



Research paper

Intelligent Transportation System based-on the Whale Algorithm in Internet of Things

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Abstract

Background and Objectives: As cities are developing and the population increases significantly, one of the most important challenges for city managers is the urban transportation system. An Intelligent Transportation System (ITS) uses information, communication, and control techniques to assist the transportation system. The ITS includes a large number of traffic sensors that collect high volumes of data to provide information to support and improve traffic management operations. Due to the high traffic volume, the classic methods of traffic control are unable to satisfy the requirements of the variable, and the dynamic nature of traffic. Accordingly, Artificial Intelligence (AI) and the Internet of Things (IoT) meet this demand as a decentralized solution.

Methods: This paper presents an optimal method to find the best route and compare it with the previous methods. The proposed method has three phases. First, the area should be clustered under servicing and, second, the requests will be predicted using the time series neural network. then, the Whale Optimization Algorithm (WOA) will be run to select the best route.

Results: To evaluate the parameters, different scenarios were designed and implemented. The simulation results show that the service time parameter of the proposed method is improved by about 18% and 40% in comparison with the Grey Wolf Optimizer (GWO) and Random Movement methods. Also, the difference between this parameter in the two methods of Harris Hawks Optimizer (HHO) and WOA is about 5% and the HHO has performed better.

Conclusion: The interaction of AI and IoT can lead to solutions to improve ITS and to increase client satisfaction. We use WOA to improve time servicing and throughput. The Simulation results show that this method can be increase satisfaction for clients.

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Introduction

Nowadays, cities face complex and great challenges. For example, in smart cities, the conventional planning of transportation is not adequate [1]. In recent years, due to increasing demand for road safety, the ITS has been considered [2]. ITS is called as a system that helps transportation flow by using information, communication, and control techniques. ITS users are

the network managers, transportation service providers, passengers, and owners of transportation fleets. Providing some of these services depends on decisions and policy-making about them. This system allows drivers and the Traffic Management Organizations (TMO) to exchange information in real-time. Therefore, road safety and efficiency are now becoming more important challenges.

ITS provides solutions for cooperation, and a reliable transportation platform. ITS services can be considered as a data chain that consists of data acquisition, communications, processing, data distribution, utilization of information, and external factors. With the amount of information collected by RFID readers and their exchange between cars and digital interfaces, it is possible to extend the evaluation of transportation systems by actual processed data. This affects the decision-making process, planning, and implementation of public policies and makes them manageable [3]. In these systems, IoT can directly affect. The IoT connects various objects to each other according to a communication protocol through various sensor devices [4]. The main goal of the IoT is to do things faster, to automate all things, and control objects remotely. Also, AI along with the IoT can enhance the ITS quality and thus, improves the traffic situation, reduces congestion, trip delays and the delay of necessary services such as ambulance and police, decrease fuel consumption and ultimately increase the satisfaction of citizens.

Transportation systems are inherently large-scale and complex due to the considerable number of elements and interactions between the elements. Collaborative control is a method to manage multi-agent systems despite the complexity and a large number of elements [5]. On the other hand, recent advances in communication between machines and also communication between cars and transportation infrastructures, cause access to vehicles around and also general information about traffic flow. Access to the information of vehicles lead to emerged control methods such as collaborative control methods or Machine Learning (ML) methods that can be applied to transportation systems. Therefore, ML techniques can help to create an advanced and efficient ITS [6]. ML applies various techniques to facilitate learning in different devices of the network to make them automatic [7].

ITS includes a large number of traffic sensors that collect a high volume of data to provide information to support and improve traffic management operations [8]. Due to the high traffic volume, the classic methods of traffic control are unable to satisfy the requirements of the variable and dynamic nature of the traffic [9]. The main purpose of the traffic control system is to propose efficient management of transportation resources so that changes in traffic conditions are taken into account. AI fulfills the demand as a decentralized solution with the introduction of the concept of smart agent. Using smart agents to automatically sense traffic changes and perform appropriate actions by referring to the knowledge-based and meta-heuristic algorithms, the traffic control system can be effectively managed. This

paper intends to minimize the distances taken by vehicles and service time to provide customer services.

In advance [10], we proposed an optimized path selection mechanism by road rescue servers based on a GWO algorithm. The GWO imitates the hunting behavior of grey wolves in nature [11]. In this paper, the WOA is used to optimize the problem of route selection in the transportation system. This research has been done to reduce customer service time. Since the WOA and the GWO are slightly different from each other, to determine the effect of these differences, we have compared the WOA with the GWO in this research. Also, according to the authors of this method, the GWO is one of the algorithms has been discovered in recent years, which has a high rate of convergence in obtaining the answer [11]. In this paper, the WOA is also has compared with the HHO. HHO is a novel population-based, nature-inspired optimization [12]. Using the HHO, the service time is reduced, but the throughput is almost equal to the WOA. According to the parameters of the problem, it seems that the WOA is suitable for this problem. In our future work, with considering the other design parameters such as energy and fuel consumption, applying the HHO algorithm can be a more efficient solution.

In this paper, we investigate the network of vehicles that have different sensors and are connected to the central server and each other via the internet. Firstly, we divide the service area by using the fuzzy clustering algorithm and take into account the cluster centers as the center of crowdedness. We also predict the number of requests using the time series neural network predictor. Finally, we find the optimal path using the whale algorithm.

The contributions of the paper are as follows:

- Using fuzzy clustering to divide the area under service.
- using time series to consider the behavioral patterns of people in the community to request vehicles.
- Applying an intelligent algorithm to find the best path.

