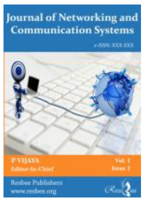
Resbee Publishers

Journal of Networking and Communication Systems

Received 12 September, Revised 23 November, Accepted 28 December



Improved GWO-CS Algorithm-Based Optimal Routing Strategy in VANET

Mukund B. Wagh
Department of Computer Engineering
Sinhgad College of Engineering
Pune, Maharashtra, India
mukundbaburaowagh@gmail.com

Dr. Gomathi N
Department of Computer Engineering
Vel-Tech Dr. RR & Dr.SR Technical University
Avadi, Chennai, India

Abstract: VANETs is a part of MANETs that lay hold of a few important responsibilities in the ITS domain because it offers consistent road safety. Several researchers' deals with the growth on VANET for enhanced routing; however, it undergoes from the severe issue for offering multi-constrained QoS to the network. Then the next solution over this issue, routing cost is solved by in view of the cost of congestion, cost of QoS awareness cost, cost of travel, and cost of collision, while the fuzzification is exploited to estimate the QoS awareness cost. In this paper, an Improved Grey wolf optimization (GSO) and Cuckoo Search (CS) algorithm are exploited in the VANET to take on the decreased routing cost. Additionally, the performance of the proposed Improved GWO-CS method is compared with the conventional methods such as GWO and CS by analyzing the cost of routing, and computational complexity. Hence, the proposed method offers consistent routing with minimized cost and computational complexity.

Keywords-VANET; MANET; vehicle; ITS; safety

Nomenclature

Abbreviations	***Descriptions***
QoS	Quality of Service
VANETs	Vehicular Ad Hoc Networks
IDS	Intrusion Detection System
VAT-MAC	adaptive Time Division Multiple Access-based MAC
ITS	Intelligent Transportation System
V2I	Vehicle-To-Infrastructure
V2V	Vehicle-to-Vehicle
TRA	Trace Authority
DAS	Drones-Active Service
MANETs	Mobile Ad Hoc Networks
IGHSOM	Improved Growing Hierarchical Self-Organizing Map
CPP	Conditional Privacy Preserving
OBUs	On-Board Units
PDD	Packet Delivery Delay
RSUs	Road Side Units

1. Introduction

VANETs are unique kinds of MANETs, in that the mobile nodes are vehicles, which are moving on the road. Additionally, the advanced development of VANET model overlays the technique for the performance of the ITS applications. Moreover, these applications are safety-oriented applications to augment traffic security and decrease road accident sufferers or non-safety based applications, which intend to handle the traffic as well as offering passengers with infotainment and relieve [1].

VANET protection is necessary due to an insufficiently intended VANET, which is susceptible to systematize to network attacks and this consecutively cooperates the safety of drivers. Safety frameworks need to assure that broadcast move towards from an accepted source and not obstructed in the path by a variety of sources [9]. If the vehicles follow the traffic policies and road limit, then the accidents can be evaded. However, the malevolent node can be able to extend out spam messages and transmit forged messages to create such as forged data of collision, stealing and heavy traffic.

VANET has developed into a growing technology of study. In this field, researchers have put plenty of hard work to make the vigorous plan and the execution of VANET network environment [10]. With the increasing number of vehicles, the streets are most probably hectic. Consequently, it is extremely significant to enlarge street security and reduce movement obstruction. By swapping the invigorated data regarding the street and movement circumstances, the communication is built up to evade road accidents and well-organized outcome of traffic in VANET. Moreover, VANET is exploited to provide the guarantee and movement information to the clients regarding crowded driving conditions, earthquake, tsunami, and so forth. Also, to decrease the road accidents, fuel utilization and offers secure driving atmosphere [11] [12].

