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DESIGNING A HYBRID INTELLIGENT TRANSPORTATION SYSTEM FOR OPTIMIZATION OF GOODS DISTRIBUTION NETWORK ROUTING PROBLEM

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Abstract: *Given that finding the right and appropriate route in the daytime and busy city with the occurred traffic limitations is a major problem that not only causes inefficient performance in distribution networks but also causes irreparable environmental damage to society. This study focuses on improving the routing of the goods distribution network using the intelligent transportation system. In this regard, first, the problem is modeled, and then an intelligent transportation system is combined with some meta-heuristic algorithms to solve it. In the proposed algorithm, we first use the clustering algorithm to cluster location of customers and then create sub-clusters based on the time window. The proposed routes are created by using the genetic and particle swarm optimization meta-heuristic algorithms as the static part of the approach, and if the traffic conditions change, the Vehicular Ad - hoc Network (Vanet), which is one of the sub-systems of the intelligent transportation system as the dynamic part of the approach checks the new traffic conditions and sends the new information to the proposed algorithms to recheck the route. The Aarhus-Denmark data set is selected due to having urban traffic information, meteorology, and urban areas. This is related to the City Pulse project. According to the obtained results, in terms of reducing the cost of transmission, including the cost of service delay and total cost of moving, the proposed method reached better solutions comparing to the meta-heuristic algorithms of literature.*

Keywords: *Goods distribution network routing; intelligent transportation system; meta-heuristic algorithm; clustering algorithm.*

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1. Introduction

Transportation has an important role in economic, production, and service systems and is a remarkable part of the Gross national product (GDP) share in each country. On the other hand, the physical distribution of products is one of the key activities of manufacturing companies in the field of transportation, because on average 20% of the cost of products is spent on their physical distribution. Therefore, improving the physical distribution system of goods, in addition to reducing costs, will also improve productivity. This is while, unlike other activities, technological progress may improve the physical distribution of goods, but the progress can never be a substitute for it. Hence, it is necessary to improve the physical distribution system of goods. A method to improve the physical distribution system is to optimize the routing of the product distribution network.

The vehicle routing problem is one of the most important problems in supply chain management. This importance stems from the fact that the optimal allocation of vehicles to different routes has a great impact on reducing costs (Bank et al., 2020). The main objectives of this model are the optimal allocation of vehicles to different routes given the traffic restrictions based on the capacity of vehicles, as well as the delivery of goods to customers within the desired time period to minimize the route and the number of vehicles required for service. By achieving this, in addition to obtaining the overall goals of the VRP, which is the delivery of goods to customers in the shortest time, through the best route and with the least number of vehicles and the lowest shipping costs, the level of customer satisfaction will also increase and customer losses will decrease.

The problem of vehicle routing is important for researchers from two points of view: 1) the problem raised is a practical problem and the success in obtaining better solutions leads to economic savings and 2) solving the problem is a challenging problem due to its complexity.

Considering that transportation is one of the most basic human needs, it has always received special attention as an important indicator in every society, information and communication technology as an efficient tool has provided the means to facilitate and accelerate the provision of services. Transportation engineers have also tried to take advantage of information technology and reduce its problems to the minimum possible. One of these technologies is the intelligent transportation system, which is actually a transportation system based on the Internet of Things and has become smarter to provide fast, safe, and reliable services to the user. Vehicles can avoid being in a specific position on routes such as traffic and road damage by using intelligent transportation system tools such as Vehicular ad hoc network and choose a more suitable alternative route.

The problem of vehicle routing is one of the most complex problems in terms of computational complexity, which requires a lot of calculations.

Considering the above problem and the importance of reducing the route and time window, we use the clustering algorithm, transportation system tools (Vehicular ad hoc network) and meta-heuristic algorithms to solve the proposed model. For this purpose, we first use the clustering algorithm to cluster the location of the customers and then create sub-clusters based on the time window of the customers to serve. Since the meta-heuristic algorithms do not choose the optimal paths, the Vehicular ad hoc network is used to find the optimal path and the solution suitable for the goals of the model (Goli et al., 2022, 2022a; Mahmoodirad and Sanei, 2016; Hiassat et al., 2017; Rohmer et al., 2019; Ullah et al., 2022, 2023; Aghaei Fishani et al., 2022; Hashemi-Amiri et al., 2023). The combination of meta-heuristic algorithms and intelligent transportation system tools to solve the routing problem can lead to the optimization of the routing of the goods distribution network. Therefore, research and study in this field is of great importance for the logistics industry.

Also, taking into account the limitations indicates the practical conditions of the problem, so it seems necessary to develop the presented models by considering the limitations in order to bring the problem closer to the real and practical world conditions.

According to the investigation of the studies conducted in the field of vehicle routing and intelligent transportation, one of the most important limitations and gaps among the researches is the lack of investigation and attention to the advantages of the intelligent transportation system to solve the routing problem. Because most of the studies have been done only by relying on mathematical modeling and solving it with heuristic and meta-heuristic algorithms. As a result, the use of intelligent transportation system in logistics routing and solving the routing problem of transportation means is strongly felt. By considering the Vehicular ad hoc network (Vanet) and using it to send traffic information, it is possible to discover optimal and more suitable routes using genetic meta-heuristic algorithms and particle swarm optimization. Also, in this research, the clustering algorithm will be used to classify (cluster) the location of customers as well as the delivery time, which will reduce the route and cost.

By storing the appropriate routes in the database, it is possible to use the past routes to create a population to find the optimal route, which is an important step towards the implementation of routing optimization in the distribution network.

Also, in order to bring this issue closer to the real world and practical conditions, the mathematical model has been developed by simultaneously considering the traffic limit and the time window.

This research seeks to answer two main questions:

1. How is the mathematical modeling of the goods distribution network done in the form of developing a vehicle routing problem?

2. How is the development of the vehicle routing algorithm developed using the intelligent transportation system?

In this regard, this research aims to optimize the routing of the goods distribution network using the tools of the intelligent transportation system (Vehicular ad hoc network) and in three phases including: modeling the problem using integer linear programming in the form of developing the vehicle routing problem with Considering the traffic limit and the time window, solving the model using meta-heuristic algorithms and intelligent transportation system technologies, and finally implementing the model and evaluation.

In fact, the main goal of this research is the mathematical modeling of the goods distribution network in the form of developing a vehicle routing problem considering the traffic limit and time window, as well as developing the algorithm for solving the vehicle routing problem using the intelligent transportation system.

Considering that the presented model has the ability to be implemented in smart cities and on the other hand Iranian cities are not smart, therefore the data set related to the smart city will be used to create and expand the smart data set.

The rest of this paper is organized as follows: Section 2 reviews the relevant backgrounds in this field. Section 3 introduces the research method. In Section 4 the data set is presented. Section 5 deals with the results and evaluation of the research method. Section 6 provides some managerial insights. Finally, Section 7 summarizes the conclusions.

2. Theoretical background

According to the conducted research, the development of modeling of the routing problem of transportation means by simultaneously considering the time window and the traffic limit and also solving it by using the clustering algorithm, the tools of the intelligent transportation system (Vehicular ad hoc network) and meta-heuristic algorithms is the innovation of this research. Comparison of research background with the present study is shown by Table 1.

3. Problem modeling and proposed research methodology

This study addresses optimization of the distribution network routing of goods using ITS in three main phases including:

Phase 1. Problem modeling using mixed integer linear programming form of a VRP problem by considering the traffic constraints and time window.

