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Optimal Route Selection for Vehicular Ad Hoc Networks Using Lion Algorithm

Mukund B. Wagh* and Dr. Gomathi N.

**Assistant Professor, Department of Computer Engineering, Sinhgad College of Engineering, Off Sinhgad Road, Pune, Maharashtra 411041, India*
Professor, VEL-TECH Dr. RR & Dr.SR Technical University, Avadi, Chennai-600 062
**Corresponding Author: mukundbaburaowagh@gmail.com*

ABSTRACT

Vehicular Ad-hoc NETworks (VANETs) are very important in the field of Intelligent Transportation system (ITS) for enhancing the safety of road. The communication between the vehicles will be covered under the VANETs. A lot of research works are there in the area of VANET development. The common problem that arises is achieving multi-constrained Quality of Service metrics. In order to solve this problem, this paper proposes an optimal routing discovery algorithm to aid the routing process in the VANET. Firstly, this paper derives a cost model for vehicle routing problems by considering the network quality metrics such as travel cost, collision, congestion, and the awareness about the quality of service (QoS). The QoS awareness is fuzzified into cost model to be included in the total routing cost. Since the routing cost model is a minimization function, a recently introduced bio-inspired optimization algorithm, called lion algorithm (LA), is used to solve the function. The performance is investigated using three renowned analyses such as convergence analysis, cost analysis, and complexity analysis. The simulated results obtained using MATLAB are compared with the existing Genetic algorithm (GA) based solution. It is found that the Lion algorithm performs better than the GA with a decrease in routing cost and complexity.

Keywords: Lion algorithm (LA); VANET; QoS; Fuzzy; Routing.

INTRODUCTION

Enhancing the road safety with timely information to the transport authorities and the drivers is of great concern. So, the better way for road safety can be provided by using the Intelligent Transportation system (ITS) (Bitam *et al.,* 2015). The ITS had wide applications such as vehicle safety, prevention of collisions, traffic monitoring, control of traffic flows, blind crossing, and real-time detour routes computation, in addition to non-safety applications such as nearby information services, automated toll payment, and infotainment services (Zeadally *et al.,* 2012).

ITS in vehicular network includes Vehicular Wireless Local Area Networks (V-WLAN) and Vehicular Cellular Network (VCN). V-WLAN is based on the set of access points fixed at traffic intersections and VCN is based on a set of fixed cellular gateways. There are many problems in vehicular networks with the ITS. The problems include high costs and geographic limitations. Because of these limitations, the transmission range in network is found to be very low, leading to communication problems (Beylot & Labiod, 2013).

In ITS, VANETs are a key technology that are envisaged to play a significant role in the futuristic smart cities by improving road safety and providing innovative services relating to traffic management and infotainment applications (Bai *et al.,* 2006). The digitalized data communication between the vehicles and Road side users can be provided using the VANET (Wu *et al.,* 2013). There have been many routing protocols proposed for VANETs. These include connection based restricted forwarding and connectionless geographic forwarding (Wang *et al.,* 2009), robust mobility adaptive clustering (Goonewardene *et al.,* 2009), Q-learning routing protocol (Wu *et al.,* 2010), estimated-distance-based routing protocol (Zhang *et al.,* 2011), etc.

Although much advancement is done in vehicular networks, there is a problem of determining optimal routes for vehicle transportation. In order to overcome these problems, various routing algorithms are developed for VANETs in recent years. The primary objectives of routing algorithm are to determine the optimal route for vehicles, where the term "optimal" refers to multiple aspects and the quality of routes such as minimum distance, high radio access, high QoS awareness, etc. Few such algorithms that are reported in the literature are discussed and reviewed below.

LITERATURE REVIEW

Related Works

In 2015, Eiza *et al.* (2015) exploited the ant colony system based algorithm and situational awareness concept in developing Situation-Aware Multi-constrained QoS (SAMQ) routing algorithm for VANETs. They estimated the feasible routes between the vehicles subject to multiple QoS constraints and selected the best route for accurate data transmission. The developed method solves the NP-hard problem of searching the feasible routes. Zhou and Wang (Zhou & Wang, 2015) have worked on Vehicle routing problem with time windows (VRPTW) and developed a local search-based multi-objective optimization algorithm. They introduced many local search methods to optimize the objects. The developed algorithm is simulated with 45 real time pieces of data and proved to show better solutions. Yang *et al.* (Yang *et al.,* 2015) developed a novel optimal electric vehicle route model to reduce total distribution costs of the electric vehicle route attributing to the other parameters as capacity of battery, time for recharging, etc. They also developed a learnable partheno-genetic algorithm with combination of subject knowledge on electric vehicle charging station and customer selection. The proposed method is challenging to reduce the carbon emission and energy saving. Ahrens *et al.* (2015) developed algorithms for routing in advanced technology nodes. They used the multi-label interval-based shortest path algorithm for long on-track connections. They combined the bonnRoute with industrial router for finding solutions to the drawbacks in the experimental design.