Each vehicle can connect with other vehicles in VANETs because they are equipped with OBUs. This types of connections known as V2V that is probable to be necessary for the majority ITS applications owing to its minimum cost and availability. Simultaneously, vehicles can connect with installed transportation, for instance, RSUs, by means of V2I communications [13] [14]. The allocation and amount of roadside units must be relying on the connection protocol needs to exploit. Nevertheless, a small number of protocols require roadside units to be owed likewise during the complete road network; a few necessitate roadside units completely at intersections, at the same time as others necessitate roadside units exclusively at area borders. Regardless of the fact that it's secure to suppose that communications subsist to a few scope and vehicles have entree to that irregularly [15]. It is recognized that the above disadvantages can be addressed simply by developing robust VANET communication route metrics and exploiting robust route optimization methods [18] [19] [20] [21][22] [23] to determine optimal routes for communication.

The main contribution of this paper is to resolve the routing issues in VANETs using Improved GWO-CS method. Moreover, it is used to resolve the route chosen issues, as a hybrid approach, which has the ability to minimize the cost and computational complexity. The rest of the paper is described as follows: Section 2 describes the literature review. Section 3 describes the objective model considered for VANET routing. Section 4 describes the optimized VANET routing. Section 5 states the results and discussions and section 6 describes the conclusion of the paper.

2. Literature Review

2.1 Related Works

In 2018, Hafez Seliem et al [2] presented a routing protocol, which utilizes infrastructure drones for improving the communications of VANETs. It was exploited to attain a less vehicle-to-drone PDD. In a two-way highway, for the probability distribution of the vehicle-to-drone PDD, a closed-form term was presented. On the basis of the closed-form term, the less drone density was calculated, which stochastically restrictions the worst condition of the vehicle-to drone PDD. Furthermore, a DAS was presented in a VANET, which was added to the position service. In addition, this examine attains dynamical and the periodical number of active drones on the basis of the present highway connectivity state.

In 2019, Junwei Liang et al [3] a novel IDS was proposed that can able to suitably exploited in the wireless as well as dynamic networks, namely VANETs. Here, a new feature extraction approach and a classifier were presented; the classifier was on the basis of the IGHSOM for IDS in VANETs. For IDS's training and investigation, the proposed feature extraction method was exploited in order to rapidly take out different features from vehicle messages. Two key features that consist of the differences in traffic flow, as well as the location, were extracted in the proposed method. To obtain the latter feature, both the voting filter method and a semi-cooperative method were designed and the former feature was computed on the basis of the range of the distance among vehicles. Moreover, two novel methods such as relabeling and recalculating mechanisms are proposed in the I-GHSOM-based classifier.

In 2018, Shengbin Cao and Victor C. S. Lee [4] presented a novel VAT-MAC protocol for VANETs. Each frame length, by calculating as well as predicting the number of vehicles precisely and adaptively VAT-MAC optimizes within the coverage of a roadside unit. Moreover, the VAT-MAC can considerably progress the system scalability and throughput by mathematical study and simulation experiment.

In 2019, Jorge Pereira et al [6], presented a general framework in a VANET environment for the exploitation of Fog Computing applications and services. Furthermore, a proof-of-conception model was provided for data analytics in a hybrid VANET/Fog background. Here, the system model exploits two fog applications such as city traffic anomaly recognition, and to calculate the bus time of arrival to feed traveler information. Through real mobility information, the consistency of those applications was examined from a large vehicular testbed. Exploiting Fog computing, the outcomes demonstrate that a small set of current regional data appropriate for this kind of applications. As the evaluations of bus arrival times and traffic anomalies were the same as those offered by the Cloud.

In 2018, Hong Zhong et al [7] presented a privacy-preserving authentication method exploiting certificate less aggregate signature with full aggregation in VANET to attain protected V2I communications. The method of aggregate signature be able to attain message authentication and significantly keep the bandwidth and calculation resources. Moreover, to understand CPP and a TRA the pseudonym was exploited, during the communication which was dependable for creating a pseudonym and tracking the real identity. Pre-calculation for some data was done, while a vehicle penetrates an area on a new RSU's coverage. Therefore, the calculation cost in sign phase able to minimize. The communication and storage overhead was reduced due to the length of the aggregated signature constant.

