit is not met, the transfer is made from the adjacent area with the highest order to the area with the lowest order (based on distances). "Memory" is placed in displacements. With the memory, in case of custom transfer to the neighboring region, to avoid the cycle, exactly the opposite of this happens for the same two regions.

Finally, the distance that each vehicle should start from the warehouse and deliver all its orders was calculated. By implementing the proposed model on different samples of orders in different regions and with the number of orders and the number of different vehicles, the output of the model has given acceptable results by considering the limitations at the same time. The example of the delivery time of the first order and the last order in different regions with a warehouse is shown in Table 4.

Table 4: Delivery time of the first order and the last order for 8 vehicles

Vehicle	Delivery of the first order	Delivery of the last order	Delivery of the first order	Delivery of the last order	Delivery of the first order	Delivery of the last order
1	**09:50:12**	**12:01:47**	**09:42:13**	**11:52:47**	**10:27:24**	**11:56:56**
2	**10:06:37**	**11:51:51**	**09:07:46**	**10:32:50**	**10:47:51**	**13:49:09**
3	**10:39:02**	**12:00:06**	**09:30:03**	**11:20:01**	**09:45:40**	**11:05:26**
4	**09:53:27**	**11:20:05**	**09:59:23**	**11:57:46**	**11:13:57**	**14:15:00**
5	**09:49:00**	**11:08:10**	**10:21:25**	**13:24:29**	**09:33:33**	**11:33:16**
6	**10:17:59**	**11:16:02**	**10:03:00**	**12:42:42**	**10:21:41**	**11:53:27**
7	**09:33:52**	**11:20:18**	**10:44:07**	**12:32:33**	**10:18:56**	**12:59:19**
8	**09:07:26**	**11:18:11**	**10:41:01**	**13:32:05**	**10:43:26**	**13:14:26**

The output of the algorithm for the number of trips of each vehicle, the route traveled, the number of orders and the average distance traveled for 8 vehicles is shown in Table 5.

Table 5: Route traveled, number of orders and average distance for 8 vehicles

Vehicle	**Number of trips**	**The path traveled**	**Order number**	**The average mileage of each order**
1	**78**	**5118**	**856**	**5.98**

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2	**78**	**4962**	**844**	**5.88**
3	**71**	**4850**	**755**	**6.42**
4	**70**	**4755**	**730**	**6.51**
5	**70**	**4415**	**791**	**5.58**
6	**68**	**4730**	**711**	**6.65**
7	**61**	**4268**	**660**	**6.47**
8	**61**	**4312**	**716**	**6.02**

According to Table 5, the average distance traveled for 8 vehicles is 6.19 km. In case, without considering the three-phase algorithm with penalty index and only by allocating orders based on the area, it was 7.67 km. Figure 7 shows the comparison of the average distance traveled in 2 zoning algorithms and the proposed algorithm. The performance effect of the 3-phase optimization algorithm with the penalty index is evident in Figure 7.

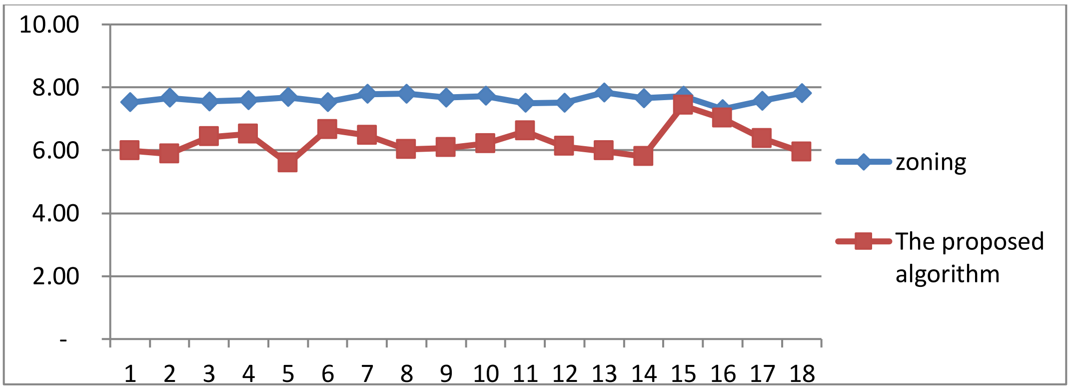

Figure 7: Comparison of the average distance traveled in the zoning algorithm and the proposed algorithm