In 2016, Eiza *et al.* (2016) proposed an innovative secure and accurate multi-constrained QoS aware routing algorithm for VANETs. They exploited the Ant colony optimization technique to find out the feasible routes in VANETs subject to the QoS, which was estimated using the data traffic type. They also had done the plausibility checks on routing control messages using the extended form of evolving graph model. The developed Secure QoS routing algorithm ensures better security in the wireless networks.

In 2016, V.V. Mandhare and V.R. Thool (2016) addressed the issue in (QoSR) Quality of Service Routing because of its dynamic nature of the network. Hence, they have proposed (MANET) Mobile Ad-hoc Network approach to finding the realistic path. Moreover, they have mainly focused on the constraint of QoS in MANET on the basis of Cuckoo Search (CS) Algorithm. Finally, the experimental results are compared with other existing algorithms such as AODV, PSO, and ACO and show that the proposed algorithm performs better.

In 2016, Aymen Al-Ani and Jochen Seitz (2015) have proposed avoidance mechanism as an enhancement and an adaptive congestion control to the QoS-aware routing protocol. Moreover, they have utilized Ant Colony Optimization (ACO) approach for the Simple Network Management Protocol. The adaptive nature of QoS-aware routing protocol (QoRA) on the basis of ACO diagnosed the sustainability of multi-rate data transmission resolute by the QoS restrictions presented on the path.

In 2014, Chao Gaoa et *al.* (2015) had worked on Cooperative QoS routing (CQR) protocols in a multi-service network application to present scalable information delivery. Moreover, they have proposed a Fading Memory Cooperative QoS Routing (FMCQR) approach on heterogeneous services, large range transmission, and three-dimensional monitor region.

In 2015, Aymen Al-Ani and Jochen Seitz (2015) had addressed the issues like scarcity of resources and node mobility in (MANETs) mobile ad-hoc network. Hence, to overcome these issues they have used ant colony optimization algorithms by QoS-aware routing approach. Nevertheless, vehicular ad-hoc networks (VANETs) also addressed the issues such as prediction of QoS parameters and change in rapid topology. Moreover, to reduce the overhead introduced to gather information from neighbor nodes and to attain a precise approximate of QoS parameters, they have used network management protocol to approximate the values locally. Finally, the simulation result shows that the Ant colony optimization on the basis of QoS Routing protocol is scalable and possesses high mobility.

In 2016, S. Kavi Priya *et al*. (2016) have developed distributed power aware routing mechanism on the basis of the fuzzy in terms of bandwidth and energy constraints. Here, the star algorithm is used to satisfy the bandwidth limitation and energy. Finally, the simulation result shows that the proposed approach reduces frequent transmissions.

In 2015, Miguel Sepulcre *et al.* (2016) had proposed Multipath QoS-driven Routing (MPAR) protocol for the industrial wireless network to assure the strict QoS levels. MPAR uses the probabilistic estimation for the reliability and multipath delay routes to recognize the nodes and routes essential to create the end-to-end connections. The MPAR is compared with the single path and multipath routing protocols.

In 2013, M. H. Eiza and Q. Ni (2013) had proposed on VoEG model and extended the evolving graph theory. The extended evolving graph aids to capture the evolving characteristics of the vehicular network topology. In addition, it decides the reliable routes pre-emptively. Here, an evolving graph based routing strategy is first proposed for VANETs so as to ease the quality-of-service (QoS) support in the routing process. To find the most reliable route in the VANET evolving graph a novel algorithm is developed from the source to the destination.

Problem Statement

As stated earlier, intelligent routing is the primary concern to accomplish the QoS for the VANETS. Our review has reported various routing mechanisms for the VANET architecture at different environments. For instance, a SAMQ based routing mechanism has been reported in Eiza *et al.* (2015), whereas the vehicle routing problem has been considered with time windows in Zhou & Wang (2015). In Yang *et al.* (2015), more realistic vehicle routing problem has been considered by introducing the environmental and resource constraints. The design issues with the BONN router have been recovered by the efforts made in Ahrens *et al.* (2015). Though the routing problem takes various such formulations, the basic inference behind them is to accomplish QoS and the basic model of routing problem can be termed as multi-constrained QoS aware routing problem, as per Eiza *et al.* (2016). The constraints can be security, efficacy, reliability, resource utility, and many more. Since the contribution of Ahrens *et al.* (2015) in the recent literature is on the architecture level, we limit our interest to the rest of the research works.