In 2018, Debasis Das and Rajiv Misra [8] presented a suitable routing protocol on the basis of the dynamic network connectivity behavior of urban track at road crossings for VANETs. On the basis of the parallel processing idea the dynamic network connectivity model for VANETs were necessary for modeling a competent routing protocol at Road Intersection in urban cases for VANETs.

3. Objective Model Considered for VANET Routing

3.1Objective Model

Cost model: In general, the cost of network routing is resolved from the evaluation of travel cost, congestion cost, QoS awareness cost, and collision cost. Consider $R_{i,j}$ as the routing issue of the network, whereas $i = 1,2....N^{paths}$ and $j = 1,2...N^{nodes}$ so that $R_{i,j} \in \{L\}$ and N^{paths} must equal to M^{veh}. In view of that, eq. (1) indicates the total cost needed for the accurate routing of a network, where $C_O^{congestion}$, C_O^{travel}, C_O^{QoS} and $C_O^{collision}$ indicates to the travel cost, congestion cost, QoS awareness cost, and collision cost.

$$C_O(R) = C_O^{congestion} + C_O^{travel} + C_O^{QoS} + C_O^{collision} \tag{1}$$

At given duration, the count of vehicles assisted by the Access point is estimated in order to determine the congestion cost. Hence, eq. (2) is exploited to estimate the $C_O^{congestion}$ whereas in eq. (3), C_f^{lt} refers to the congestion limit of f^{th} Access Point.

$$C_O^{congestion}(j) = \begin{cases} C_f^{over}(j), C_f^{over} > 0 \\ 0, \text{otherwise} \end{cases} \tag{2}$$

$$C_O^{over}(j) = \sum_{\substack{i=1 \\ j \neq 1}}^{N^{path}} CS_f(i,j) - C_f^{lt} \tag{3}$$

$$CS_f(i,j) = \begin{cases} 1, \text{if } \; R_{i,j} \in C_f \\ 0, \text{otherwise} \end{cases} \tag{4}$$

The total cost continued to travel the vehicle from one position to another in terms of distance, fuel time, or a combination of all indicated as the travel cost. Hence, eq. (5) is used to determine the C_O^{travel} in terms of a distance matrix, whereas the Euclidean distance among the nodes from the distance matrix is represented as $D(.)$.

$$C_O^{travel} = \sum_{i=1}^{N_{path}} \sum_{j=j+1}^{1N^{nodes}} D(R_{i,j\ 1}, R_{i,j}) \tag{5}$$

Similarly, to estimate the cost of QoS awareness C_O^{QoS}, the fuzzy interference system is exploited. With the substantiation of the cost, it has the ability to determine the congestion level of the Access point and received signal strength (RSS).

The total probability of the collision among the vehicles traveling between the specified positions is referred to as the collision cost $C_O^{collision}$. The model for the determination of collision cost is exhibited in algorithm 1 where F_p indicates the penalty function and $N^{col.veh}$ indicated as the total count of colliding vehicles.

ALGORITHM 1: COST ESTIMATION of COLLISION
Input: $R_{i,j}$ //vehicles path
Output: $C_O^{collision}$ //collision cost
Initialize the cost of collision as $C_O^{collision} = 0$
for $i = 1 : N^{nodes}$ 1
Establish the unique number of nodes $U^j \ \forall i$
Calculate the count of colliding vehicles $N^{col.veh}$
$C_O^{collision} = F_p \times N^{col.veh} + C_O^{collision}$
Return $C_O^{collision}$

3.2 System Model

Fig 1 illustrates the systematic model of the movement of vehicles in several directions. In the system model, V_j is assumed as the number of vehicles, $j = 1, \ldots M^{veh}$ and the several locations are presumed as $L1, L2, L3, L4, L5, L6, L7, L8$ and $L9$.