Phase 2. Solving the model using the intelligent transportation system and in three steps. In the first step customer location is created using clustering algorithm, clustering and sub-clusters according to the delivery time window. In the second step by applying genetic and PSO meta-heuristic algorithms an initial solution as the obtained routes is determined. In the third step using the tools of the intelligent transportation system (Vehicular ad hoc network) as a dynamic part of the model the final solution is obtained.

Phase 3. Evaluating the proposed method. Finally, the proposed method is implemented and evaluated using the data set related to the smart city.

Flowchart of the proposed methodology is shown by Figure 1.

3.1. Problem definition and mathematical modeling (Phase 1)

An important issue in transportation and logistics systems is the vehicle routing problem, in which the goal is to determine the optimal routes for a number of vehicles located in the distribution center that must refer to a set of customers, each with a specific demand, and provide a service. The proposed solution is a set of routes containing an ordered queue of customers in which a vehicle exits the depot, visits these customers in turn, and returns to the depot. The problem is aimed to minimize the total distance of travel and the number of vehicles by considering the time window as well as minimizing the shipping costs. A mathematical model of this problem is given in this section.

The problem of distribution network routing includes a fleet of vehicles with a certain capacity, a distribution center (depot), several demand centers (retailers), and routes between the distribution center and the demand centers. Each vehicle starts to move from a common node called the depot to meet the demand, and while visiting the demand places, supplies the demand and returns to the depot. In the classical definition of this problem the following assumptions are considered.

Table 1. Comparison of research background with the present study

Study	Routing using mathematical modeling				ITS		Case Study	Method of solution
	Traffic restrictions	The objective function		Time window	VANET network	ITS sensor		
		Single goal	Multiple goals					
Hiassat et al. (2017)		×					Carrying goods	GA algorithm
Rohmer et al. (2019)		×					Carrying goods	Local search algorithm
Azad et al. (2019)		×					Perishable products	GA algorithm
Fazayeli et al. (2018)			×	×			Carrying goods	GA algorithm
Rahimi et al. (2017)			×				Carrying goods	Mathematical modeling
Nikfarjam & Moosavi (2020)			×				Carrying goods	Mathematical modeling and GA algorithm
Saragih et al. (2019)			×				Carrying goods	SA algorithm
Tavakkoli-Moghaddam et al. (2013)			×				Carrying goods	Mathematical modeling
Zhu & Hu, (2019)		×					Carrying goods	GA and PSO algorithms
Chen et al. (2020)		×				×	Carrying goods	Fireworks differential algorithm

Table 1 (continued). Comparison of research background with the present study

Study	Routing using mathematical modeling				ITS		Case Study	Method of solution
	Traffic restric tions	The objective function		Time window	VANET network	ITS sensor		
		Single goal	Multiple goals					
Gómez-Montoya et al. (2020)		×					Foodstuffs	PSO algorithm
Qin et al. (2019)			×	×			Carrying goods	GA algorithm
Bouk et al. (2017)						×		Review of ITS
Menouar et al. (2017)						×		UAV-enabled ITS
Gohar et al. (2018)						×		Internal storage and internal analysis for ITS data
Abbas et al. (2019)						×		Extended Kalman filter based on several models to predict the future location of the vehicle
Al-Qutwani & Wang, (2019)						×		The issue of traffic congestion,and also reducing the waiting time of vehicles at road intersections
Swarnamugi & Chinnaiyan, (2020)						×		Challenging sensor data with a context-aware pattern

Table 1 (continued). Comparison of research background with the present study

Study	Routing using mathematical modeling				ITS		Case Study	Method of solution
	Traffic restric tions	The objective function		Time window	VANET network	ITS sensor		
		Single goal	Multiple goals					
Lee & Chiu, (2020)						×		New traffic signal scheme specifically for the EVSP scenario
Skabardonis, (2020)						×		Evaluation of transportation system and emerging technologies
Rahimi & Jamali, (2018)					×			Fuzzy logic and DTN transport approach
Raw et al. (2018)					×			Performance of two routing protocols, MaxProp and packet-oriented routing (POR)
de Andrade et al. (2016)					×			Mathematical model of HBR protocol

Table 1 (continued). Comparison of research background with the present study

Study	Routing using mathematical modeling				ITS		Case Study	Method of solution
	Traffic restrictions	The objective function		Time window	VANET network	ITS sensor		
		Single goal	Multiple goals					
Jain & Kashyap, (2020)					×			Improved OLSR routing protocol
Oyakhire & Gyoda, (2020)					×			Game theory on the OLSR routing protocol
Zhang et al. (2018)					×			GA algorithm based on GABOR routing protocol
Muniyandi et al. (2020)					×			Proposed RALAR protocol using GA algorithm
Chahal & Harit, (2019)					×			Optimization of discrete particle swarms
Gupta & Kumar, (2014)					×			Routing protocol and GA algorithm
Kasana & Kumar, (2017)					×			Geo-routing protocol GR
Ye et al. (2020)					×			Routing protocol TDMP

Table 1 (continued). Comparison of research background with the present study

Study	Routing using mathematical modeling				ITS		Case Study	Method of solution
	Traffic restric tions	The objective function		Time window	VANET network	ITS sensor		
		Single goal	Multiple goals					
Wille et al. (2016)					×			Genetic network protocol (G-net)
Okulewicz & Mańdziuk, (2017)								DVRP protocol and 2MPSO algorithm
The present study	×	×		×	×	×	Carrying goods	Use of clustering, GoogleMap and VANET routing protocol with GA-PSO meta-heuristic algorithm

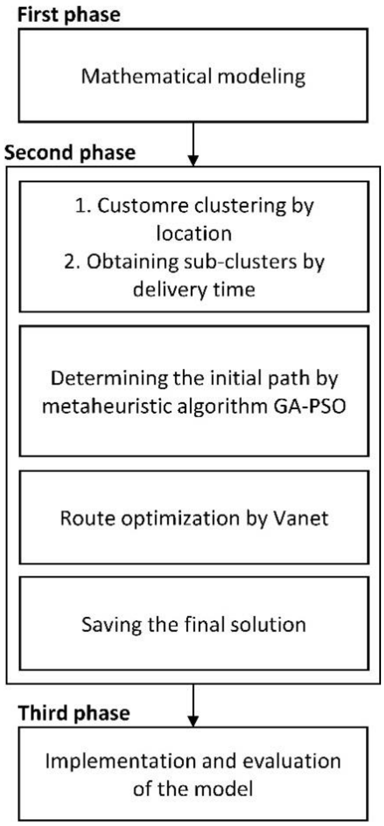

Figure 1. Flowchart of the proposed research methodology

- Each vehicle starts moving from the distribution center and eventually has to return to the center.
- Each demand center receives service only from one distributor vehicle.
- The demand of each center is less than the capacity of the vehicle.
- None of the vehicles are loaded more than their capacity.
- Each demand center has a specific time window to receive the service and each vehicle must start service during this period.
- The maximum distance that the vehicle can travel is specified and no more than that is allowed.
- The main objective of this study is to minimize the total travel distance and transportation costs by directing vehicles to optimal routes.