Among the reviewed works, the swarm intelligence, specifically ant colony optimization, plays vital role. In Eiza *et al.* (2015), an ant colony system (ACS) has been introduced to solve SAMQ and the traditional ant colony optimization (ACO) has been used to solve the multi-constrained routing problem. Though the ant colony based swarm intelligence remains renowned for its fine grained searching ability, it is a local search optimization algorithm. Hence a multimodal environment will pose a great challenge to these algorithms, because of its huge number of local optimal points and the inability of the algorithm to evade from those points. On the other hand, the evolution based algorithms such as genetic algorithm have been endorsed as promising (Yang *et al.,* 2015). However, the basic characteristic and the drawback of these algorithms are its coarse grained searching ability and the extreme random searching. In order to overcome these effects, a customized optimization algorithm has also been reported in Zhou & Wang (2015), yet the problem area is multi-objective and the searching nature of the algorithm is based on local neighbourhood. Hence a suitable intelligent algorithm can play substantially well to handle the vehicle routing problem.

Our Solution

As solution to the characteristics of routing cost models, this paper adopts newly introduced lion algorithm (Rajakumar, 2014). The lion algorithm has been introduced as the search algorithm (Rajakumar, 2012) and came out with few restructurings in 2014. Since the algorithm has been proven for its ability to search in the large scale problem domain, we have exploited for solving our route selection model. However, the primary operations of lion algorithm such as encoding, crossover, and mutation are not suitable to handle our problem model. Hence, we introduce two-dimensional crossover and mutation process and customized encoding principle for our paper. Accordingly, the contributions of this paper are given as follows.

Contribution 1: This paper derives a route selection model by considering significant routing costs such as travel cost, congestion cost, and collision cost. Fuzzy intelligence is exploited to derive the cost to be incurred by QoS.

Contribution 2: The recently introduced optimization algorithm, called lion algorithm (Rajakumar, 2014), is used for which a customized version of encoding, crossover, and mutation operations is proposed. These operations are performed in two-dimensional rather than the conventional one-dimensional operation.

ROUTE SELECTION MODEL

Network Model

A schematic representation of the vehicles moving to different locations is shown in Fig. 1. The selected network consists of vehicles (referred to as V_n, where n is the index of the vehicle) moving to different locations L1, L2, L3, L4, L5, L6, L7, L8, and L9. The vehicles are assumed to move in a constant speed to reach the locations. Each location is covered by a specific access point (AP) represented as AP1, AP2, AP3, and AP4 with equal coverage areas. Most of the vehicles move from location 4 to location 6. The coverage problem occurs if the route selection is not optimal. So, it is better to select a right route for obtaining the maximum coverage. Also, if there is no traffic hub with no collision. For each AP, there is a capacity to handle the number of vehicles. Exceeding the number of vehicles often causes congestion in the particular coverage area. For instance, the vehicles moving to the locations 1, 2, 4, and 5 share a common access point AP1 and vehicles moving to the locations 3 and 6 share a common access point AP2. The instant AP3 is shared by vehicles moving to the locations 5 and 8. It is well seen that the congestion level is more around the access point 4, which covers locations 5, 6, 8, and 9. The quality of service must be enhanced with reduction in cost.

Let us assume the location where the designated vehicles move as L_i and represented by $L_i : i = 1,2,...,N_{nodes}$, where N_{nodes} is the number of nodes/location and i is the ith location/node. Let V_j be the jth vehicle and it is given by $V_j : j = 1,2,...,N_{vehicles}$, where $N_{vehicles}$ is the number of vehicles considered in the network. The APs deployed throughout the network is represented as $A_k : k = 1,2,\ldots,N_{AP}$, where N_{AP} is the total number of access points.