In order to optimize vehicle routing problems as much as possible, we need to consider more constraints according to the real world at the same time. After applying restrictions for big issues, we must consider the risk and replacement of programs in special and critical times, which will be a very complicated task. With the proposed algorithm of this article, a visible effect was observed in the average distance traveled for each order from 7.67 km to 6.19 km. As a result, the order delivery time and variable transportation costs will be significantly reduced.

5.5. Fuzzy factors of system sustainability

In the proposed model to achieve the sustainability of the system, 3 social, environmental and economic dimensions are considered in a fuzzy manner, and finally the output of the proposed model will be 3-dimensional.

- Effects of the proposed DVCVRP model on each of the 3 social, environmental and economic dimensions: Very low (VL) - Low (L) - Medium (M) - High (H) - Very high (VH)
- System sustainability under the influence of the proposed model: Decrease (D) - Decreasing trend (DT) - constant (C) - Increasing trend (IT) - Increase (I)

For example, Table 6 shows the different states of two social and economic dimensions when the environmental dimension scores very low.

Table 6: The sustainability of the system with the proposed model in different states of two social and economic dimensions with very little environmental dimension

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System sustainability with very little environmental dimension		Economic dimension				
		VL	L	M	H	VH
Social dimension	VL	D	D	D	DT	C
	L	D	D	DT	DT	C
	M	D	D	DT	C	IT
	H	D	D	DT	IT	I
	VH	D	D	C	I	I

In the proposed 3D fuzzy model, we have 125 rules, for example, if we give low (L), high (H) and very low (VL) points to the social, economic and environmental dimensions respectively, the sustainability of the system is placed in the declining trend (DT) state.

To show the fuzzy values of variables, figures 8, 9 and 10 are obtained as follows:

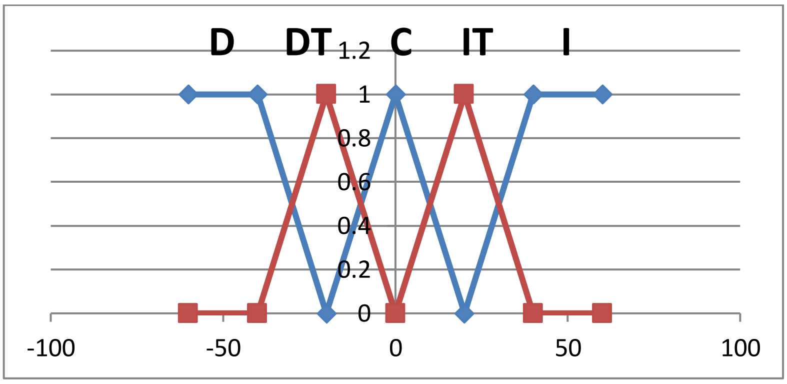

Figure 8: Fuzzy values of system sustainability

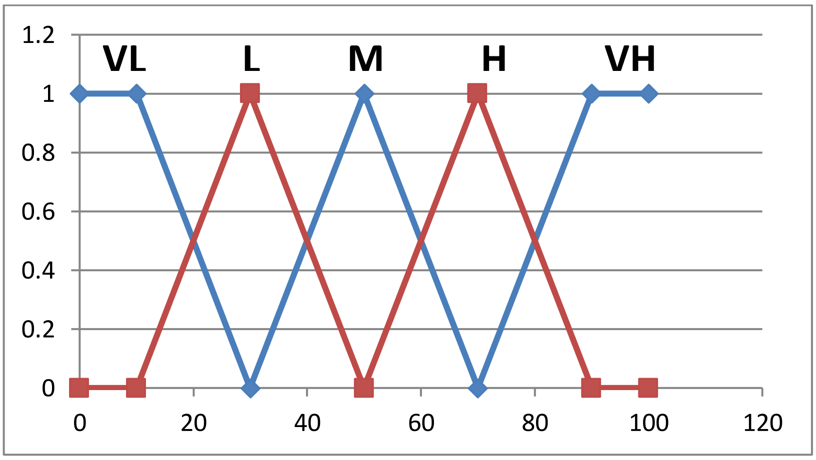

Figure 9: Fuzzy values of each of the social, environmental and economic dimensions