Comparing the simulation results with previous methods indicates that the distance has been improved and thus the total time of servicing and increased the satisfaction of service providers.

The rest of the paper is organized as follows: first, the related work is investigated in second Section. In third Section, we will provide the proposed method and the simulation results are discussed in fourth Section. Finally, the conclusion of the paper is presented in fifth Section.

Related Work

Various researches have been conducted on ITS, which in most of them have been used only from one of

the technologies of AI or IoT, and quantitative research has dealt with the combination of AI and IoT. In this section, some examples of related work will be described.

Kuppusamy et al. [13] proposed a framework for traffic control and data processing was provided using IoT. This framework includes a local server and a remote server that improve the processing time of the traffic signal. As a result, waiting times for vehicles, air pollution, and overtime are reduced at intersections. Dubey et al. [14] designed a system to control traffic signals so that signal lights are decided based on less wait time and less pollution. This system is designed for IoT applications. In [15] a smart traffic management system using the IoT is presented. A hybrid approach was used to optimize traffic flow on the road. Pyykonen et al. [16] offered a smart traffic control system for IoT applications. The roadside system measures and calculates a series of values that are stored in the database and sent to users through the 802.11 protocol. Bojan et al. [17] offered an IoT-based intelligent transportation system, that consists of three components: display, monitoring, and sensor. Geetha et al. [18] using IoT, provided a system for public transportation. Sutar et al. [19] have presented a framework for intelligent public transportation that deals with determining the position of buses and responding to passenger demand. Datta et al. [20] introduced a framework with data-driven architecture, which contributed to the design of a smart road rescue system in smart cities. Desai et al. [21] provided a vehicle regulatory system through software and hardware for routing and monitoring and supervision of the vehicles and finally, the cost savings were followed. Al-Dweik et al. [22] have presented a roadside unit for utilizing as the portion of a comprehensive ITS based on IoT. First, the information is collected by sensors and cameras. It is then sent to a central server for operations such as setting speed limits and issuing weather warnings. Jalaney et al. [23] reviewed the IoT-based architectures for intelligent public transport. Zhu et al. [24] discussed the role of IoT in creating parallel transportation systems and examining the impact of the system in several Chinese cities. Qureshi et al. [25] used various types of smart transport system applications and their technologies. Murad et al. [26] have proposed an integrated system IoT-based. This system simplifies the provision of information such as bus scheduling and online payment. Thakur et al. [27] investigated IoT-based solutions in the intelligent transportation system. Also in this research, the road safety techniques, communications between vehicles, and wireless communication techniques suitable for channels were studied. Sodhro et al. [28] proposed a QoS-aware

algorithm to support multimedia transmission. Second, they proposed a novel QoS optimization scheme. Third, they proposed several QoS metrics to analyze the performance of V2V networks. Sodhro et al. [29] first, developed a system model for reliability and optimization of connection in the intelligent transportation system, and a SSLO algorithm. then, they proposed a reliability framework. Sodhro et al. [30] proposed 5G-based self-adaptive green and novel 5G-driven algorithms and, a reliable framework.

In recent investigations, the IoT has been used to improve the ITS. As follows, we review the researches in which AI has played the most important role. Odeh in [31] applied Genetic Algorithm (GA) to manage traffic signals. In this research, a video system was used to collect information, and a decision-making system based on the GA was applied. Using video images, the authors achieved the number of vehicles and ultimately optimized the time of green lights by applying GA. The comparison of the real and simulated results showed about a 40% decrease in the lights lag. Li et al. [32] have dealt with the optimization of traffic signals in smart cities by using the GA. In this research, a bi-level optimization framework was provided. The high-level problem reduces the travel time of the drivers, and the low-level problem, using the computational at the top level, helps to balance the network. If the lights are properly designed, it reduces the travel time of the drivers, traffic control, and congestion reduction which reduces environmental concerns. Zhou et al. [33] developed a signal timing system based on multi-objective optimization. The results of the implementation are: reducing the number of stops and latency and thus improving traffic. As previously discussed, AI can realize the interactive performance of information between objects and people, for example, help to expand intelligent transportation. In the following researches, the combination of these two technologies has been used.

Osuwa et al. [34] used AI including fuzzy logic and neural networks in IoT. Hamidouche et al. [35] applied the Grey Wolf and Whale algorithms, to exchange data on a heterogeneous wireless sensor network, taking into account the buffer overflow problem. Yadav et al. [36] proposed a traffic signal management system, through GA and the IoT. The purpose of designing this system is to reduce the waiting time of vehicles in traffic signals. It should be noted that a neural network has been trained to allocate green light time to each road. Liu et al. [37] designed a system for traffic emergency response by using IoT and data mining.

In the reviewed researches, a framework or architecture for traffic control using the IoT or AI was often presented. Less attention has been paid to

emergency services and the use of AI in the IoT and ITS. Therefore, in this paper, using a combination of AI and IoT, we improve a routing algorithm and thus reduce the time to provide services to customers. The traditional ant colony algorithm has been often used for routing while we apply the Whale algorithm in this research. Due to the mechanisms that the whale algorithm has in prey encircling, the problem of transport optimization with this algorithm is investigated in this paper.

Proposed Method

The proposed method consists of three steps as follows:

1. Segmentation of the area under service.
2. Predicting the number of requests of each segment.
3. Finding the best path.