In this study, in order to present the VRP model, a graph G (V, A) has been used in which V = (0, 1, 2.3,…, n) is the sum of nodes and A = {(u, v) / u, v∈V, u ≠ v} is the set of arcs in it. In this case, each node u, except node 0 that represents the central depot node, represents a demand center that has a demand for q_u. Each arc in A corresponds to the distance d_{uv}, which is the distance between customers u and v. On the other hand, there is a fleet of K different types of vehicles at the source, so that each vehicle has a load capacity of Q_k and I_{uv}^{-} is a set of vehicles i, which cannot travel between the nodes u, v due to traffic restrictions. Each node also comes with a demand value q_u, service time s_u, and a time window$[e_u, l_u]$. Each arc (V_u and V_v) is related to the travel time t_{uv} between nodes V_u and V_v. If the vehicle arrives at the customer earlier than V_u, it can wait until e_u to provide customer service or provide its services. If the vehicle arrives after l_u, it can provide service for V_u after paying the fine W_2 . The cost of moving per unit of distance is shown by W_1, which a cost is allocated based on the route traveled, and is considered as the route cost. Also, the fixed cost of using each vehicle is a fixed value indicated by F^k. The variable γ^k is the fixed cost of using VANET equipment. θ_{uv} is the coefficient of route type in calculating the cost of distance. Choosing an inappropriate path creates additional costs due to fuel and depreciation.

Based on the above explanations, the below mathematical formulation is presented for the described problem.

MinZ=

$$W_1(\sum_{k=1}^{K}\sum_{u=0}^{N}\sum_{v=0}^{N} d_{uv}x_{uv}^{k}\,\theta_{uv})+ \quad (1)$$

$$W_2[\sum_{u=0}^{N} Max\big((t_u^k - l_u),0\big)]+ \quad (2)$$

$$\sum_{k=1}^{K}\sum_{v=0}^{N} x_{0v}^{k}\,(F^k + \gamma^k) \quad (3)$$

$$x_{uv}^{k} = \begin{cases} 1, & \text{If vehicle K moves from u to v} \\ 0, & \text{Otherwise} \end{cases} \quad (4)$$

$$\sum_{u=0}^{N} x_{uv}^{k} - \sum_{u=0}^{N} x_{vu}^{k} = 0\ (u \neq v, \forall v = 1,2,\dots N; \forall k = 1,2,\dots,K) \quad (5)$$

$$\sum_{k=1}^{K}\sum_{u=0}^{N} x_{uv}^{k} = 1 \quad (u \neq v, \forall u = 1,2,\dots n) \quad (6)$$

$$\sum_{k=1}^{K}\sum_{v=0}^{N} x_{uv}^{k} = 1 \quad (u \neq v, \forall u = 1,2,\dots n) \quad (7)$$

$$\sum_{v=0}^{N} x_{0v}^{k} \leq n_k \quad ; \forall k = 1,2,\dots,K) \quad (8)$$

$$\sum_{u=0}^{N} q_u x_{uv}^{k} \sum_{v=0}^{N} x_{uv}^{k} \leq Q_k \quad (u \neq v, \forall k = 1,2,\dots k) \quad (9)$$

$$x_{uv}^{k} \leq 0\ for\ k \in \{K_{uv}^{-}\}\ \forall_{u,v} = 0,1,2,\dots,n,\ \ u \neq v \quad (10)$$

$$t_u^k + s_u + t_{uv} \leq (1 - x_{uv}^{k}).M + t_v^k \quad (\text{u} \neq v, \forall u = 0,1,\dots,N;\ \forall k = 1,2,\dots,K) \quad (11)$$

$$e_v \sum_{u=0} x_{uv}^{k} \leq t_v^k \leq l_v \sum_{u=0} x_{uv}^{k} \quad (\text{u} \neq v, \forall u = 0,1,\dots,N;\ \forall k = 1,2,\dots,K) \quad (12)$$

The objective function of this problem is the minimization of total costs. Equation (1) In the objective function representing the cost of the total movement of all trips, the cost of choosing the wrong route, which is multiplied by the previous cost as a factor. Equation (2) In the objective function, it represents the cost of not complying with the earliest time of the soft time window. Equation (3) It represents the total fixed cost of using the Vehicular ad hoc network equipment. Equation (4) The decision variable is 0 & 1. Equation (5) Every vehicle that enters a node must leave it. Equation (6) and (7) show service limits. Equation (8) It shows that the number of used vehicles of the k type should be at most n_k Equation (9) It shows that the total requests of customers served by a vehicle cannot exceed its capacity. Equation (10) It guarantees the restriction of vehicle traffic in some routes. Equation (11) and (12) define the limits of the soft time window.

3.2. The solution approach (Phase 2)

With regard to the NP-hard nature of the vehicle routing problem (VRP), the solution and the optimal route solution for shipping good is determined using a combination of genetic algorithms (GA) and particle swarm optimization (PSO). To create the initial population, a controlled method is used to prevent the creation of random populations, a very small percentage of which may form a route. This method is fulfilled in three steps in continue.

Step 1: Clustering using data mining technique

In this step, customers are clustered based on their locations using one of the data mining techniques called k-means clustering where all customers in a specific area are placed in a cluster. The number of clusters is determined as k based on the number of regions. Each cluster is then subdivided into other sub-clusters based on time constraints so that customers in a cluster are divided into sub-clusters based on the priority of the good delivery time.

Step 2: Determining the initial population (routes) using GA-PSO algorithms

Initial routing using GA-PSO algorithms. The vehicle routing problem considered in our system is the large scale of the time window routing. This type of problem has multiple characteristics: (1) The customer time window seems to be difficult because the early vehicle has to wait for the customer to open and arrive late to be carried out. (2) The customer request is real-time information, which means that when starting the routing process, not all customer request information is known by the planner and customer information enters the system before the routing starts. (3) Travel time or speed between customer and depot can fluctuate depending on the departure time. (4) Customer demand is very high.

Over the past few years, to solve optimization problems, new methods have been developed with recent advances in learning techniques called hybrid optimization. By adapting the parameters in the routing protocols, this method can transfer the computational load from the development stage of the solution based on online planning and protocol to the offline stage. As a result, the decision-making process can be accelerated rapidly, where the quality of the solutions is highly dependent on the architecture of the selected meta-heuristic algorithms. A wide range of research problems uses meta-heuristic methods to solve integrated distribution problems. These methods are aimed to achieve an almost optimal solution to a certain problem. Extensive use of GA algorithms along with various meta-heuristic methods is a common solution to such problems, and in this study, the PSO algorithm is used to escape the local optimum in GA.

Step 3: Optimizing routing using VANET

During the planning period and route selection, if real-time demand or traffic information changes, the system must automatically set vehicle routes using routing protocols. Hence, the GPSR routing protocol is used. This protocol is a routing protocol used in VANET car Ad Hoc networks and is one of the best location-based protocols. The events of selected routs by the Google Map are examined Using the VANET network routing protocol, and finally, the possible routes are identified as the initial population of the GA-PSO meta-heuristic algorithm. If traffic conditions change, the VANET network, as the dynamic part of the model, examines new traffic conditions and sends new information to the meta-heuristic algorithm to re-examine the route.

Given that the main objective of this study is to minimize the entire travel route by directing vehicles instead of using long distances, hence, both comprehensive search capabilities (GA algorithm) and local (PSO algorithm), as well as VANET network routing, will be used simultaneously for achieving the best possible solution with better performance. After providing the best route to the user, the route is stored in the database and used in future routing.

Step 4: Save the final answer in the database

In this section, all transportation routes are stored with the average time, along with the day, date and time of sending. After collecting the above items until at least 10 records are recorded for each retailer/customer, the operation of choosing the best route for each customer/retailer based on the day and time of departure is performed and shown as a solution for population formation.