Consider, at a constant speed the vehicles are traveling to acquire to the particular positions. Then, the four Access Points (AP) denoted as AP_1, AP_2, AP_3 and AP_4 covers the above-represented locations with equal coverage region. Usually, the movement of vehicles can be tremendously high in some locations. The particular route must optimally choose under such cases. In the network, occasionally the erroneous chosen of routes may cause coverage issue. Consequently, by choosing the best route, the maximum coverage area is attained. In addition, to hold the count of vehicles the ability of each AP is restricted. On the other hand, the issues of congestion happen in the specific coverage region if the number of vehicles moving away from the limit. For example, the AP_1 holds the vehicles moving to the location 1, 4, 2 and 5 while the AP_2 handles the vehicles moving to the location 7 and 8. In addition, the vehicles moving to the location 5 and 6 are attainment to share the access point AP_3 and vehicles passing to the location 5, 8, 6 and 9 shares the AP_4. Additionally, the cost decrease may enhance QoS.

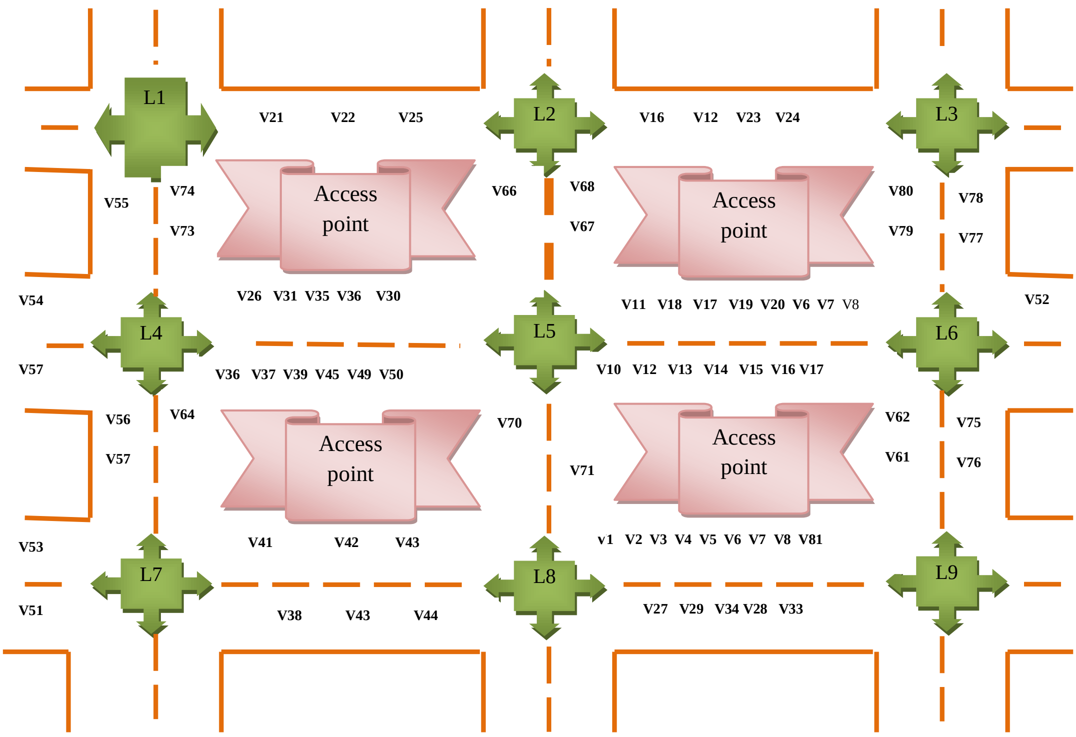


Fig. 1. *Systematic diagram of VANET covered by several Access points*

4 Optimized VANET routing

4.1 Fuzzified QoS Estimation

By the QoS factors namely RSS and congestion level, the QoS awareness cost is estimated using a fuzzy logic system create employ of non-numeric linguistic variables. Generally, the aforementioned linguistic variables are allocated with a numeric value that demonstrates the membership function of the fuzzy logic. Table 1 show that the principles of fuzzy needed for the estimation of cost as well as QoS factors. The QoS cost is zero, maximum and maximum equivalence with the minimum, moderate and maximum at fair and better RSS. On the other hand, the QoS value is allocated to be low, maximum and maximum in related to a minimum, moderate and congestion level at poor RSS. The value of RSS, congestion, and QoS cost in terms of the fuzzy membership function.