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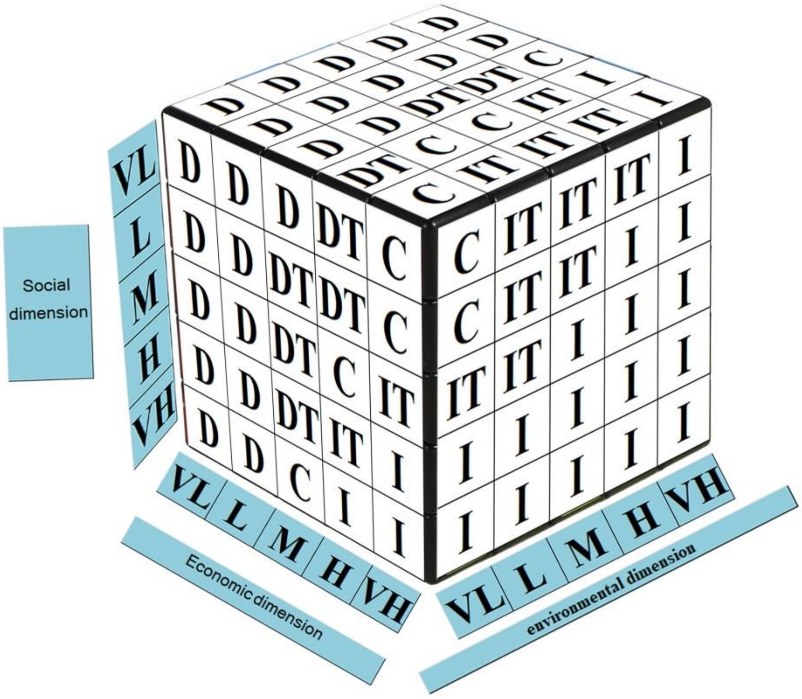

Figure 10: Fuzzy 3D design of system sustainability under the influence of social, environmental and economic dimensions

6. Conclusion

The main goal of most vehicle routing problems is to minimize transportation costs. In the proposed model, due to the fact that several restrictions are combined, the fines for crossing the restrictions are considered with a negative factor. Transportation costs are divided into two categories: fixed (per vehicle) and variable (based on the number of orders delivered and mileage).

-Fixed cost of each vehicle: 250 thousand units per day

-Bonus for each delivered order: 2 thousand units

- Fuel and depreciation costs: 500 units per kilometer

To allocate 2000 orders to 10 primary vehicles, the distances traveled are calculated according to Table 7:

Table 7: Mileage in 3 allocation modes

Allocation of 2000 orders to 10 primary vehicles			
Vehicle	No capacity limit	maximum The capacity is 250 and the minimum capacity is 120	The maximum capacity is 250 and the minimum capacity is 150
1	**218**	**234**	**224**
2	**221**	**225**	**231**
3	**255**	**257**	**249**
4	**223**	**231**	**239**
5	**227**	**211**	**256**
6	**209**	**240**	**242**

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7	**214**	**246**	**250**
8	**234**	**229**	**224**
9	**215**	**229**	
10	**229**		
distance total	**2245**	**2101**	**1911**
Average distance	**224**	**233**	**239**

The value of the objective function is 7622500 units in the first case, 7300500 units in the second case, and 6955500 in the third case.

In common operational research problems, the optimal solution never gets better with the addition of any constraint (either it doesn't change or it gets worse). In the proposed model of this article, despite the addition of the maximum and minimum capacity restrictions to the problem, by dynamically considering the number of vehicles and using star clustering, the cost of delivering orders has been reduced to 667 thousand units (8.7%). It is also clear from Figure 11 that despite the reduction in the number of vehicles, all 2000 orders (without significant changes in the distance traveled by the vehicles) have been delivered to the customers.