3.3. Model evaluation and implementation (Phase 3)

Implementation of the proposed algorithm is carried out in Python programming language with regard to the traffic to optimize the distance and transportation costs. In this case, the primary goal is to minimize the total distance traveled and the cost of transportation. Therefore, in order to evaluate different algorithms, these two parameters must be considered.

4. Data set

Given the issue that we do not have access to a complete smart city, we need a smart city data set to simulate such a city. Surveys in this area revealed three smart city projects: Aarhus-Denmark, Brasov-Romania, and Sari-UK, among which the Aarhus-Denmark data set was selected due to its data on urban traffic, meteorology and urban areas, as well as the ability to merge and expand. The data sources used for this smart city include meteorology, traffic, sights, and street network structure, which is known as metropolitan data and shows the dynamics of the city. Data sources in this smart city are divided into two categories: static and dynamic. Static data sources are land use data, waterways, buildings, roads, facilities, and urban areas. Dynamic data sources are meteorological and traffic data.

The data used in this research is related to the City Pulse project[1] that raw data was collected in the period 2013 to 2016 and is shown in the figure and table below. Since the common point of meteorological and traffic data is from February to June and August to September (month 2 to month 6 months and month 8 to month 9), the simulations are based on these months. Due to the fact that air pollution data is only available in the period from the 8th month to the 10th month, the data for the 2nd month to the 6th month have been simulated and created based on the data of those two months (see Figure 2 and Table 2).

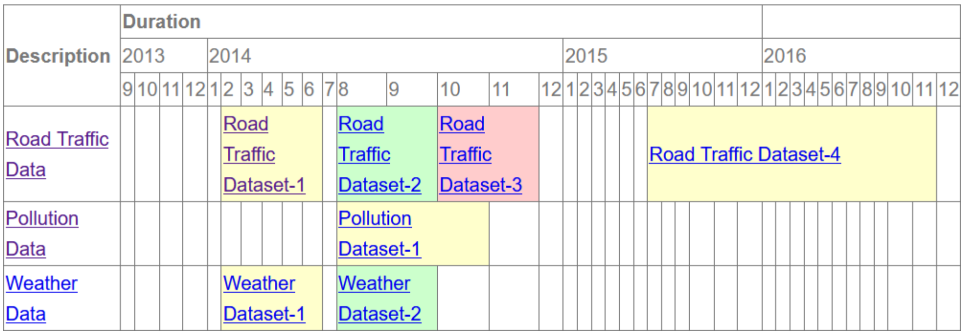

Figure 2. Interval of the data set used

Table 2. Some details of the data sets

Data description	Time interval	location
Vehicle traffic data	2/2014 - 6/2014	Aarhus-Denmark
Meteorology data	8/2014 - 9/2014	Aarhus-Denmark
Parking data	10/2014 - 11/2014	Aarhus-Denmark

Because the data used in this study (traffic data and air quality information) is an extended version of the City Pulse project data, other data collected from other online sources such as meteorological data from the Underground website, urban areas, and the city road structure is extracted from GoogleMap and added to it. Also,

[1] http://iot.ee.surrey.ac.uk:8080/datasets.html

meteorological and traffic data were recorded 12 times per hour with a time interval of five minutes and a total of 14124555 data samples were created in the desired time period, which is characterized by the data used in Table 3.

Table 3. Details of the metrological, air pollution, and traffic data

Metrological and Weather Sensor Data (WEA)	Air Pollution Sensor Data (POU)	Taffic Sensor Data (TD)
Temp-high, Temp-avg, Temp- low, Dewpoint-low, Humidity-high, Humidity- avg, Humidity-low, Sea Level-high, Sea Level-avg, Sea Level-low, Wind-high, Wind-avg, Wind-low.	Ozone, carbon_ monoxide, sulfure_dioxide, nitrogen_dioxide, particular_mater	avgSpeed, vehicleCount

According to the data set, 20 regions were randomly selected as the desired customers for service in the city, and 1 distribution center is selected, which is the distribution center with the number 1, and other numbers are the customer as shown in Figure 3.

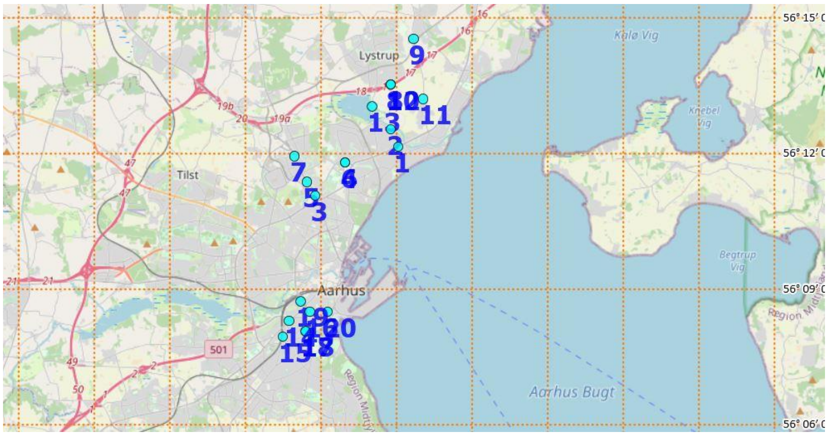

Figure 3. Selected areas for depot and service provision

4.1. Simulation of time and route traffic

In order to simulate the travel time between service areas, first, the longitude and latitude database of the source and destination are recalled and the route and travel time are extracted by Google routing. Although the Google Map forecast is relatively accurate, we used the 7-month data to make the forecast more accurate. In other words, for each day of the week for the desired 7 months, the travel time and distance traveled are extracted and the average of each day is calculated. For example, the time and distance is calculated between the two routes on Saturday at 11 o'clock, and for all Saturdays at the same time for the desired 7 months, the distance and time traveled is extracted, and the average time and distance traveled is considered for processing. An example of point-to-point routing to extract distance and time between points is shown by Figure 4.

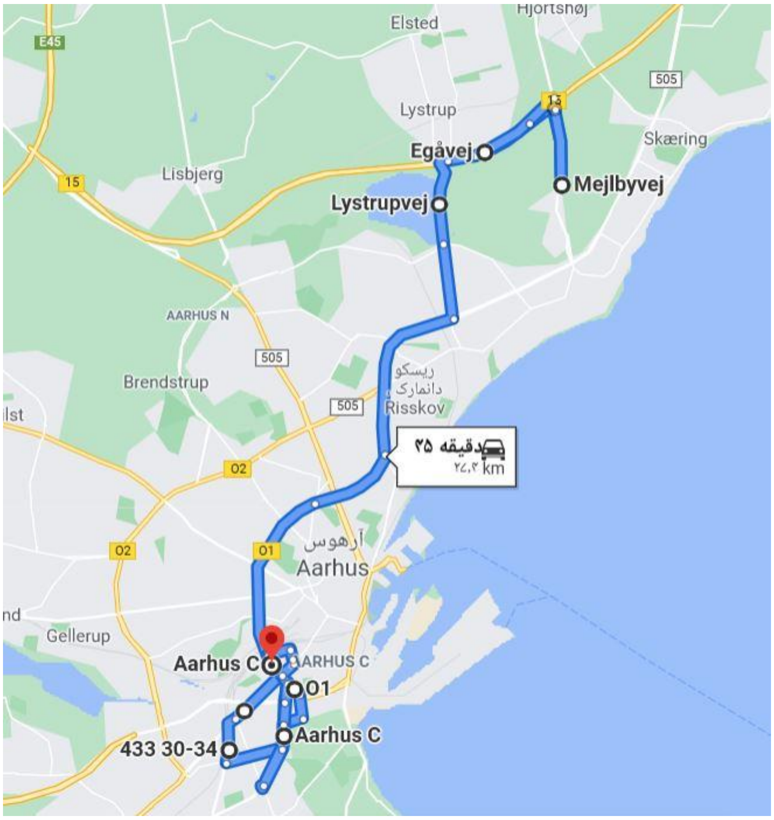

Figure 4. An example of point-to-point routing to extract distance and time between points

Due to the above mathematical problem, the cost information is given in Table 4.