Table 1: *Rules of fuzzy with Congestion level and Cost*

Sl. No.	RSS	QoS cost	Congestion level
1	poor	minimum	minimum
2	poor	maximum	moderate
3	poor	maximum	maximum
4	fair	zero	minimum
5	fair	maximum	moderate
6	fair	maximum	maximum
7	better	zero	minimum
8	better	maximum	moderate
9	better	maximum	maximum

4.2 Conventional Optimization Algorithms

GWO: A novel population-based nature-inspired approach known Grey Wolf Optimization (GWO) was developed in [16]. In nature, the GWO method imitates the social leadership and hunting behavior of grey wolves. Here, four kinds of grey wolves like α , β , χ and ω are exploited for imitating the command hierarchy. The first three optimal position wolves are represented as α , β , χ who direct the other wolves ω of the crowds to shows potential areas of the search space. The location of each wolf of the group is updated exploiting the eq. (6). Also, eq. (7) is exploited to compute the encircling behavior of each agent of the crowd.

$$\vec{s} = \left| c.\vec{z}_p^{\,t} - z^t \right| \tag{6}$$

$$\vec{z}^{\,t+1} = \vec{z}_p - \vec{a} \cdot \vec{s} \tag{7}$$

Using eq. (8) and (9), the vector a and c are computed.

$$\vec{a} = 2l.r_1 \tag{8}$$

$$\vec{c} = 2l.r_2 \tag{9}$$

To scientifically imitate the hunting behavior, the alpha, beta, and delta are presumed that have enhanced knowledge about the possible location of prey. The subsequent equations are developed and considered.

$$\vec{s}_\alpha = \left| \vec{c}_1 \bullet \vec{z}_\alpha - \vec{z} \right| \tag{10}$$

$$\vec{s}_\beta = \left| \vec{c}_2 \bullet \vec{z}_\beta - \vec{z} \right| \tag{11}$$

$$\vec{s}_\chi = \left| \vec{c}_3 \bullet \vec{z}_\chi - \vec{z} \right| \tag{12}$$

$$\vec{z}_1 = \vec{z}_\alpha - \vec{a}_1 \bullet \left(\vec{d}_\alpha \right) \tag{13}$$

$$\vec{z}_2 = \vec{z}_\beta - \vec{a}_2 \bullet \left(\vec{d}_\beta \right) \tag{14}$$

$$\vec{z}_3 = \vec{z}_\chi - \vec{a}_3 \bullet \left(\vec{d}_\chi \right) \tag{15}$$

$$\vec{z}^{\,t+1} = \frac{\vec{z}_1 + \vec{z}_2 + \vec{z}_3}{3} \tag{16}$$

The $\vec{a}$ is arbitrary value in the space [-2a, 2a]. While arbitrary value $|\vec{a}| < 1$,the wolves are strained to harass the prey. Exploration ability represents the searching for prey and exploitation ability represents attacking of the prey. The random values $\vec{a}$ are exploited to force the search to diverge from the prey. When $|\vec{a}| > 1$, the members of the population are forced to move away from the prey.

Cuckoo Search: The Cuckoo Search (CS) technique [17] is stimulated from the distinctive nesting approach of levy-flight-style and cuckoo birds. The reproduction schemes of a few cuckoos are individual because they do not produce their own offspring. While the host moves away from the nest the cuckoo lay down their eggs in the host's nest, occasionally they also take away host bird's eggs. Few of the host birds can identify that the eggs belong to a stranger, as well as it could subsequently move the stranger's eggs and throw away the nest, and identify somewhere besides to build a new one.

For numerous animals, the Levy-flight-style is a classic feature of flight behaviors. Basically, it indicates to the individual in a less significant collection of activities, although it can include a small probability of long-range jump. Furthermore, it might have a little probability of important divergence from the mean value of the activities, as the power to the CS approach bounding out of the local optimum. However, the CS approach requires fitting the subsequent three idealized principles.