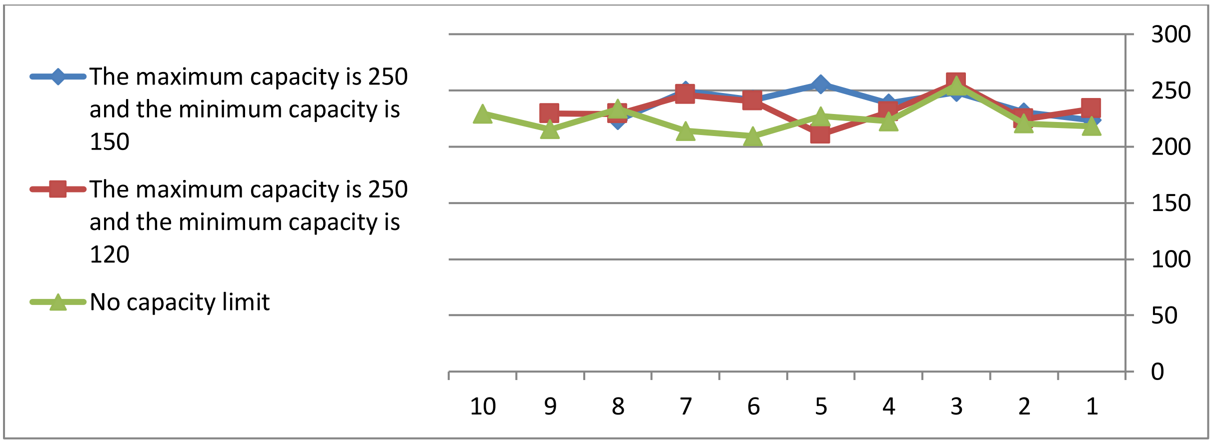

Figure 11: The distance traveled by each of the vehicles in 3 different modes

By summarizing the quantitative results obtained from the research data, the amount of system sustainability improvement using the proposed 3-phase model with the number of dynamic areas and vehicles is as follows:

- **Social aspect:** Considering that the average distance traveled for each order is reduced from 7.67 km to 6.19 km, the time for orders to reach customers is improved by 19.3%.
- **Environmental aspect:** regarding the amount of fuel consumption and air pollution, the total distance traveled is reduced from 2245 km to 1911 km, which reduces fuel consumption by 14.9% and thus air pollution.
- **Economic aspect:** according to the objective function of the problem, which is to reduce costs, the proposed model of this article has reduced costs by 8.7%.

Considering that the weight of social, environmental and economic aspects is obtained by considering the goals of large companies and organizations, in figure 12 the level of system sustainability is shown in 6 different coefficient modes for the proposed model of this research.

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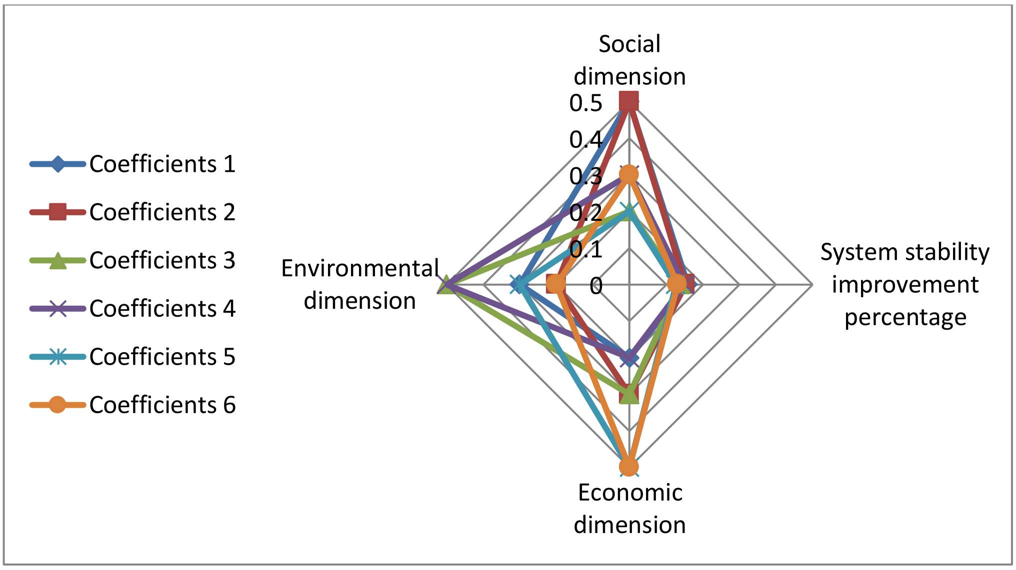