Fig. 1 shows the flowchart of the proposed method. The proposed method includes the number of vehicles in one or more deployment locations that must be referred to a set of customers and provide the service. These clients have a certain movement pattern. In fact, by predicting the number of transportation requests in each segment of the smart grid, we intend to move vehicles in such a way that the total distance traveled, the total travel time, and the number of required vehicles is minimized. At the same time, customer satisfaction is intended to be maximized. Network traffic is modeled through a set of links and nodes. For example, a simple traffic diagram is shown in Fig. 2.

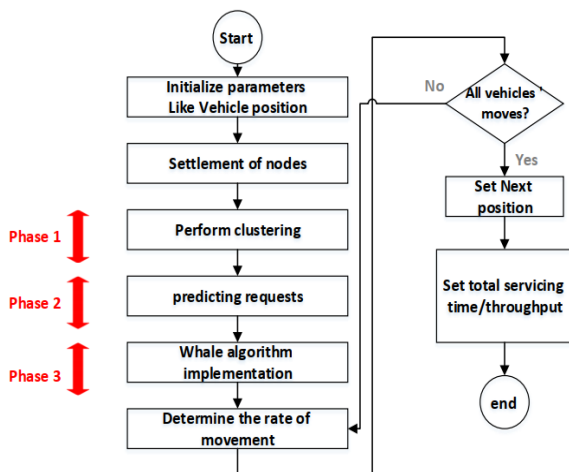


Fig. 1: The flowchart of the proposed method.

In the proposed method, the service area is divided into blocks with variable sizes. The location of sending requests is calculated using the random function and will be inserted as a service location in a two-dimensional coordinate system and, we have tried to cluster these points. We consider the center of clusters as points with the request for high transport servicing, and it is called as a traffic point.



Fig. 2: A simple traffic diagram [38].

In the first step, Fuzzy C-Means (FCM) clustering is applied. In this method, each data belongs to a specific degree of each cluster and according to the degree of belonging, the presence of data to a cluster is determined [39]. This method is based on the C-Means function, which is a well-known unsupervised clustering algorithm and is successfully used to solve different clustering problems. This method is used in partitioning the network into some clusters [40]. This algorithm can divide the space of nodes into K clusters according to the distance between the cluster head and other nodes. This algorithm minimizes the objective function mentioned in the following equation which is a square error function.

$$J = \sum_{i=1}^c \sum_{k=1}^n u_{ik}^m \cdot d_{ik}^2 = \sum_{i=1}^c \sum_{k=1}^n u_{ik}^m \cdot \|x_k - v_i\|^2 \tag{1}$$

In (1), the exponent m is used to adjust the weighting effect of membership values. Large m will increase the fuzziness of the function. m is a real number $m > 1$ which is selected in most cases as $m = 2$. x_k represents the k th sample and v_i stands for the center of the i th cluster. u_{ik} variable shows the amount of sample belongs to the i sample in cluster k . Mark $\|*\|$ shows the similarity rate of the instance form the center of the cluster. Based on u_{ik} , a U-matrix can be defined that has c rows and n columns, and its components can take a value between 0 to 1.

In Fig. 3, the result of fuzzy clustering is shown in a two-dimensional environment. Colored stars, red squares and green squares indicate user requests, current requests, and server vehicles, respectively.

The second step of the proposed method is to consider the behavior patterns of community people to apply for vehicles in determining the optimal routing, which is used to measure the number of requests in each block of the intelligent transportation network. In this method, the traffic is computed and controlled by diffusion.

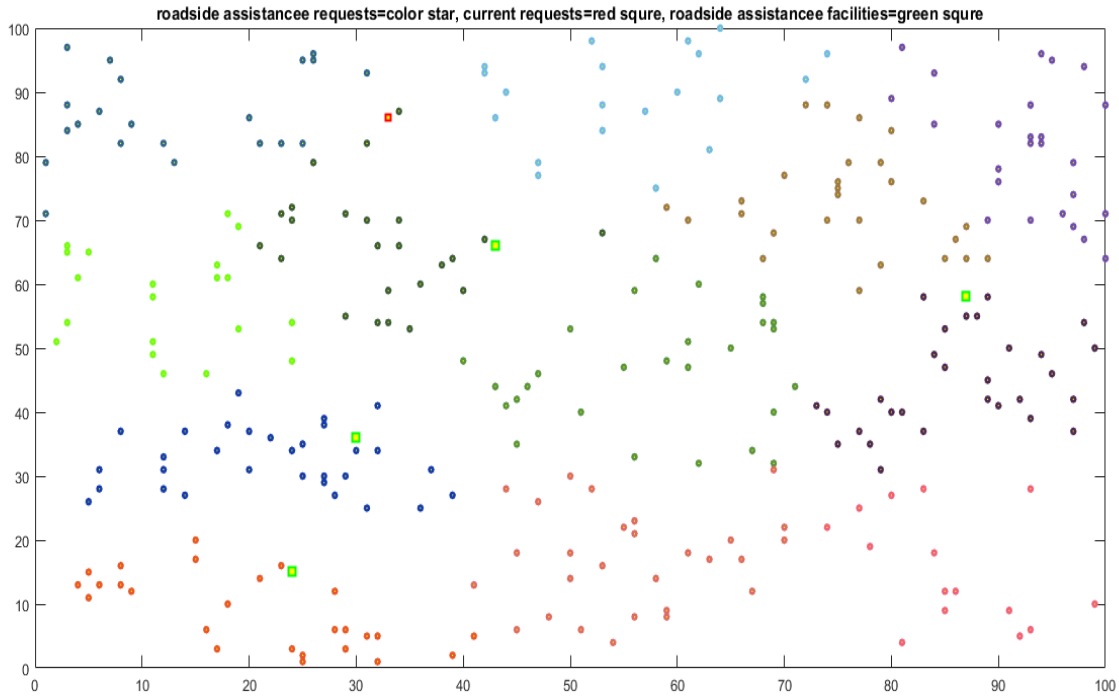


Fig. 3: Form clusters based on the location of the request in user points.