Initially, cuckoo birds select the nest arbitrarily as well as they lay only one egg at one time. Next, only the optimal nests will stay to be future generations. Finally, the number of bird's nests and the probability that the eggs are identified are fixed. During the iteration using eq. (17), the host bird will throw away the nest and construct a new one if outsider's egg is identified by the host bird. By fulfilling these three principles, the nests are updated.

$$z_i(t+1) = z_i(t) + \beta \oplus Levy'(\lambda), \quad i = 1,2,3...n \tag{17}$$

Here, the product $\oplus$ indicates the entrywise multiplication $z_i(t+1)$ indicates the novel solution for cuckoo i, $z_i(t)$ indicates the current solutions. Since $\beta > 0$, control the step size in many circumstances, it set to 1. The eq. (18) indicates the levy-flight.

$$Levy' \approx v = t^{\lambda}, (1 < \lambda < 3) \tag{18}$$

As a result, the CS approach has the ability to search the solution space in a well-organized manner since its step alters with short distance exposure and intermittent long distance walking and the length of step is much elongated in long run.

4.3 Proposed Algorithm

The GWO approach updates the positions from eq. (6), by the development of investigation done in the individuals with maximum fitness values that is key-group. As a result, it tends to a feeble global-search capability that might be simple to descend into the local optimum, particularly while it exploits few high-dimension data sets. By arbitrary walk and levy-flights, the CS method updates the locations of the nest, when the search path is extended or small with approximately the similar probabilities, as well as the direction is extremely arbitrary. Therefore it is easier to jump from the present regions to other regions. In accordance with this feature of CS, the CS method is subsequently incorporated to develop the GWO method. The improved GWO method incorporated with CS is presented as the IGWO-CS method, with its pseudo code. By means of the proposed approach, reliable routing with computational complexity and minimized cost can be achieved. The algorithm 2 describes the pseudo code of proposed algorithm.

Algorithm 2: Pseudo code of IGWO-CS

```
Initialize the position of grey wolves
Initialize a⃗, s⃗, P_a
Calculate the fitness of each search agent
Based on the fitness set z_α, z_β, z_χ
t = 1
While (t < Max)
        For each wolf
            Using eq. (10) update the position
        End for
        Update a⃗, s⃗
        Calculate the fitness of each search agent
        Update the z_α, z_β, z_χ
        For z_α, z_β, z_χ
            Using eq. (17) update the position
            If an arbitrary number> P_a
                Arbitrary changes wolf's position
            According to the fitness calculate the fitness value and update
```

```
            t = 1
End while
Output z_α
```

5 Results and Discussions

5.1 Experimental Procedure

In VANET, the route chosen model in VANET was experimented in MATLAB by adopting the proposed IGWO-CS method. With respect to the variation of time and count of vehicles, the experimentation of route chosen model was executed in four configurations such as “70 nodes and 40 vehicles (A), 80 nodes and 50 vehicles (B), 90 nodes and 60 vehicles (C) as well as 100 nodes and 70 vehicles (D)”. Moreover, the performance of the proposed IGWO-CS was compared with the traditional GWO [16] and CS [17] to confirm the effectiveness of the proposed method.

5.2 Statistical Analysis

In this section, the statistical report of the proposed and conventional methods for 40 vehicles with 70 nodes, 50 vehicles with 80 nodes, 60 vehicles with 90 nodes, 70 vehicles with 100 nodes are shown. In Table 2, for the best case scenario, the proposed algorithm is 37% and 35% superior to the conventional GWO and CS algorithms.

Table 2: *Statistical report of the proposed Algorithm and Existing Algorithms for 40 vehicles and 70 nodes.*

Statistics	GWO	CS	Proposed
Best	3,229,881	3,100,311	2,01,0112
Worst	5,261,110	5,000,992	5,000,100
Mean	4,314,193	4,132,309	4,022,167
Median	3,221,118	3,113,572	3,003, 675
Std deviation	75,012	74,113	70,333

Table 3 exhibits for best case scenario the proposed method is 25% superior to the existing GWO and 21% superior to the existing CS approach. Table 4 states the proposed technique is 21% superior to the existing GWO and 14% superior to the existing CS approach for the mean case. Table 5 represents the proposed technique is 17% superior to the GWO and 18% superior to the CS technique.