Figure 12: The percentage of improving the sustainability of the logistics system with different coefficients of social, environmental and economic dimensions

By applying the opinion of experts and considering the values of 3 social, environmental and economic dimensions calculated for the output of the DVCVRP model, relations 7 to 12 are obtained:

$\mu_M(\mathrm{SO}) = 0.5175$ (7)

$\mu_H(\mathrm{SO}) = 0.4825$ (8)

$\mu_M(\mathrm{EN}) = 0.6275$ (9)

$\mu_H(\mathrm{EN}) = 0.3725$ (10)

$\mu_M(EC) = 0.7825$ (11)

$\mu_H(\mathrm{EC}) = 0.2175$ (12)

which is obtained as a result of Tables 8 and 9 for system sustainability (S):

Table 8: System sustainability in different states of the social and environmental dimension and the average state of the economic dimension

$\mu_M(EC) = 0.7825$	$\mu_M(\mathrm{SO}) = 0.5175$	$\mu_H(\mathrm{SO}) = 0.4825$
$\mu_M(\mathrm{EN}) = 0.6275$	$0.5175 , \mu_C(\mathrm{S})$	$0.4825 , \mu_C(\mathrm{S})$
$\mu_H(\mathrm{EN}) = 0.3725$	$0.3725 , \mu_{IT}(\mathrm{S})$	$0.3725 , \mu_{IT}(\mathrm{S})$

Table 9: System sustainability in different states of the social and environmental dimension and the high state of the economic dimension

$\mu_H(\mathrm{EC}) = 0.2175$	$\mu_M(\mathrm{SO}) = 0.5175$	$\mu_H(\mathrm{SO}) = 0.4825$
$\mu_M(\mathrm{EN}) = 0.6275$	$0.2175 , \mu_{IT}(\mathrm{S})$	$0.2175 , \mu_{IT}(\mathrm{S})$
$\mu_H(\mathrm{EN}) = 0.3725$	$0.2175 , \mu_{IT}(\mathrm{S})$	$0.2175 , \mu_I(\mathrm{S})$

In relation 13, the objective function of the model is given:

$$\mu_{agg} = MAX\left\{min\left(0.5175 , \mu_C(S)\right), min\left(0.3725 , \mu_{IT}(S)\right), min\left(0.2175 , \mu_I(S)\right)\right\} \qquad (13)$$

With the fuzzy weighted average method, a value of 14.58 is obtained, which means a 14.58% increase in system sustainability in the implementation of the proposed three-phase DVCVRP model.

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6.1. Management insight

One of the main challenges of managers in companies is the management of human resources (in logistics companies, the most important forces are vehicle drivers). In order to increase employee motivation, the number of manpower, expected duties and salaries should be proportionate. One of the goals of this research is to pay special attention to the economic aspect of vehicle managers and drivers. In the proposed model of this article, the number of dynamic vehicles is considered in order to use human resources optimally. By analyzing the sensitivity of the model outputs, the logistics costs of the studied company decreased by 8.7%.