That is, we use the smart agents and network nodes to measure the number of future requests per block. We will use the time series neural network to predict the number of requests [41], [42]. In each science, the collected statistics are called time series, which are to be predicted and available in past periods. A time series of statistical data is collected at equal and regular intervals.

Neural networks can be used in various cases such as data storage and review, a general mapping of an input set into an output set, grouping, and classification of similar data, optimization, and prediction. Neural networks, such as regression, are tools for an approximation of functions and finding a relationship between independent and dependent variables. Neural networks are composed of units called Neuron, which is processing unit. The Neurons produce a value of output through the defined relationships between them and their weights. In the last step, we intend to determine the best movement direction of vehicles using the whale algorithm. So that it is closer to high traffic areas and can service more users in less time and with less distance. Therefore, we have provided the fitness function in which the parameters of moving vehicles and servicing rate, or the density of service demand in the scroll blocks have been included. The amount of service demand density was obtained based on the predicted amount of the time series neural network. Thus, it will be tried to move the vehicles to help blocks with greater demand density. According to the above-mentioned materials, the fitness function in the proposed method is defined

as the following, which is tried to be maximized.

$$Fitness(S_i) = \frac{\sum_{j \in S_i} SERV(j)^\alpha}{sumDis(S_i)^\beta} \tag{2}$$

Equation (3) calculates the distance between two points, and (4) shows the relationship between time and distance. The distance and time parameters are directly related. The Speed parameter is considered constant in this equation.

$$Dis = \sqrt{(X - x)^2 + (Y - y)^2} \tag{3}$$

$$t = \frac{Dis}{s} \tag{4}$$

In (3), X, Y represent the location parameter (X, Y) at the destination, and x, y represent the location parameter (X, Y) at the source. In (4), t represents the service time and s represents speed.

S_i represents a solution as a sequence of blocks met as a route moving vehicles, $SERV(j)$ is the rate of service in block j and the variable $sumDis(S_i)$ is the sum of the distances of the vehicles, α and β coefficients are the most important parameters for determining the level of fitting the solution. In the current method, each solution represents a moving block trail of the vehicles. In other words, the content of each home is equal to a block number that has passed or crosses an existing vehicle from that block. Therefore, the length of the solution is equal to the number of blocks in non-zero houses; the number of block meeting order is inserted by vehicles.

In Fig. 4, first, service to users in block 5 will then move in 2,7,4,8 blocks, respectively. In the following, how to determine the optimal solution in the whale algorithm will be described.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 0 | 2 | 0 | 4 | 1 | 0 | 3 | 5 |
|---|---|---|---|---|---|---|---|

Fig. 4: A solution in Whale algorithm with 8 blocks.

Also, we can consider an array as a solution. For example, block 1 is serviced by vehicle (server) 1, block 2 is served by vehicle 2, and so on as depicted in Fig. 5.

| | | | | |
|----------------|---|---|---|---|
| Block Number | 1 | 2 | 3 | 4 |
| Service Number | 1 | 2 | 3 | 4 |

Fig. 5: an array as a solution.

Fig. 6 shows how three users are served by two servers. The squares represent the servers and the circles represent the clients. Fig. 6(a) shows the initial state of placement of requests and servers. After clustering and executing the algorithm, the result is shown in the following figures. Fig. 6(b) shows the current request as a grey circle. Server 1 responds to the first request. Fig. 6(c) the second request is served by Server 2 (The answered Requests are displayed as black circles), and then in Fig. 6(d), the third request is served by Server 2.

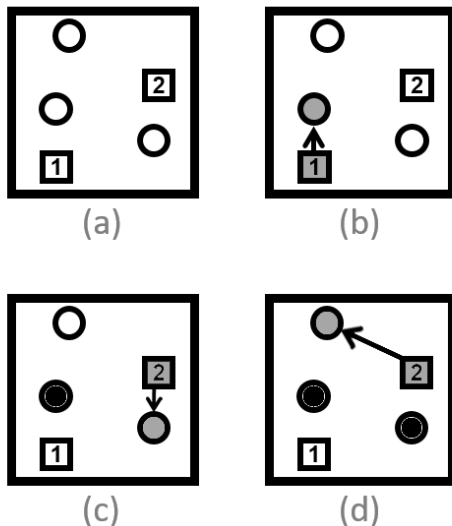


Fig. 6: Execution of whale algorithm for three clients and two servers.

The whale algorithm is a meta-heuristic optimization algorithm nature-inspired [43] by the hunting strategy in whales. The main difference between this algorithm and the GWO is simulated hunting behavior by using random techniques or the best search agent to chase prey and

utilize a spiral to mimic the bubble-net attacking strategy of a whale. Randomization plays a very crucial role in exploration and exploitation. In each iteration, the number of search agents is generated and the optimal answer is selected. Mathematical modeling of the WOA divides into three phases of prey encircling, bubble network attacking method and, hunting search (exploration phase) that is provided in (5) to (10) [43].