Table 4. Cost data of the case studies

Criteria	Cost
F^k =vehicle constant cost	500
γ^k =constant cost of vanet usage	50
W_1= The cost of moving per unit of distance	0.1
W_2 =The cost of the fine resulting from not complying with the longest customer service time in the soft time window for one unit of time	0.1

Also, in order to serve the customers and observe the scheduling, a time interval is defined for each customer, which is the beginning of the service and its end. For example, the start time of service provision for customer no.2 is from 8 to 8:20, and the start time of service provision for customer no.3 is from 8:35 to 8:55, which are calculated using the distance and travel time among customers.

5. Evaluation

The cost of the route for each customer from the source, which is the distribution center, and other subsequent destinations are specified in Table 5.

According to the mathematical model and input information for it, as well as the parameters set for GA-PSO algorithms, the performance of GA, PSO, GA-PSO algorithms with clustering (for customer clustering based on location and time are divided into 2 clusters) And without clustering is compared as shown in Table 6.

GA= 1-8-10-11-2-13-6-8-7-5-3-19-14-15-18-17-16-20-1
PSO= 1-2-6-4-13-8-10-11-7-5-3-19-16-20-17-18-14-15-1
GA-PSO=1-2-11-8-10-13-6-4-7-5-3-19-16-14-15-17-18-20-1
Cluster1=1-2-11-8-10-13-4-6-7-3-5
Cluster1=5-19-16-20-18-17-15-14-1

According to the above table, the results of the GA-PSO algorithm with customer clustering performed better than the results of any algorithm for both optimizations, which is related to obtaining no solution for the local optimum in GA. The problem is eliminated by combining the algorithm with PSO and the hybrid algorithm has selected the most optimum rote in local search.. The use of clustering algorithms also reduced the overall cost and overall distance traveled.

The cost of the route using the vent for customers is shown in Table 7, in which the performance of the proposed method is calculated according to the costs of the new route.

The proposed method, which used the VANET protocol in routing, has reduced the total distance by approximately 1.8 km, which is due to the fact that in some routes, in order to escape from traffic, it has to travel longer distances, and vice versa, in some routes, VANET provided shorter routes than the proposed algorithm without running the VANET, which all distances traveled are totally 47.52 km. Also, the reduction in cost optimization compared to GA-PSO algorithms using clustering is due to the fact that although the fixed cost of using the VANET has been added to the total costs, but the total cost of service delays has been greatly reduced, which reduces the total cost.

Table 5. Route costs regardless of VANET routing

Route	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	2.2	12.4	6.2	12	7.4	6	6	16	6	3.6	14	3.2	21.2	26.4	21	16	16.2	19	26.4
2	2.2	0	12	7	12.2	7	7	5.6	13.8	5.6	6.6	12	3	22.2	23.8	22	26.6	27	19.8	22.2
3	12.4	12	0	6	5	4.6	4.6	20	25.2	19.2	18.6	23.6	19	18.2	20	16	22	22.2	14.4	14.6
4	6.2	7	6	0	5.8	0.2	7	10.6	22.4	10.6	10.6	17	7.8	16.6	18.4	16.6	20.1	20.2	16	17.4
5	12	12.2	5	5.8	0	24	6	7	16.2	25.6	16	23	10.8	21.4	20	13.6	18.2	18.4	14	14
6	7.4	7	4.6	0.2	24	0	3.2	10.7	22.6	10.8	10.8	18	7.8	16.8	18.6	16.8	20.2	20.4	16	17.8
7	6	7	4.6	7	6	3.2	0	12.8	24	13.4	19	21.4	13.2	22	22	19.8	24.6	25.6	17.8	17.8
8	6	5.6	20	10.6	7	10.7	12.8	0	18.6	0.2	5.6	6.4	7.6	31	33	31	44	44.2	26.6	31.6
9	16	13.8	25.2	22.4	16.2	22.6	24	18.6	0	13.8	5	5	6.2	37.8	38	30	44	44.2	26.2	31.2
10	6	5.6	19.2	10.6	25.6	10.8	13.4	0.2	13.8	0	6	6.4	7.6	39.2	40.6	39	44	44.2	27.4	38
11	3.6	6.6	18.6	10.6	16	10.8	19	5.6	5	6	0	4.2	7.6	32.4	27.2	25.4	31	31.2	23.2	26.2
12	14	12	23.6	17	23	18	21.4	6.4	5	6.4	4.2	0	13	30	27	31.2	39	39.2	23	32
13	3.2	3	19	7.8	10.8	7.8	13.2	7.6	6.2	7.6	7.6	13	0	23	27.2	21.8	31.2	31	20.2	31.6
14	21.2	22.2	18.2	16.6	21.4	16.8	22	31	37.8	39.2	32.4	3.	23	0	0.44	4.6	4.6	4.8	4.4	3.6
15	26.4	23.8	20	18.4	20	18.6	22	33	38	40.6	27.2	27	27.2	0.44	0	6.2	3	3.2	5.6	6
16	21	22	16	16.6	13.6	16.8	19.8	31	30	39	25.4	31.2	21.8	4.6	6.2	0	11	11.2	3	3.2
17	16	26.6	22	20.1	18.2	20.2	24.6	44	44	44	31	39	31.2	4.6	3	11	0	0.2	4.6	4.6
18	16.2	27	22.2	20.2	18.4	20.4	25.6	44.2	44.2	44.2	31.2	39.2	31	4.8	3.2	11.2	0.2	0	4.8	4.6
19	19	19.8	14.4	16	14	16	17.8	26.6	26.2	27.4	23.2	23	20.2	4.4	5.6	3	4.6	4.8	0	3
20	26.4	22.2	14.6	17.4	14	17.8	17.8	31.6	31.2	38	26.2	32	31.6	3.6	6	3.2	4.6	4.6	3	0

Table 6. Evaluation results of the proposed method without using VANET

Objective function	Method			
	GA algorithm	PSO algorithm	GA-PSO algorithm	GA-PSO algorithm using the clustering
Distance optimization	57.32km	55.02 km	53.62km	**47.52km**
Cost optimization	712.984	697.716	687.724	**666.364**

According to Table 7, Table 8 shows the distance and cost optimized using the VANET and without it.

In Table 9, the total delay time for the proposed method with and without the VANET is calculated, which in total reduces the delay time and also the cost of delay in service provision.

According to the table above, the proposed method reduces the delay time by 76 minutes and reduces the total delay costs by 7.6 units compared to the method without VANET. According to the traffic and meteorological data set, the proposed method was implemented again in the above two cases and the results are presented in Table 10.