References

[1] Mahnaz Naghshnilchi (2019), A Capacitated Vehicle Routing Problem considering Satisfaction Level of Customers: A Genetic Algorithm, *Iranian Journal of Operation s Research* Vol. 10, No. 1, 2019, pp. 117 -127 DOI: 10.29252/iors.10.1.117

[2] B. Tootooni , A. Sadegheih, H. Khademi Zare , M. A. Vahdatzad (2020), A novel type I and II fuzzy approach for solving single allocation ordered median hub location problem, *Iranian Journal of Operations Research* Vol. 11, No. 2, 2020, pp. 65-79 DOI

[3] Zhang, Guoan, Wu, Min, Duan, Wei, & Xinming Huang (2018). Genetic Algorithm Based QoS Perception Routing Protocol for VANETs. Hindawi Wireless Communications and Mobile Computing, Article ID 3897857, 10 pages

[4] Hamza Toulni and Benayad Nsiri (2015). A Hybrid Routing Protocol for VANET Using Ontology, Procedia Computer Science 73, 94 – 101

[5] J.M. García-Campos , J. Sánchez-García , D.G. Reina , S.L. Toral, F. Barrero (2016). An evaluation methodology for reliable simulation based studies of routing protocols in VANETs, Simulation Modelling Practice and Theory 66, 139–165

[6] Omar Sami Oubbati, Abderrahmane Lakas, Fen Zhou, Mesut G¬unesü, Nasreddine Lagraa, Mohamed Bachir Yagoubi (2017). Intelligent UAV-Assisted Routing Protocol for Urban VANETs, Computer Communications

[7] Saifullah Khan, Muhammad Alam, Martin Fränzle, Nils Müllner, Yuanfang Chen (2018). A Traffic Aware Segment-based Routing protocol for VANETs in urban scenarios, Computers and Electrical Engineering 68, 447–462

[8] Mazzuco, D. E, Carreirão Danielli, A. M, Oliveira, D. L, Santos, P. P. P, Pereira, M.M., Coelho, L. C, Frazzon, E. M (2018). A concept for simulation-based optimization in Vehicle Routing Problems, IFAC PapersOnLine 51-11, 1720–1725

[9] N.V. Dharani Kumari, B.S. Shylaja (2019). AMGRP: AHP-based Multimetric Geographical Routing Protocol for Urban environment of VANETs, Journal of King Saud University – Computer and Information Sciences 31, 72–81

[10] Merve Keskin, Bülent Çatay, Gilbert Laporte (2020). A Simulation-Based Heuristic for the Electric Vehicle Routing Problem with Time Windows and Stochastic Waiting Times at Recharging Stations, Computers and Operations Research

[11] Binbin Pan, Zhenzhen Zhang, Andrew Lim (2020). Multi-trip time-dependent vehicle routing problem with time windows, European Journal of Operational Research

[12] Wenli Li, Kunpeng Li, P N Ram Kumar, Qiannan Tian (2021). Simultaneous product and service delivery vehicle routing problem with time windows and order release dates, Applied Mathematical Modelling 89, 669–687

[13] Duygu Taş (2020). Electric vehicle routing with flexible time windows: a column generation solution approach, Transportation Letters, DOI: 10.1080/19427867.2020.1711581

[14] Gabriel Policroniades Chípuli, Idalia Flores de la Mota (2021). Analysis, Design and Reconstruction of a VRP Model in a Collapsed Distribution Network Using Simulation and Optimizatio, Case Studies on Transport Policy

[15] Olivier Quirion-Blais, Lu Chen (2020). A case-based reasoning approach to solve the vehicle routing problem with time windows and drivers' experience, Omega

[16] Yuanzhi Jin, Xianlong Ge, Long Zhang, Jingzheng Ren (2021). A two-stage algorithm for bi-objective logistics model of cash-in-transit vehicle routing problems with economic and environmental optimization based on real-time traffic data, Journal of Industrial Information Integration

[17] Yong Wang, Qin Li, Xiangyang Guan, Jianxin Fan, Maozeng Xu, Haizhong Wang (2021). Collaborative multi-depot pickup and delivery vehicle routing problem with split loads and time windows, Knowledge-Based Systems 231,107412

[Downloaded from iors.ir on 2026-01-31]

[18] Michael Saint-Guillain, Celia Paquay, Sabine Limbourg (2020). Time-dependent stochastic vehicle routing problem with random requests: Application to online police patrol management in Brussels, European Journal of Operational Research