In the prey encircling, search agents try to update their location towards the best search agent after each iteration. This behavior of whales is defined according to the following equations.

$$\vec{D} = |\vec{C} \cdot \vec{X}^*(t) - \vec{X}(t)| \tag{5}$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \tag{6}$$

In these equations, t denotes the current iteration while \vec{A} and \vec{C} are the coefficient vectors. $\vec{X}^*(t)$ is the position of the best and $\vec{X}(t)$ vector is the reference position. If there are better answers, $\vec{X}^*(t)$ it will be updated. Vectors \vec{A} and \vec{C} are calculated according to the following equations:

$$\vec{A} = 2 \vec{a} \cdot \vec{r} - \vec{a} \tag{7}$$

$$\vec{C} = 2 \cdot \vec{r} \tag{8}$$

where is \vec{r} a random vector with the value in the range [0,1]. The values of \vec{a} are reduced linearly from 2 to 0.

In the attack phase, two methods for modeling the behavior of the Whale Bubble Network are presented:

- 1) Shrinking encircling mechanism: This method is used to reduce the value of \vec{a} . According to (7) with a decrease in the amount of \vec{a} , the value of \vec{A} is also reduced and, the value is placed in a range of [-a, a] that is reduced linearly by \vec{a} from 2 to 0.
- 2) Spiral updating position: this method calculates the distance of the whale, which is in the position (X, Y) to make the hunt, which is the position (X^*, Y^*) . Then the spiral path is formed between the position of the whale and the prey. The spiral update equation is given in the following equations:

$$\vec{X}(t+1) = \vec{D}' \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}^*(t) \tag{9}$$

$$\vec{D}' = |\vec{X}^*(t) - \vec{X}(t)| \tag{10}$$

It should be noted that whales swim around the prey in a spiral-shaped path simultaneously. To model this simultaneous behavior, we assume that there is a probability of 50% to choose between either the shrinking encircling or the spiral model. If $p < 0.5$, the position is updated based on (6), and if $p \geq 0.5$ the (9). p is randomly selected between 0 and 1. The value of p can determine the type of movement in the whale algorithm.

The third phase is the hunting search. This method

uses the way to change \vec{A} to search for hunting. Each of the whales is randomly searched for the position. Therefore, for a vector \vec{A} , we randomly assign values greater than 1 or less than -1 so that the search agent searches for positions farther from the reference whale. Unlike the exploitation phase, in this step, the search agent's position is randomly updated. Exploration follows two conditions. Mathematical equations related to this behavior of whales are given below:

$$\vec{D} = |\vec{C} \cdot \vec{X}_{rand} - \vec{X}| \tag{11}$$

$$\vec{X}(t + 1) = \vec{X}_{rand} - \vec{A} \cdot \vec{D} \tag{12}$$

where \vec{X}_{rand} is a random position vector chosen from the current population. Finally, follows these conditions [44]:

- $|\vec{A}| \geq 1$ enforces exploration to WOA. This prevents local optimization to find the global optimal.
- $|\vec{A}| < 1$ for updating the position of current search agent/best solution is selected.

From the theoretical point, the whale algorithm can solve the optimization problems in different types, which is due to gradient-free mechanism, flexibility, and high local optima avoidance in this algorithm [45].

Results and Discussion

We have used MATLAB software to simulate the proposed method. To service customers' requests in the smart network of transportation, the number 500 transportation requests from 100 clients are collected in different parts of the area under monitoring and entered into a database.

The area is divided into blocks based on the frequency of past requests. We need to move four vehicles between these blocks (In scenario 4, the number of vehicles can be variable) so that the total traveled distance and the total travel time are minimized and the number of services provided per unit of time (throughput) is maximized.

This is shown as an example in Table 1. It should be noted that one of the sensors used in this research is the location sensor of vehicles.

Table 1: An example for throughput

| Method Type | Round (min) | Distance (m) | Service Time(min) | Throughput |
|-------------|-------------|--------------|-------------------|------------|
| (1) | 100 | 50 | 25 | 4 |
| (2) | 100 | 30 | 15 | 6 |

The System specifications to implement the proposed method, parameters of the simulation, and the meta-heuristic algorithm are shown in Table 2, Table 3, and Table 4, respectively.

Table 2: System specifications to implement the proposed method

| Specifications | Value |
|----------------|------------|
| CPU | Core i5 |
| RAM | 4 G |
| OS | Windows 10 |

Table 3: Simulation parameters

| Simulation Parameters | Value |
|-----------------------------------|---------------------|
| Number of simulation execution | 5 |
| Number of clients | 100 |
| Number of servers (Vehicle) | 2,4,8,10,12,25 |
| Environmental dimensions | 100*100m |
| Number of transportation requests | 100,200,300,400,500 |
| Number of clusters | 2,4,6,8,10,12,24,26 |
| Request time period | 50 minutes |

Table 4: Meta-heuristic algorithms' parameters

| Optimization Parameters | Value |
|--|----------------------------|
| Maximum number of repetitions | 30 |
| Primary population | 30 |
| Size of a solution | Number of blocks |
| The range of values allowed for a solution | Meeting Priority of Blocks |

To evaluate the impact of different conditions, including the number of clusters, the number of vehicles, and the number of requests, we have defined different scenarios. In scenarios 1 and 2, the number of clusters is different and we have placed them in an array. In scenarios 3, 4 and, 5, we have considered the number of clusters to be constant and equal to 8.