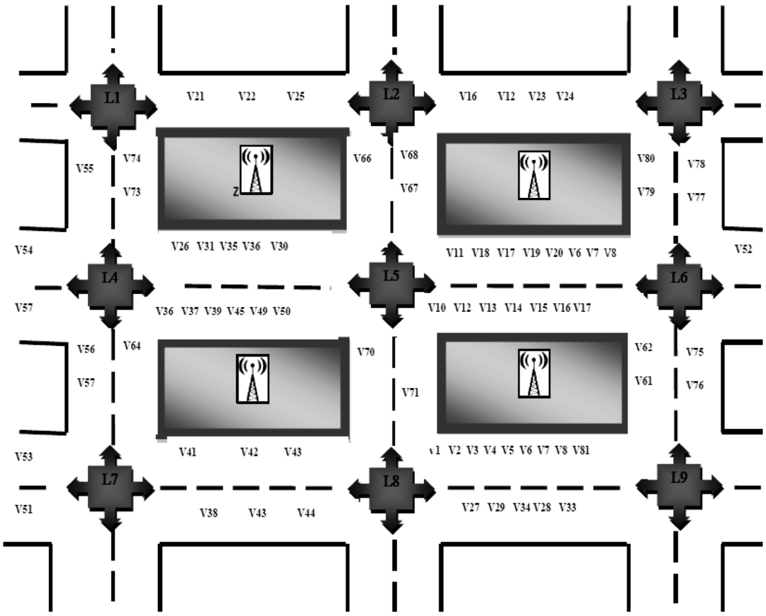


Fig. 1. A simple network of vehicles moving at different paths.

The AP has its own coverage area under which the network locations fall and the vehicles are covered. The coverage area of each AP can be represented as C_k in such a way that $C_k \subset L$. Hence, the cardinality of the coverage area is given as $\|C_k\| \approx \frac{N_{nodes}}{N_{AP}}$.

Condition 1: L_i is said to be in the coverage of A_k, only if $D(L_i, A_k) < R_c$ where R_c is the coverage radius.

Theorem 1: The diagonal length of the network to provide coverage to all the nodes can be given as $= \sqrt{2L_{net}^2}$, where L_{net} is the dimension of the network.

Proof: Assume that the locations of all the nodes are in the same plane. Hence, $X^{\max} \approx Y^{\max}$, where $X^{\max} = \max(L_i(x))$ and $Y^{\max} = \max(L_i(y))$. Since L_i is represented in the x-y coordinate system, $L_i(x)$ refers to the x[th] coordinate of L_i and $L_i(y)$ refers to the y[th] coordinate of L_i. If the network nodes begin from origin, the corner nodes can be determined as $(X^{\max}, 0)$ and $(Y^{\max}, 0)$.

Considering the Euclidean distance between the two points, we get the diagonal distance as

$$D^{diag} = \sqrt{\left(X^{\max} - 0\right)^2 + \left(X^{\max} - 0\right)^2} \tag{1}$$

$$D^{diag} = \sqrt{2X^{\max^2}} \tag{2}$$

where $X^{\max}$ is the length of node from origin, L_{net}. Hence, Eq. (2) becomes

$$D^{diag} = \sqrt{2L_{net}^2} \tag{3}$$

Cost Model

Consider $P_{m,n}$ as a solution for the routing problem (obtained from LA, since more detailed explanation is given in the following Sections), where $P_{m,n} : m = 1,2,...,N_{paths}$ and $n = 1,2,...,N_{nodes}$ in such a way that $P_{m,n} \in \{L\}$, and $N_{paths} = N_{vehicles}$. The total routing cost of the solution P is a combination of travel cost, collision cost, congestion cost, and QoS awareness cost as represented in Eq. (4).

$$F(P) = F_{travel} + F_{collision} + F_{congestion} + F_{QoS} \tag{4}$$

The travel cost F_{travel} can be given as the cost incurred to travel from one location to another location in terms of distance or time or fuel or in combination of all these. Considering them as a distance matrix, the F_{travel} can be represented by Eq. (5).

$$F_{travel} = \sum_{m=1}^{N_{path}-1} \sum_{n=n+1}^{N_{Nodes}-1} D\left(P_{m,n-1}, P_{m,n}\right) \tag{5}$$

where $D(A, B)$ is the Euclidean distance between nodes A and B determined from the distance matrix.

The collision cost $F_{collision}$ is the probability of collision among the vehicles when they travel among the locations. It can be determined using Algorithm 1 given below.

Algorithm 1: Determine Cost of Collision	
Input	$P_{m,n}$ // path of vehicles
Output	$F_{collision}$ // collision cost
1	Set $F_{collision} = 0$ // Initialize collision cost
2	for every node till $N_{Nodes} - 1 \quad \forall m$
3	Determine U_n // unique number of nodes available $\forall m$
4	Determine N_{coll} // Number of coding vehicles
5	$F_{collision} = P_F \times N_{coll} + F_{collision}$
6	return $F_{collision}$

Under the collision possibility, a penalty function P_F is multiplied with the number of colliding vehicles N_{coll}, where N_{coll} can be determined as the number of vehicles that come together to a location at a single instant of time; say at n^{th} instant.

The congestion cost $F_{congestion}$ is determined based on the number of vehicles being served by the AP at a given instant.

$$F_{congestion}(n) = \begin{cases} C_k^{over}(n); if\ C_k^{over} > 0 \\ 0;\ otherwise \end{cases} \tag{6}$$

$$C_k^{over}(n) = \sum_{\substack{m=1 \\ n \neq 1}}^{N_{paths}} CS_k(m,n) - C_k^{\lim} \tag{7}$$

$$CS_k(m,n) = \begin{cases} 1; if\ p_{m,n} \in C_k \\ 0;\ otherwise \end{cases} \tag{8}$$

where $C_k^{\lim}$ in Eq. (7) refers to the congestion limit of the k^{th} AP.