As shown in Table 10, the time and cost of delay, as well as the distance traveled in heavy traffic and rainy weather, have increased compared to the average of normal days, consequently, the total cost has also increased. The cost of the proposed method with heavy traffic and rainy weather has increased compared to the average of normal days, but it is still lower than the proposed method without the VANET. In order to summarize the obtained results, first the following experiments are defined, and then the obtained results are shown by Figure 5 and Figure 6 in terms of total traveled distance and total cost respectively. According to these figures superiority of the proposed approach can be seen easily.

- Experiment 1: GA algorithm;
- Experiment 2: PSO algorithm;
- Experiment 3: GA-PSO algorithm;
- Experiment 4: GA-PSO algorithm using the clustering;
- Experiment 5: Proposed method without VANET;
- Experiment 6: Proposed method with VANET;
- Experiment 7: The proposed method on normal days;
- Experiment 8: Proposed method with heavy traffic;
- Experiment 9: Proposed method with rainy weather;
- Experiment 10: Proposed method with heavy traffic and rainy weather.

Table 7. Route costs by considering the VANET routing

Route	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	2.2	12.4	6.2	11.2	7.4	6	6	13.6	6	3.6	11.8	3.2	20	22.6	21	11	11.2	19	21.8
2	2.2	0	11.2	6.6	12.2	6.6	7	5.6	13.8	5.6	6	12	3	22.2	23.8	22	26.6	27	19.8	22.2
3	12.4	11.2	0	6	5	4.6	4.6	17.2	25.2	19.2	18.6	23.6	19	18.2	20	16	22	22.2	14.4	14.6
4	6.2	6.6	6	0	5.8	0.2	5.8	10.6	18.6	10.6	10.6	17	6	16.6	18.4	16.6	20.1	20.2	14.6	16
5	11.2	12.2	5	5.8	0	24	6	5	16	22	16	16	10.8	13.8	15.4	13.6	18.2	18.4	11.6	12.6
6	7.4	6.6	4.6	0.2	24	0	3.2	10.7	18.6	10.8	10.8	18	7.8	16.8	18.6	16.8	20.2	20.4	14.6	16
7	6	7	4.6	5.8	6	3.2	0	12.8	21.6	13.4	19	19.8	10	19.4	21	19.2	24	24	17.2	17.2
8	6	5.6	17.2	10.6	5	10.7	12.8	0	18.6	0.2	5.6	6.4	7.6	31	33	31	26	44.2	26.6	31.6
9	13.6	13.8	25.2	18.6	16	18.6	21.6	18.6	0	13.8	5	5	6.2	30.2	32.2	30	35.2	44.2	26.2	31
10	6	5.6	19.2	10.6	22	10.8	13.4	0.2	13.8	0	6	6.4	7.6	31	32.6	31	35.6	35.8	26.6	31.6
11	3.6	6	18.6	10.6	16	10.8	19	5.6	5	6	0	4.2	6.8	25.6	27.2	25.4	31	31.2	23.2	26.2
12	11.8	12	23.6	17	16	18	19.8	6.4	5	6.4	4.2	0	13	24.4	27	25.2	30	39.2	23	26
13	3.2	3	19	6	10.8	7.8	10	7.6	6.2	7.6	6.8	13	0	23	23.8	21.8	26.6	26.8	20.2	22.6
14	20	22.2	18.2	16.6	13.8	16.8	19.4	31	30.2	10	25.6	24.4	23	0	0.44	3.2	3.4	3.8	3.6	3.6
15	22.6	23.8	20	18.4	15.4	18.6	21	33	32.2	32.6	27.2	27	23.8	0.44	0	6.2	2.6	2.8	4.6	4.6
16	21	22	16	16.6	13.6	16.8	19.2	31	30	31	25.4	25.2	21.8	3.2	6.2	0	11	11.2	2.2	2.6
17	11	26.6	22	20.1	18.2	20.2	24	26	35.2	35.6	31	30	26.6	3.4	2.6	11	0	0.2	4	4.6
18	11.2	27	22.2	20.2	18.4	20.4	24	44.2	44.2	35.8	31.2	39.2	26.8	3.8	2.8	11.2	0.2	0	4.2	4.6
19	19	19.8	14.4	14.6	11.6	14.6	17.2	26.6	26.2	26.6	23.2	23	20.2	3.6	4.6	2.2	4	4.2	0	3
20	21.8	22.2	14.6	16	12.6	16	17.2	31.6	31	31.6	26.2	26	22.6	3.6	4.6	2.6	4.6	4.6	3	0

Table 8. Comparison of the proposed method with and without VANET

Objective function	Method	
	Proposed method with VANET	Proposed method with VANET
Distance optimization	45.72km	47.52km
Cost optimization	652.824	666.364

Table 9. Total delay time for the proposed method with VANET and without VANET

Time (min.)	Method	
	Proposed method with VANET	Proposed method with VANET
Delay overall time	95	171
Delay overall cost	9.5	17.1

Table 10. Comparing the proposed method in different situations

Objective function	Method			
	The proposed method on normal days	The proposed method with heavy traffic	The proposed method with rainy weather	The proposed method with heavy traffic and rainy weather
Overall delay time	95	112	134	183
Overall delay cost	9.5	11.2	13.4	18.3
Overall cost	652.824	654.524	656.724	661.624
Overall distance	45.72	46.54	46.2	46.54

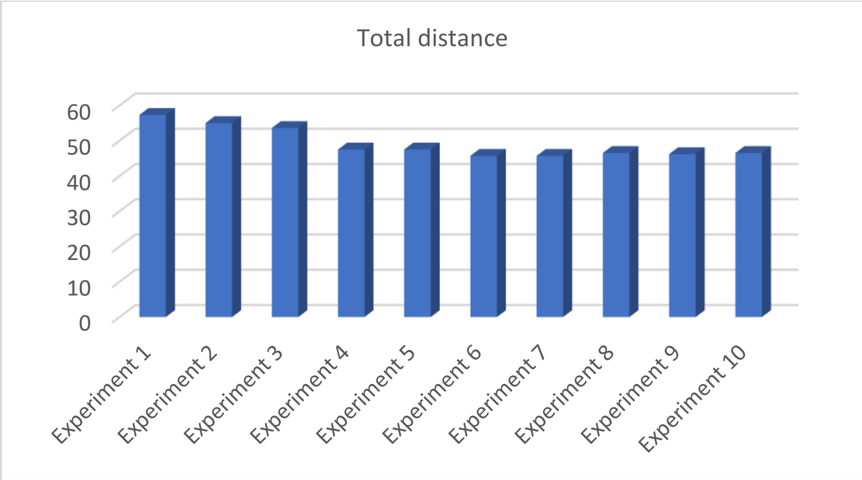

Figure 5. Comparison of the total distance among all algorithms

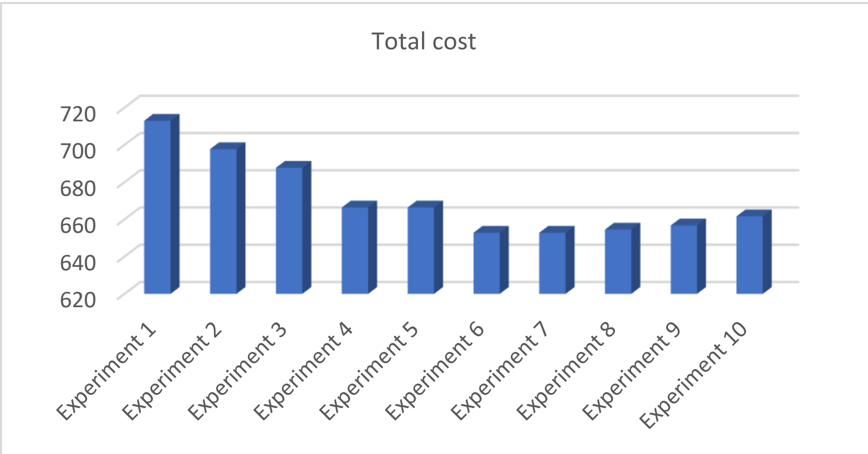

Figure 6. Comparison of the total cost among all algorithms

6. Managerial implications

The procedure and results show the following implications from managerial point of view,

- For industrial holdings the model and solution approaches of this study can be used to establish their transportation routing.
- The solution methodology can be used for other supply chain network design problems easily.