The first scenario: Investigation of evaluation parameters during simulation time. To investigate the optimality of vehicle movement in the proposed (Whale) method, we have performed the simulation for 100 minutes and compared the performance of the three methods in terms of servicing time in fulfilling customers' transportation requests over time. The result is shown in Fig. 7. In the obtained results, we see that the total servicing time fluctuates so much that it is not possible to comment on the superiority of one method over another. Therefore, the cumulative value was calculated for this parameter. As it can be figured out in Fig. 8, the total servicing time in the proposed (Whale) method is less than the methods of Random Movement and GWO about 48% and 29%, respectively, and more than HHO about 8%. To evaluate the efficiency of the proposed method in the effective management of the transportation system, we have compared the throughput of the method in providing service to customers during the simulation run. In Fig. 9, we see that the number of services provided per unit time in the

proposed (Whale) method is more than the methods of Random Movement and GWO about 67% and 1%, respectively, and but it is almost equal to HHO. Therefore, the proposed (Whale) method, using the spiral mechanism in simulating the bubble network attack, has been able to reduce the servicing time and increase throughput by selecting the optimal path of vehicles in the blocks resulting from the clustering of crowded points. The noteworthy point in all scenarios is that the difference in parameters in compared meta-heuristic methods is small. Population-based meta-heuristic optimization algorithms have one thing in common, regardless of their nature. The search process is divided into two phases: exploration and exploitation [43]. To prove their strength, these algorithms must focus on these two phases and strike a good balance between them.

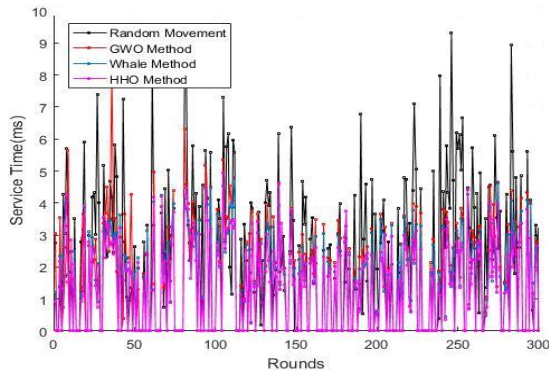


Fig. 7: The performance of Random Movement, GWO, Whale and HHO methods in terms of total service time in first scenario.

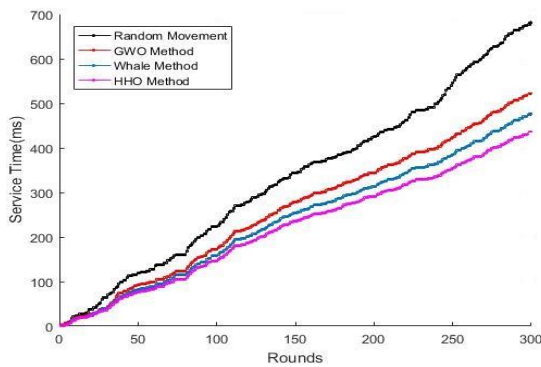


Fig. 8: The performance of Random Movement, GWO, Whale and HHO methods in terms of cumulative total service time in first scenario.

The main difference between the algorithms studied in this research is in the besiege of prey and its attack. In comparison to GWO and WOA, one of the most important factors of difference is the bubble attack in the whale method. Comparing HHO and WOA, different besiege mechanisms make the difference between the two methods. The HHO uses a series of search strategies based on prey energy and prey escape probability, and

then selects the best move. Also in this method, the strength of random jumping helps to balance the phases of exploration and exploitation. Therefore, it can be said that these cases help to improve the parameters of the problem. As mentioned before, according to the conditions and parameters of the problem, the WOA is more suitable for this problem and the same throughput in these two methods confirms this.

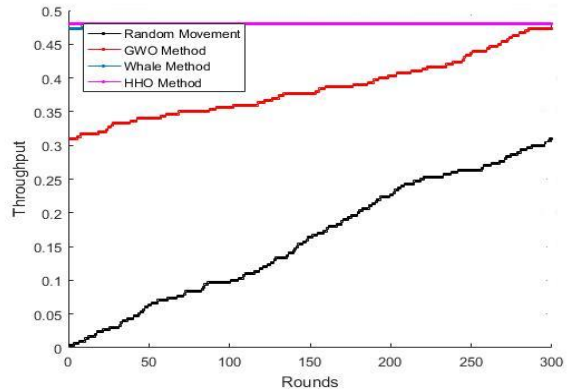


Fig. 9: Throughput comparison of Random Movement, GWO, Whale and HHO methods in first scenario.

The second scenario: Investigation of performance evaluation parameters with different clusters. In this scenario, we will investigate the performance of the proposed (Whale) method with some different cluster sizes. In Fig. 10, it can be concluded that the service time in the proposed (Whale) method is less than the methods of Random Movement and GWO about 35% and 18%, respectively, and more than HHO about 6%. Fig. 11 also specifies that the throughput of the model in providing customer service in the proposed (Whale) method is improved than Random Movement and GWO about 69% and 8%, respectively but it is almost equal to the HHO.

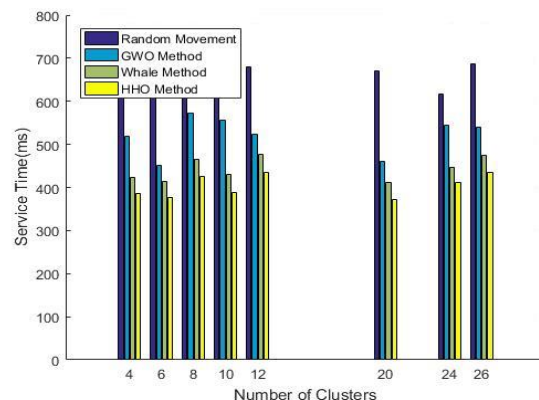


Fig. 10: The performance of Random Movement, GWO, Whale and HHO methods in terms of total service time in second scenario.