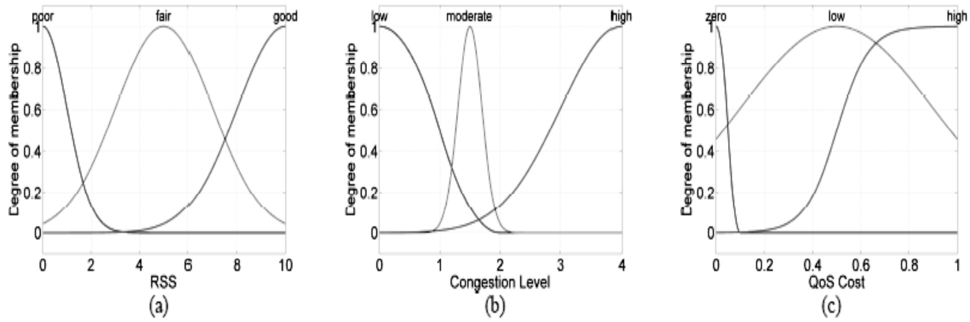


Fig. 2. Fuzzification of QoS factors such as RSS and congestion level to determine QoS Cost. (a) represents network with 40 vehicles and 70 nodes and fuzzification of RSS, congestion cost and QoS cost are given in (a), (b), and (c), respectively.

Table 1. Fuzzy Rules Among QoS Factors and Cost.

Sl. No.	RSS	Congestion level	QoS cost
1	poor	low	low
2	poor	moderate	high
3	poor	high	high
4	fair	low	zero
5	fair	moderate	high
6	fair	high	high
7	good	low	zero
8	good	moderate	high
9	good	high	high

The QoS awareness cost F_{QoS} is determined from the fuzzy inference system that estimates the QoS factors such as received signal strength (RSS) and the congestion level of the AP.

Fuzzification of QoS Factors

Fuzzy logic (Klir *et al.,* 1997) utilizes the non-numeric linguistic variables for the QoS factors, RSS, congestion, and QoS cost. Each linguistic variable is assigned with a numerical value, which represents the fuzzy membership function. Table I represents the fuzzy rules between the QoS factors and the cost involved. With respect to the congestion level of low, moderate, and high at fair and good RSS, the QoS cost is zero, high, and high. But at poor RSS condition with low, moderate, and high congestion level, the QoS cost is set as low, high, and high, respectively. Fig. 3 shows the fuzzy membership function of the various QoS factors that follow the Gaussian model. The degree of membership of congestion is set as low, when it is in the range [0, 2], moderate in [1, 2], and high in [1, 4]. While considering the RSS factor, the degree of membership in the range [0, 3] is referred to as poor, [0, 10] as fair, and [4, 10] as good. In the fuzzification of QoS cost, the degree of membership ranges at [0, 0.1] is linguistically referred to as zero, [0, 1] as low, and [0.2, 1] as high.

OPTIMAL ROUTE SELECTION USING LION ALGORITHM

Background

Based on the lion's natural behaviour (Bauer *et al.,* 2003), the Lion algorithm (Rajakumar, 2012) was developed in the year 2012. Fig. 4 represents the block diagram of the LA. According to LA, for defeating a random solution (can be the nomadic lion), the solution (can be a territorial lion) must be strong and so, the disappearance of the weak solutions (weak lions) occurs from the solution pool. The solution that won among the other solutions will be a stronger solution (succeeded lion in the territorial takeover/territorial defence) that arises due to the failure of some solutions (laggard lion). This paper exploits the LA proposed in (Rajakumar, 2014), which is modified from its previous version (Rajakumar, 2012). The modifications have been done with the addition of fertility evaluation phase, altering the crossover operation and gender clustering method. The algorithm is detailed in Rajakumar (2014), yet we have given the steps in sequence.

Limitations of using existing LA (Rajakumar, 2014): The LA has been proposed to solve a general optimization problem, which considers a row vector as the solution model. However, our problem requires a matrix as the solution model. Hence, the LA or any other current optimization algorithms cannot be exploited as they are. Such limitations persist through the LA procedures such as encoding, crossover, and mutation, which are the major processing steps of LA.