7. Conclusion

Genetic algorithms, particle optimization, and their combination have been implemented on standard and extended datasets of the smart city of Aarhus, Denmark, and the results have been obtained. Adjacent customers were considered in a cluster using the clustering algorithm and served based on time constraints. The closer customers are served by one vehicle, the distance traveled, and the spent time saved. The hybrid genetic-particle optimization algorithm explores the problem space much more. As mentioned earlier, the genetic algorithm may not be able to find the local optimum well or vice versa encounter challenges in a local optimum. The use of particle optimization algorithm along with the genetic algorithm increases the chances of finding a global optimum. The use of the GPSR protocol also improved the results compared to the time when we only used clustering alone in meta-heuristic algorithms.

Regarding the fact that the main question of this study was related to the optimization of routing of goods distribution network using meta-heuristic and intelligent transport algorithms, it can be said that according to the findings of the results section, the combination of these two algorithms together outperforms the two algorithms alone and results were acceptable. As mentioned before, the genetic algorithm was inefficient in finding the local optimum solutions, hence, the problem was solved by combining the algorithm with the PSO algorithm, and the hybrid algorithm has selected the most optimized route in the local search. The use of the GPSR-based protocol also improved the total distance traveled along with shipping costs. The use of VANET technology also reduced service provision delays, which reduced the delay cost. Shipping was reduced compared to the same method without the use of VANET.

The current study in which the vehicle routing problem was solved by mathematical modeling and using meta-heuristic algorithms as the static part and intelligent transportation system tools as the dynamic part, compared to previous studies that either used meta-heuristic algorithms to solve the vehicle routing problem or have used intelligent transportation system tools for routing, have achieved better results.

One of the limitations of this research is the lack of access to the smart city to collect real data, this forced us to use the existing data of the smart city and simulation for the time periods when information was not available. Finally, it can reduce the accuracy of the results.

Given that cities are moving towards ITS, this study can be used to implement distribution routing systems. The use of clustering algorithms has reduced the use of vehicles, which has a significant impact on reducing costs and depreciation for the supply chain.

Because GA and PSO metaheuristic algorithms are used in this study, other researchers can use a combination of other metaheuristic algorithms along with clustering and the VANET network for routing. Other clustering and classification algorithms can also be used to classify the data set. In this study, two VANET network protocols were used that other researchers can use other position-based and location-based protocols and compare the results with this study. With regard to the fact that the execution time on the system was very long, it is recommended to use big data tools such as Hadoop, Spark, etc. for implementation that can reduce the execution time significantly by creating a Master-Slave structure and dividing the processing is divided between the slaves.

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References

Abbas, M. T., Jibran, M. A., Afaq, M., & Song, W. C. (2019). An adaptive approach to vehicle trajectory prediction using multimodel Kalman filter. *Transactions on Emerging Telecommunications Technologies*, *31*(5), e3734. https://doi.org/10.1002/ett.3734

Aghaei Fishani, B., Mahmoodirad, A., Niroomand, S., & Fallah, M. (2022). Multi-objective location-allocation-routing problem of perishable multi-product supply chain with direct shipment and open routing possibilities under sustainability. *Concurrency and Computation: Practice and Experience*, *34*(11), e6860. https://doi.org/10.1002/cpe.6860

Al-Qutwani, M., & Wang, X. (2019). Smart traffic lights over vehicular named data networking. *Information*, *10*(3), 83. https://doi.org/10.3390/info10030083

Azad, N., Aazami, A., Papi, A., & Jabbarzadeh, A. (2019, July). A two-phase genetic algorithm for incorporating environmental considerations with production, inventory and routing decisions in supply chain networks. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion* (pp. 41-42). https://doi.org/10.1145/3319619.3326781

Bouk, S. H., Ahmed, S. H., Kim, D., & Song, H. (2017). Named-data-networking-based ITS for smart cities. *IEEE Communications Magazine*, *55*(1), 105-111. https://doi.org/10.1109/MCOM.2017.1600230CM

Bank, M., Mazdeh, M., & Heydari, M. (2020). Applying meta-heuristic algorithms for an integrated production-distribution problem in a two level supply chain. *Uncertain Supply Chain Management*, *8*(1), 77-92. http://dx.doi.org/10.5267/j.uscm.2019.8.004

Chahal, M., & Harit, S. (2019). Optimal path for data dissemination in vehicular ad hoc networks using meta-heuristic. *Computers & Electrical Engineering*, *76*, 40-55. https://doi.org/10.1016/j.compeleceng.2019.03.006

Chen, D., Zhang, X., Gao, D., Gao, K., Wen, M., & Huang, Z. (2020). Logistics Distribution Path Planning Based on Fireworks Differential Algorithm. In *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* (pp. 2797-2802). IEEE. https://doi.org/10.1109/SMC42975.2020.9283001 de Andrade, G. E., de Paula Lima, L. A., Calsavara, A., de Oliveira, J. A., & Michelon, G. (2016, July). Message routing in vehicular delay-tolerant networks based on human behavior. In *2016 10th International Symposium on Communication Systems, Networks and Digital Signal Processing (CSNDSP)* (pp. 1-6). IEEE. https://doi.org/10.1109/CSNDSP.2016.7573904

Fazayeli, S., Eydi, A., & Kamalabadi, I. N. (2018). Location-routing problem in multimodal transportation network with time windows and fuzzy demands: Presenting a two-part genetic algorithm. *Computers & Industrial Engineering*, *119*, 233-246. https://doi.org/10.1016/j.cie.2018.03.041

Gohar, M., Muzammal, M., & Rahman, A. U. (2018). SMART TSS: Defining transportation system behavior using big data analytics in smart cities. *Sustainable Cities and Society*, *41*, 114-119. https://doi.org/10.1016/j.scs.2018.05.008

Goli, A., Golmohammadi, A. M., & Edalatpanah, S. A. (2022). Application of Artificial Intelligence in Forecasting the Demand for Supply Chains Considering Industry 4.0. *A Roadmap for Enabling Industry 4.0 by Artificial Intelligence*, 43-55. https://doi.org/10.1002/9781119905141.ch4

Goli, A., Golmohammadi, A. M., & Verdegay, J. L. (2022a). Two-echelon electric vehicle routing problem with a developed moth-flame meta-heuristic algorithm. *Operations Management Research*, *15*(3-4), 891-912. https://doi.org/10.1007/s12063-022-00298-0

Gómez-Montoya, R. A., Cano, J. A., Cortés, P., & Salazar, F. (2020). A discrete particle swarm optimization to solve the put-away routing problem in distribution centres. *Computation*, *8*(4), 99. https://doi.org/10.3390/computation8040099