Since in this scenario four vehicles are considered to provide the service, increasing the clusters does not have much effect on the servicing time. The reason for the superiority of the Whale method towards the

Random Movement, the clever selection of path and, the GWO method, is the use of a spiral mechanism that reduces distance and ultimately reduces the service time. It should be noted that in all methods and scenarios, constant speed is considered.

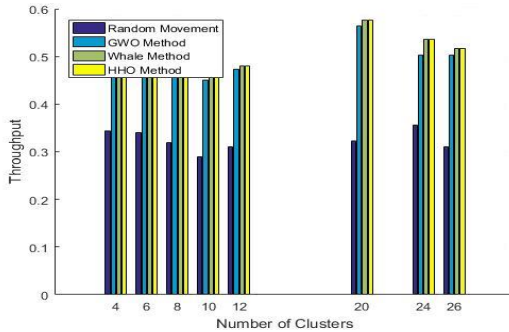


Fig. 11: Throughput comparison of Random Movement, GWO, Whale and HHO methods in second scenario.

The third scenario: Investigation of performance evaluation parameters with the number of different requests. In this scenario, we investigated the performance of the proposed (Whale) method with some different service requests (100 to 500 requests). As shown in Fig. 12 the total service time, despite the number of different requests in the proposed (Whale) method, is always less than Random Movement and GWO about 38% and 17%, respectively, and more than HHO about 5%. Also, as shown in Fig. 13, the method's throughput is increased compared to the Random Movement method of 84% and compared with the GWO method of 6%.

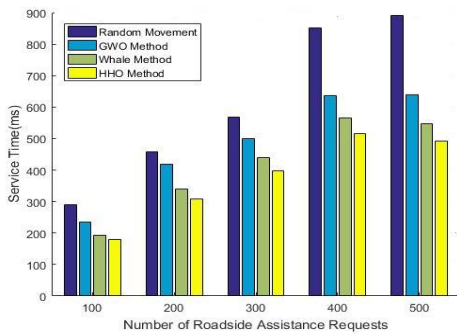


Fig. 12: The performance of Random Movement, GWO, Whale and HHO methods in terms of total service time in third scenario.

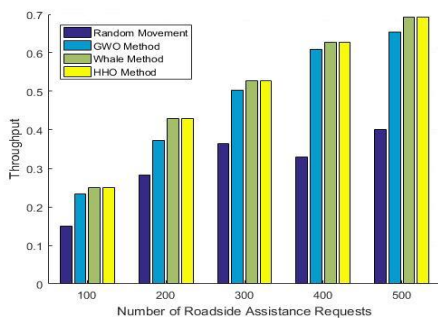


Fig. 13: Throughput comparison of Random Movement, GWO, Whale and HHO methods in third scenario.

This means that the proposed (Whale) method increases the efficiency of resources, due to the use of intelligent methods and the application of the spiral mechanism in the attack phase of the whale algorithm, and it can respond to the more number of requests in little time. The throughput in HHO and WHO is almost equal.

The fourth scenario: Investigation of performance evaluation parameters with different Vehicles (server). In this scenario, we investigated the performance of the proposed (Whale) method with different vehicles (2, 4, 8, 10, 12, 25). As shown in Fig. 14 and Fig. 15 the service time is lower than in previous methods despite the number of different vehicles in the proposed (Whale) method. However, when vehicles increase, the time of service of the Random Movement method decreases significantly, but the proposed (Whale) method still has better performance.

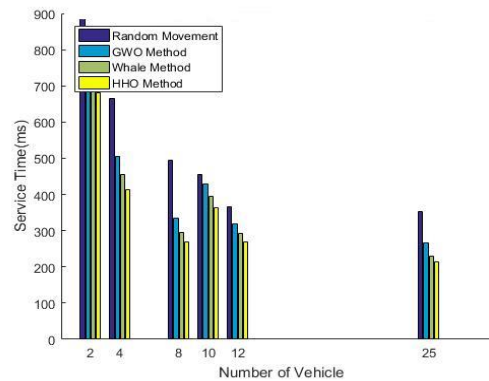


Fig. 14: The performance of Random Movement, GWO, Whale and HHO methods in terms of total service time in fourth scenario.

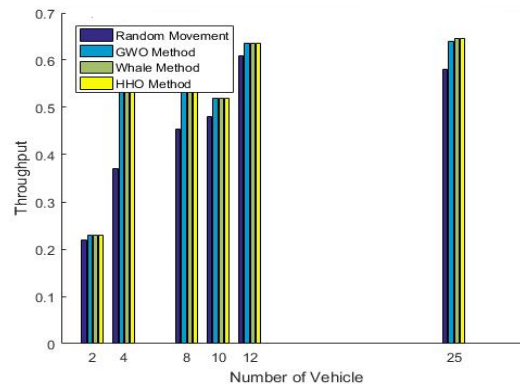


Fig. 15: Throughput comparison of Random Movement, GWO, Whale and HHO methods in fourth scenario.