[19] Vinícius R.Máximo, MariáC.V.Nascimento (2021). A hybrid adaptive iterated local search with diversification control to the capacitated vehicle routing problem, European Journal of Operational Research 294, 1108–1119

[20] Feng Wang, Fanshu Liao, Yixuan Li, Xuesong Yan, Xu Chen (2021). An ensemble learning based multi-objective evolutionary algorithm for the dynamic vehicle routing problem with time windows, Computers & Industrial Engineering 154,107131

[21] Paweł Sitek, Jarosław Wikarek, Katarzyna Rutczyn´ ska-Wdowiak, Grzegorz Bocewicz, Zbigniew Banaszak (2020). Optimization of capacitated vehicle routing problem with alternative delivery, pick-up and time windows: A modified hybrid approach, Neurocomputing

[22] Nikolaus Frohner, Matthias Horn, G¨unther R. Raidl (2021). Route Duration Prediction in a Stochastic and Dynamic Vehicle Routing Problem with Short Delivery Deadlines, Procedia Computer Science 180, 366–370

[23] Nikolai Holeczek (2021). Analysis of different risk models for the hazardous materials vehicle routing problem in urban areas, Cleaner Environmental Systems 2, 100022

[24] Isidoros Marampoutis, Marina Vinot (2022). Lorraine Trilling, Multi-objective vehicle routing problem with flexible scheduling for the collection of refillable glass bottles: A case study, EURO Journal on Decision Processes 10, 100011

[25] Amalia Utamima, Arif Djunaidy (2022). Agricultural routing planning: A narrative review of literature, Procedia Computer Science 197, 693–700

[26] Arit Thammano, Petcharat Rungwachira (2021). Hybrid modified ant system with sweep algorithm and path relinking for the capacitated vehicle routing problem, Heliyon 7, e08029

[27] Juan Camilo Fonseca-Galindo, Gabriela de Castro Surita, José Maia Neto, Cristiano Leite de Castro, André Paim Lemos (2022). A multi-agent system for solving the Dynamic Capacitated Vehicle Routing Problem with stochastic customers using trajectory data mining, Expert Systems With Applications 195, 116602

[28] Jian Zhang, Kelin Luo, Alexandre M. Florio, Tom Van Woensel (2022). Solving Large-Scale Dynamic Vehicle Routing Problems with Stochastic Requests, European Journal of Operational Research

[29] Anees Abu-Monshar , Ammar Al-Bazi (2022). A multi-objective centralised agent-based optimisation approach for vehicle routing problem with unique vehicles, Applied Soft Computing 125, 109187

[30] Francesco Pilati, Riccardo Tronconi (2022). Social-economic sustainable Vehicle Routing Problem for local e-commerce platforms, IFAC PapersOnLine 55-10, 470–475

[31] Hassana Abdullahi, Lorena Reyes-Rubiano, Djamila Ouelhadj, Javier Faulin, Angel A. Juan (2020). Modelling and Multi-criteria Analysis of the Sustainability Dimensions for the Green Vehicle Routing Problem, European Journal of Operational Research

[32] Goran Jelen, Jurica Babic, Vedran Podobnik (2022). A multi-agent system for context-aware electric vehicle fleet routing: A step towards more sustainable urban operations, Journal of Cleaner Production, Volume 374, 134047

[33] Hasan Dündar, Mine €Omürg€onülsen, Mehmet Soysal (2021). review on sustainable urban vehicle routing, Journal of Cleaner Production 285, 125444

[34] Shuai Zhang, Mingzhou Chen, Wenyu Zhang, Xiaoyu Zhuang (2019). Fuzzy optimization model for electric vehicle routing problem with time windows and recharging stations, Expert Systems With Applications

[35] Juan Carlos Figueroa–García, Jhoan Sebastián Tenjo–García, Carlos Franco (2021). A global satisfaction degree method for fuzzy capacitated vehicle routing problems, Heliyon 8, e09767

[Downloaded from iors.ir on 2026-01-31]