Algorithm Steps

1. Pride Generation: The X^{male}, X^{female} and the X_1^{nomad} of X^{male} and the X^{female} of the pride are initialized, where X^{male}, X^{female} and the X_1^{nomad} are arbitrary solutions, which are referred to previously as P. The elements of X^{female}, X^{male}, X_1^{nomad} such as $X^{female}(l)$, $X^{male}(l)$ and $X_1^{nomad}(l)$ are the arbitrarily selected locations.

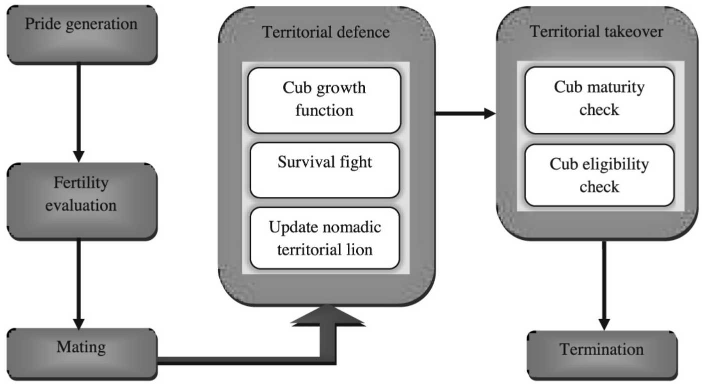


Fig. 3. Block diagram of LA.

2. Fitness Evaluation: The fitness of X^{male}, X^{female} and the X_1^{nomad}, termed as $f\left(X^{mfemale}\right)$, $f\left(X^{male}\right)$ and $f\left(X_1^{nomad}\right)$ is determined using Eq. (4). Subsequently, the initializations are done as $f^{ref} = f\left(X^{male}\right)$ and $N_g = 0$, where N_g refers to generation counter, which is applied in the termination step. The X^{male} and X^{female} are saved for further references.

3. Fertility evaluation: The pseudo code for the fertility evaluation process is given in Algorithm 2.

Algorithm 2: Fertility Evaluation

Input: X^{male}, X^{female}, f^{ref}, S_r and T_r

Output: X^{male}, X^{female}, f^{ref}, S_r and T_r

```
// X^male Evaluation
If f^ref ≤ f(X^male)
        T_r ← T_r + 1
else
        Reset T_r
        f^ref ← f(X^male)

// X^female Evaluation
If S_r is not tolerable
        Set u_c and g_c to zero
        Do
            Calculate X^female+
            g_c ← g_c + 1
            If f(X^female+) < f(X^female)
                u_c ← 1
                X^female ← X^female+
                Reset S_r
        Until g_c reaches g_c^max

Return X^male, X^female, f^ref, S_r and T_r
```

In fertility evaluation, the fertility of both gender lions is checked and evaluated for eliminating the problem of convergence at the local optima. The $X^{female+}$, f^{ref}, S_r, T_r, g_c and u_c refer to the updated female lion, reference fitness, sterility rate, laggardness rate, female generation count, and female update count, respectively. The S_r and T_r are initialized and they obtain the determined value at the last proceedings of the fertility evaluation process. It is necessary to check whether the tolerance level of S_r reaches the maximum $S_r^{\max}$. The value of $S_r^{\max}$, $T_r^{\max}$ and $g_c^{\max}$ and determining LA elements are determined as per the guidelines given in Rajakumar (2014).

4. Mating: In the mating process of LA, the X^{male} and X^{female} undergo crossover and mutation operation, similar to any evolutionary optimization processes (Fogel *et al.,* 1966; Doerr & Happ, 2012; Back *et al.,* 1993; Jong, 1975). The crossover operation is performed based on the littering rate of lion (Packer & Pusey, 1997) to produce X^{cubs}. Equal numbers of new cubs X^{new} are produced, when the X^{cubs} undergoes mutation with mutation probability M_r and the cubs are located in the cub pool. After crossover and mutation, the male cub X^{m-cub} and female cub X^{f-cub} among the X^{cubs} are determined based on fitness levels (Rajakumar, 2014).

5. Cub growth: Cub growth function refers to the local solution search function in which X^{m-cub} and X^{f-cub} are allowed for a random mutation with a given rate of G_r. The mutated X^{m-cub} and X^{f-cub} may replace the old X^{m-cub} and X^{f-cub} if the mutated X^{m-cub} and X^{f-cub} are better than the old X^{m-cub} and X^{f-cub}. The cub's growth function is represented at each iteration and A_{cub} is increased by one at each level of the cub's growth and the best local solutions for X^{m-cub} and X^{f-cub} are searched with the G_r rate less than 0.2.

6. Territorial Defense: The territorial defense helps in identifying the search space with the LA and can be easily ordered as survival fight, nomad coalition, and pride. The territorial defense is given below in Algorithm 3 (Rajakumar, 2014).