Table 3: *Statistical report of the proposed Algorithm and Existing Algorithms for 50 vehicles and 80 nodes.*

Statistics	GWO	CS	Proposed
Best	3,229,881	3,10,311	2,01,011
Worst	4,314,193	4,132,309	4,022,167
Mean	3,221,118	3,113,572	3,003, 675
Median	75,012	74,113	70,333
Std deviation	50, 321	49,052	48,012

Table 4: *Statistical report of the proposed Algorithm and Existing Algorithms for 60 vehicles and 90 nodes.*

Statistics	GWO	CS	Proposed
Best	4,223,206	4,000,331	3,000,001
Worst	75,012	74,113	70,333
Mean	3,229,881	3,10,311	2,01,011
Median	9,033,012	8,567,123	8,345,001
Std deviation	3,332,112	3,200,00	3,022,143

Table 5: *Statistical Report Of The Proposed Algorithm And Existing Algorithms For 70 Vehicles And 100 Nodes.*

Statistics	GWO	CS	Proposed
Best	50, 321	49,052	48,012
Worst	3,332,112	3,200,00	3,022,143
Mean	3,229,881	3,10,311	1,01,011
Median	4,314,193	4,132,309	4,022,167
Std deviation	3,221,118	3,113,572	3,003, 675

5.3 Computational Analysis

***Table 6:** Performance Analysis Of The Proposed Algorithm With The Existing Algorithms For 50 Vehicles And 80 Nodes.*

Configurations	GWO	CS	Proposed
A	4,464,193	4,003,309	3,022,167
B	3,229,881	3,10,311	1,01,011
C	4,314,193	4,132,309	3,835,160
D	50, 321	49,052	48,012

Table 6 summarizes the computational time, which is needed for the experimentation exploiting the proposed method as well as the conventional GWO and CS methods. For all the four configurations A, B, C and D, the computational time is stated. The time needed for the computation of proposed method is 42% superior to conventional GWO and 12% better than the conventional CS under the configuration A. The proposed approach attains higher computational time than the existing approaches in some configurations. Therefore, proper routing by the proposed approach in VANET is superior to the existing techniques.

6 Conclusion

In recent years, VANET is the most recent technology that offers safe routing for vehicles. On the other hand, multi-constrained QoS was lifted as the forthcoming confront in this area. Generally, reliable routing in the network can be offered in view of the routing cost. For that reason, this paper has considered the routing cost associated with the cost of congestion, cost of QoS awareness, cost of travel, and cost of a collision. By considering that cost was reduced in this simulation experiment exploiting proposed IGWOCS approach, additionally, the performance was compared with the existing techniques such as GWO and CS. This comparison was adopted by verifying the complexity and cost of the complete approaches. Hence, it has forecasted that the performance of the proposed approach is better than the conventional approaches by increasing above with diminished complexity and cost in the calculation.

References

[1] Guiyang Luo , Quan Yuan , Haibo Zhou , Nan Cheng , Zhihan Liu , Fangchun Yang , Xuemin Sherman Shen, "Cooperative vehicular content distribution in edge computing assisted 5G-VANET," in China Communications, vol. 15, no. 7, pp. 1-17, July 2018.

[2] H. Seliem, R. Shahidi, M. H. Ahmed and M. S. Shehata, "Drone-Based Highway-VANET and DAS Service," IEEE Access, vol. 6, pp. 20125-20137, 2018.

[3] H. Seliem, R. Shahidi, M. H. Ahmed and M. S. Shehata, "Probability Distribution of the Re-Healing Delay in a One-Way Highway VANET," IEEE Communications Letters, vol. 22, no. 10, pp. 2056-2059, Oct. 2018.

[4] S. Cao and V. C. S. Lee, "A Novel Adaptive TDMA-Based MAC Protocol for VANETs," IEEE Communications Letters, vol. 22, no. 3, pp. 614-617, March 2018.

[5] Y. Xia, X. Qin, B. Liu and P. Zhang, "A greedy traffic light and queue aware routing protocol for urban VANETs," in China Communications, vol. 15, no. 7, pp. 77-87, July 2018.