Gupta, D., & Kumar, R. (2014, September). An improved genetic based routing protocol for VANETs. In *2014 5th international conference-confluence the next generation information technology summit (confluence)* (pp. 347-353). IEEE. https://doi.org/10.1109/CONFLUENCE.2014.6949271

Hashemi-Amiri, O., Mohammadi, M., Rahmanifar, G., Hajiaghaei-Keshteli, M., Fusco, G., & Colombaroni, C. (2023). An allocation-routing optimization model for integrated solid waste management. *Expert Systems with Applications*, *227*, 120364. https://doi.org/10.1016/j.eswa.2023.120364

Hiassat, A., Diabat, A., & Rahwan, I. (2017). A genetic algorithm approach for location-inventory-routing problem with perishable products. *Journal of Manufacturing Systems*, *42*, 93-103. https://doi.org/10.1016/j.jmsy.2016.10.004

Jain, R., & Kashyap, I. (2020). Energy-Based improved MPR selection in OLSR routing protocol. In *Data Management, Analytics and Innovation: Proceedings of ICDMAI 2019, Volume 1* (pp. 583-599). Springer Singapore. https://doi.org/10.1007/978-981-32-9949-8_41

Kasana, R., & Kumar, S. (2017, February). A geographic routing algorithm based on Cat Swarm Optimization for vehicular ad-hoc networks. In *2017 4th International Conference on Signal Processing and Integrated Networks (SPIN)* (pp. 86-90). IEEE. https://doi.org/10.1109/SPIN.2017.8049921

Lee, W. H., & Chiu, C. Y. (2020). Design and implementation of a smart traffic signal control system for smart city applications. *Sensors*, *20*(2), 508. https://doi.org/10.3390/s20020508

Mahmoodirad, A., & Sanei, M. (2016). Solving a multi-stage multi-product solid supply chain network design problem by meta-heuristics. *Scientia Iranica*, *23*(3), 1428-1440. https://doi.org/10.24200/sci.2016.3908

Menouar, H., Guvenc, I., Akkaya, K., Uluagac, A. S., Kadri, A., & Tuncer, A. (2017). UAV-enabled intelligent transportation systems for the smart city: Applications and challenges. *IEEE Communications Magazine*, *55*(3), 22-28. https://doi.org/10.1109/MCOM.2017.1600238CM

Muniyandi, R. C., Qamar, F., & Jasim, A. N. (2020). Genetic optimized location aided routing protocol for VANET based on rectangular estimation of position. *Applied Sciences*, *10*(17), 5759. https://doi.org/10.3390/app10175759

Nikfarjam, A., & Moosavi, A. (2021). An integrated (1, t) inventory policy and vehicle routing problem under uncertainty: an accelerated benders decomposition algorithm. *Transportation Letters*, *13*(2), 104-124. https://doi.org/10.1080/19427867.2020.1714843

Okulewicz, M., & Mańdziuk, J. (2017). The impact of particular components of the PSO-based algorithm solving the dynamic vehicle routing problem. *Applied soft computing*, *58*, 586-604. https://doi.org/10.1016/j.asoc.2017.04.070

Oyakhire, O., & Gyoda, K. (2020). Improved proactive routing protocol considering node density using game theory in dense networks. *Future Internet*, *12*(3), 47. https://doi.org/10.3390/fi12030047

Qin, G. Y., Tao, F. M., & Li, L. X. (2019, December). A green vehicle routing optimization model with adaptive vehicle speed under soft time window. In *2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)* (pp. 1-5). IEEE. https://doi.org/10.1109/IEEM44572.2019.8978666

Rahimi, M., Baboli, A., & Rekik, Y. (2017). Multi-objective inventory routing problem: A stochastic model to consider profit, service level and green criteria. *Transportation Research Part E: Logistics and Transportation Review*, *101*, 59-83. https://doi.org/10.1016/j.tre.2017.03.001

Rahimi, S., & Jabraeil Jamali, M. A. (2019). A hybrid geographic-DTN routing protocol based on fuzzy logic in vehicular ad hoc networks. *Peer-to-Peer Networking and Applications*, *12*, 88-101. https://doi.org/10.1007/s12083-018-0642-4

Raw, R. S., Kadam, A., & Loveleen. (2018). Performance analysis of DTN routing protocol for vehicular sensor networks. In *Next-Generation Networks: Proceedings of CSI-2015* (pp. 229-238). Springer Singapore. https://doi.org/10.1007/978-981-10-6005-2_24

Rohmer, S. U. K., Claassen, G. D. H., & Laporte, G. (2019). A two-echelon inventory routing problem for perishable products. *Computers & Operations Research*, *107*, 156-172. https://doi.org/10.1016/j.cor.2019.03.015

Saragih, N. I., Bahagia, N., & Syabri, I. (2019). A heuristic method for location-inventory-routing problem in a three-echelon supply chain system. *Computers & Industrial Engineering*, *127*, 875-886. https://doi.org/10.1016/j.cie.2018.11.026

Skabardonis, A. (2020). Traffic management strategies for urban networks: smart city mobility technologies. In *Transportation, Land Use, and Environmental Planning* (pp. 207-216). Elsevier. https://doi.org/10.1016/B978-0-12-815167-9.00011-6

Swarnamugi, M., & Chinnaiyan, R. (2020). Context—aware smart reliable service model for intelligent transportation system based on ontology. In *Proceedings of ICRIC 2019: Recent Innovations in Computing* (pp. 23-30). Springer International Publishing. https://doi.org/10.1007/978-3-030-29407-6_3

Tavakkoli-Moghaddam, R., Forouzanfar, F., & Ebrahimnejad, S. (2013). Incorporating location, routing, and inventory decisions in a bi-objective supply chain design problem with risk-pooling. *Journal of Industrial Engineering International*, *9*, 1-6. https://doi.org/10.1186/2251-712X-9-19

Ullah, I., Liu, K., Yamamoto, T., Shafiullah, M., & Jamal, A. (2022). Grey wolf optimizer-based machine learning algorithm to predict electric vehicle charging duration time. *Transportation Letters*, 1-18. https://doi.org/10.1080/19427867.2022.2111902

Ullah, I., Liu, K., Yamamoto, T., Zahid, M., & Jamal, A. (2023). Modeling of machine learning with SHAP approach for electric vehicle charging station choice behavior prediction. *Travel Behaviour and Society*, *31*, 78-92. https://doi.org/10.1016/j.tbs.2022.11.006

Wille, E. C., Del Monego, H. I., Coutinho, B. V., & Basilio, G. G. (2016). Routing Protocols for VANETs: An Approach based on Genetic Algorithms. *KSII Transactions on Internet & Information Systems*, *10*(2). https://doi.org/10.3837/tiis.2016.02.006

Ye, M., Guan, L., & Quddus, M. (2021). TDMP: Reliable target driven and mobility prediction based routing protocol in complex vehicular ad-hoc network. *Vehicular Communications*, *31*, 100361. https://doi.org/10.1016/j.vehcom.2021.100361

Zhang, G., Wu, M., Duan, W., & Huang, X. (2018). Genetic algorithm based QoS perception routing protocol for VANETs. *Wireless Communications and Mobile Computing*, *2018*. https://doi.org/10.1155/2018/3897857

Zhu, L., & Hu, D. (2019). Study on the vehicle routing problem considering congestion and emission factors. *International Journal of Production Research*, *57*(19), 6115-6129. https://doi.org/10.1080/00207543.2018.1533260

http://iot.ee.surrey.ac.uk:8080/datasets.html