Algorithm 3: Territorial defense

Get nomad coalition

  Select $x^{e-nomad}$

  If $x^{e-nomad}$ wins

    $x^{male} \leftarrow x^{e-nomad}$

    Remove $x^{e-nomad}$ from nomad world

    Kill X^{m-cub} & X^{f-cub}

    Reset age(cubs)

    Defense result $\leftarrow 1$

  Else

    Update nomad coalition

    Defense result $\leftarrow 0$

The X_2^{nomad} is initialized the same as X_1^{nomad}, when X^{male} is not laggard, else the X_2^{nomad} is initialized as the updated type of X^{male} with mutation rate of 1-M_r. The territorial fight occurs between the nomadic lions based on the pride and nomad coalition (Packer & Pusey, 1982). Here, the winner take approach (Kohonen, 1984) is considered and so, the winning nomadic lion gets engaged within the coalition in the territorial defense.

The nomad $X^{e-nomad}$ is selected from the survival fight only if it meets the coalition constraints (Rajakumar, 2014). The pride is updated, when the X^{male} is replaced by $X^{e-nomad}$ and the nomad coalition is updated, if the $X^{e-nomad}$ is defeated. One X^{nomad} is selected during the updating process based on selection constraint (Rajakumar, 2014).

7. Territorial takeover: It can be defined as the process of providing territory to the X^{f-cub} and X^{m-cub}, when they become mature and more stronger than the X^{male} and X^{female}. The pseudo code for territorial takeover is given below.

Algorithm 4: Territorial Takeover

Input: X^{male}, X^{m_cub}, X^{female}, X^{f_cub}, S_r

If $f\left(X^{male}\right) > f\left(X^{m\_cub}\right)$

$X^{male} = X^{m\_cub}$

$X^{old} = X^{female}$

If $f\left(X^{female}\right) > f\left(X^{f\_cub}\right)$

$X^{female} = X^{f\_cub}$

If X^{female} $X^{female} \neq X^{old}$

Clear S_r

The process is initiated only if $A_{cub} \geq A_{\max}$, else cub growth occurs. When X^{f_cub} is found better than the X^{female}, X^{f_cub} occupies the X^{female} position. This type of X^{f_cub} will be mostly fertile. Hence the S_r reoccupies the zero position and $A_{\max}$ is proportional to the maturity of cubs. Therefore, one generation is complete and the n_g is increased by 1.

8. Termination: The termination of algorithm occurs when the number of fitness evaluations is beyond the limit. Once the algorithm is terminated, the X^{male} is returned as the optimal routes for the network vehicles.

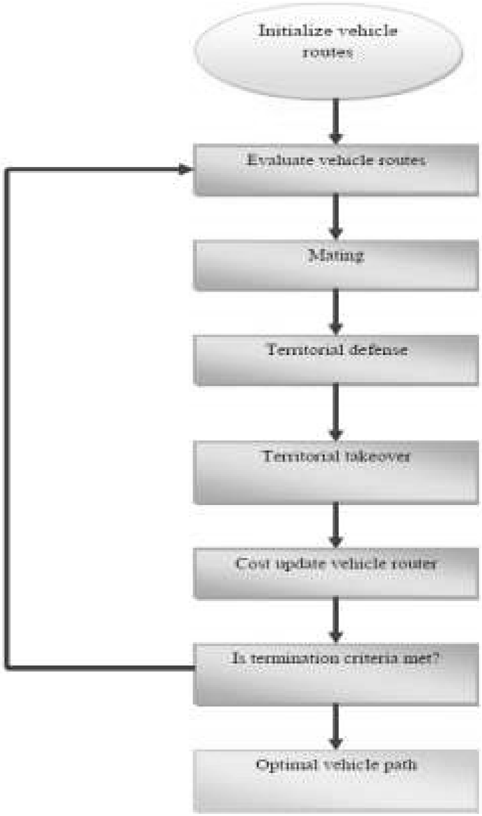


Fig. 4. Flowchart of Lion Algorithm.