[6] Jorge Pereira, Leandro Ricardo, Miguel Luís, Carlos Senna, Susana Sargento, "Assessing the reliability of fog computing for smart mobility applications in VANETs", Future Generation Computer Systems, vol. 94, pp. 317-332, May 2019.

[7] Hong Zhong, Shunshun Han, Jie Cui, Jing Zhang, Yan Xu,"Privacy-preserving authentication scheme with full aggregation in VANET", Information Sciences, vol. 476, pp. 211-221, February 2019.

[8] Debasis Das, Rajiv Misra,"Improvised dynamic network connectivity model for Vehicular Ad-Hoc Networks (VANETs)", Journal of Network and Computer Applications, vol. 122, pp. 107-114, 15 November 2018.

[9] S. Bitam, A. Mellouk, S. Zeadally, Bio-inspired routing algorithms survey for vehicular ad hoc networks, IEEE Commun. Surv. Tutor. 17 (2) (2015) 843–867.

[10] S. Zeadally, R. Hunt, Y.-S. Chen, A. Irwin, A. Hassan, Vehicular ad hoc networks (VANETs): status, results, and challenges, Telecommun. Syst. 50 (4) (2012) 217–241.

[11] T. Kohonen, Self-organization and Associative Memory, Springer-Verlag, Berlin, Germany, 1984.

[12] A.L. Beylot, H. Labiod, CONVOY: a new cluster-based routing protocol for vehicular networks, in: Vehicular Networks: Models and Algorithms, first ed., John Wiley & Sons, London, UK, 2013, pp. 91–139 (Chapter 3).

[13] L.J. Fogel, A.J. Owens, M.J. Walsh, Artificial Intelligence through Simulated Evolution, Wiley Publishing, New York, 1966.

[14] F. Bai, H. Krishnan, V. Sadekar, G. Holland, T. ElBatt, Towards characterizing and classifying communication-based automotive applications from a wireless networking perspective, Proc. AutoNet, San Francisco, CA, USA, 2006.

[15] C. Wu, S. Ohzahata, T. Kato, Flexible, portable, and practicable solution for routing in VANETs: a fuzzy constraint Q-learning approach, IEEE Trans. Veh. Technol. 62 (9) (2013) 4251–4263.
[16] Kaiping Luo, "Enhanced grey wolf optimizer with a model for dynamically estimating the location of the prey", Applied Soft Computing, vol. 77, pp. 225-235, April 2019.
[17] M. Mareli, B. Twala,"An adaptive Cuckoo search algorithm for optimisation", Applied Computing and Informatics, vol. 14, no. 2, pp. 107-115,July 2018.
[18] Vijayakumar Polepally, K Shahu Chatrapati,"DEGSA-VMM: Dragonfly-based exponential gravitational search algorithm to VMM strategy for load balancing in cloud computing";Kybernetes, vol.67, no.6;pp.1138-1157;2018.
[19] SB Vinay Kumar, PV Rao, Manoj Kumar Singh,"Multi-culture diversity based self adaptive particle swarm optimization for optimal floorplanning",Multiagent and Grid Systems, vol14, no.1, pp.31-65, 2018.
[20] G Singh, VK Jain, A Singh, "Adaptive network architecture and firefly algorithm for biogas heating model aided by photovoltaic thermal greenhouse system",Energy & Environment, vol. 29 (7), pp.1073-1097,2018.
[21] A Shankar, J Natarajan,"Base Station Positioning in Wireless Sensor Network to aid Cluster Head Selection Process", International Journal of Intelligent Engineering and Systems", vol. 10, no.(2), pp.173-182, 2017.
[22] RM Chintalapalli, VR Ananthula,"M-LionWhale: multi-objective optimisation model for secure routing in mobile ad-hoc network",IET Communications,vol. 12, no.(12), pp.1406-1415,2018.
[23] MNKMSS Dr. N. Krishnamoorthy,"Performance Evaluation of Optimization Algorithm Using Scheduling Concept in Grid Environment", The IIOAB Journal, vol. 7 no.9, pp. 315-323, 2016.