Service time in the proposed method has been reduced compared to the Random Movement method by 23% and the GWO method by 11% and increased compared to the HHO by about 4%. The throughput parameter is not very different in the four methods when service vehicles increase but on average, this parameter increased by 20% compared to the Random Movement method and increased by 1% compared to

the GWO method and it is almost equal to the HHO method. It can be said that the reason for improving parameters in this method, like in previous scenarios, is using a spiral mechanism in the attack phase of the Whale algorithm.

The fifth scenario: Investigation of performance evaluation parameters with different values the importance of fitness function variables. As stated before in the proposed scheme, using the whale optimization algorithm, the near-optimum route of vehicles is determined so that it can serve more users in less time and over a shorter distance. Hence, a fitting function is used which includes two indicators of the total traveled distances by vehicles and the density of demanded services in the tracked blocks. To determine the importance of each of these two parameters in determining the degree of the fitness of the solution, we used the values of α and β as the exponent values somehow the sum of them is equal to one (i.e., $\alpha+\beta=1$).

In the last step, we evaluated the proposed intelligent transport system based on different exponent values of the coefficients. Fig. 16 shows that in our proposed method, despite the different values of the two effective indicators, the total service time is 35% less than the Random Movement method, 12% less than the GWO method, and 5% more than the HHO method. Since the whale algorithm uses a bubble method to attack, it reduces the distance and thus the service time. Fig. 17 also specifies that the throughput of the model in the proposed (Whale) method is more than Random Movement and GWO about 82% and 5%, respectively, and almost equal to the HHO method.

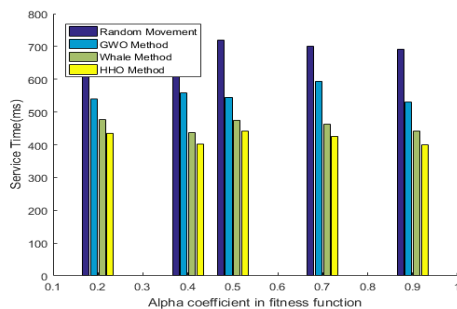


Fig. 16: The performance of Random Movement, GWO, Whale and HHO methods in terms of total service time in fifth scenario.

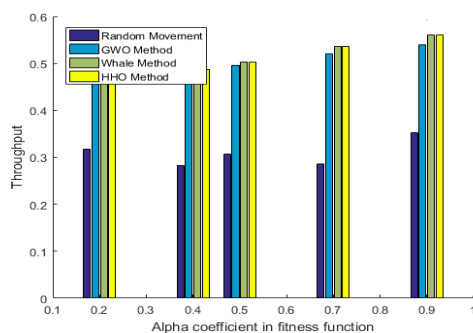


Fig. 17: Throughput comparison of Random Movement, GWO, Whale and HHO methods in fifth scenario.

Also, after performing several round of simulations, we found that the best answers are obtained when $\alpha=0.9$ and $\beta=0.1$. Therefore, since these two exponent values show the effect of the parameters of the fitness function, the effect of the demanded service density is more than the sum of the travelled distances.

Conclusion

ITS is a system that uses information, communication, and control techniques to assist the flow of transportation. ITS tools have three basic and pivotal features: information, communication, combination, and cohesion, which these three characteristics help transportation and passengers to make better and more coordinated decisions. In this paper, we used the combination of AI and IoT to improve the ITS. The results of this research show that the interaction of AI and IoT can lead to solutions to improve ITS and increase client satisfaction. In this paper, we have used the FCM to block the area under servicing, the time series neural network to predict requests, and the whale algorithm to find the best path. The proposed method was evaluated under different conditions including the number of variable requests, the different times, the number of different vehicles, and the number of different clusters. The simulation results show that the throughput is increased by 5%, compared to the method that the grey wolf was used to optimize and 82%, compared to a randomly selected path. Throughput in HHO and Whale method is almost equal. In our future work, we intend to achieve an optimal vehicle movement plan in smart cities by considering other environmental characteristics and using new meta-heuristic methods, so that the convergence time will be reduced to the optimal response. Also, by applying a new fitness function, we will determine the number of optimal vehicles to service users' requests. In this method, we will be able to move only some vehicles at some point in time and others will remain in place to reduce the cost of service.

Author Contributions

Z. Boujarnezhad designed the experiments, collected data, and carried out the data analysis. Z. Boujarnezhad and M. Abdollahi interpreted the results and wrote the manuscript.

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Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely observed by the authors.

Abbreviations

| | |
|------------------|---|
| α | Level of significance |
| β | Observed value |
| AI | Artificial Intelligence |
| A | Coefficient vector |
| C | Coefficient vector |
| c | Number of rows |
| DLS | Damped Least-Squares |
| FCM | Fuzzy C-Means |
| GWO | Grey Wolf Optimizer |
| HHO | Harris Hawks Optimizer |
| IoT | Internet of Things |
| ITS | Intelligent Transportation System |
| K | Number of clusters |
| ML | Machine Learning |
| r | Random vector |
| S_i | a solution as a sequence of blocks met as a route moving vehicles |
| s | speed |
| t | Service time |
| TMO | TRAFFIC MANAGEMENT ORGANIZATIONS |
| U_{ik} | shows the amount of sample belongs to the i sample in cluster k |
| V_i | stands for the center of the i_{th} cluster |
| WOA | Whale Optimization Algorithm |
| X_k | Represents the K_{th} sample |
| $\vec{X}(t)$ | The position of the best |
| $\vec{X}^*(t)$ | Reference position |
| \vec{X}_{rand} | Random position |
| (X, Y) | Whale position |
| (X^*, Y^*) | Hunt position |

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