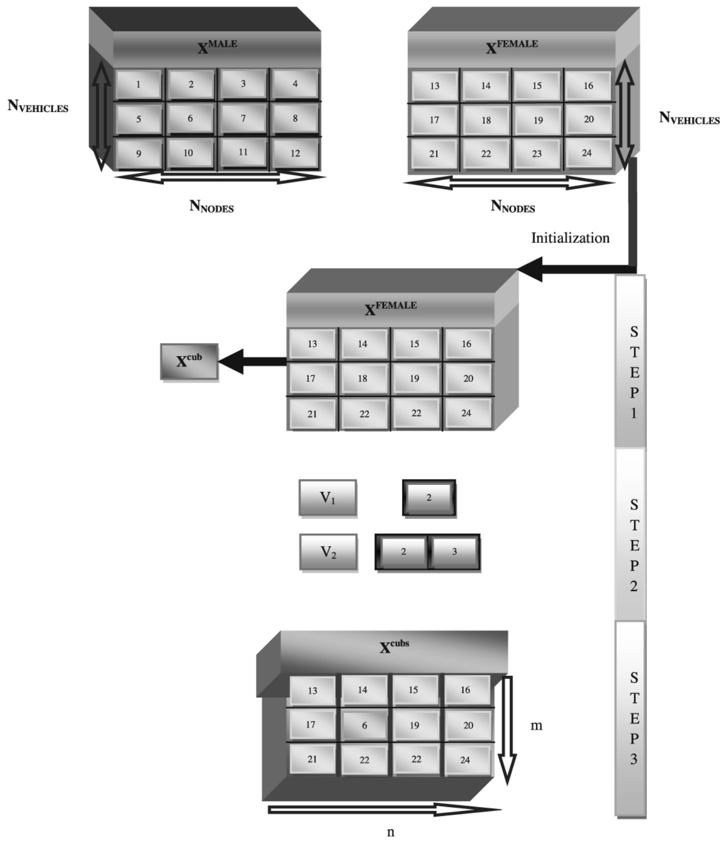


Fig. 5. Proposed two-dimensional crossover.

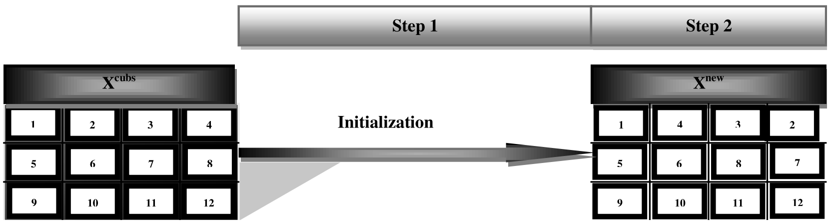


Fig. 6. Proposed two-dimensional mutation.

Two dimensional (2D) Crossover and Mutation

1. 2D Crossover: The existing crossover method provides only the one-dimensional solution. The problem of congestion and vehicles covering all cities arises due to the movement of all vehicles to the selected destination. Considering this problem, the novel 2D crossover method is proposed and it is represented in Fig. 4. The termination of algorithm occurs when the number of fitness evaluations is beyond the limit. Once the algorithm is terminated, the X^{male} is returned as the optimal routes for the network vehicles.

Let us consider V_1 and V_2 be the number of vectors and they are given as

$$V_1 = \Gamma\left(N_{vehicles} \mid R_1\left(N_{vehicles} - 1\right)\right) \tag{9}$$

$$V_2 = \Gamma\left(N_{Nodes} \mid R_2\left(N_{Nodes} - 1\right)\right) \tag{10}$$

where $R_{u|u-1,2}(x)$ represents the random integer generated within the $[1, x]$ interval and $\Gamma(x \mid y)$ gives y permutated element of the sequence $1\,to \ldots x$.

In the crossover operation, X^{cubs} are initialized by X^{female} and then the X^{male} elements are initialized only if they satisfy the condition number of vehicles, m and number of nodes, n belong to V_1 and V_2 respectively.

2. 2D Mutation: For handling the two-dimensional problem in mutation, the 2D mutation is proposed and illustrated in Fig. 5. According to it, the $X_{c,m}^{cubs}$ takes the input and $X_{c,m}^{new}$ is generated. Subsequently, the mutation points, M_{P1} and M_{P2} are calculated using eq. (11) and (12), respectively.

$$M_{P1} = \max\left(1, \lceil M_r \times N_{nodes} \rceil\right) \tag{11}$$

$$M_{P2} = \Gamma\left(N_{nodes} \mid M_{p1}\right) \tag{12}$$

The mutated solutions $X_{c,m}^{new}$ are determined as

$$X_{c,m,q}^{new} = \begin{Bmatrix} X_{c,m,q+1}^{cubs}; if\ M_{p2}(q) < M_{P1} \\ X_{c,m,1}; otherwise \end{Bmatrix} : q = 1,2,\ldots \left\| M_{p2} \right| \tag{13}$$

EXPERIMENTAL RESULTS

Simulation

Simulation of the route selection model is done in MATLAB with four selected network areas using two algorithms, LA and GA. The experimentation is done in four configurations-at varying instants and vehicle numbers, namely, 70 cities with 40 vehicles, 80 cities with 50 vehicles, 90 cities with 60 vehicles, and 100 cities with 70 vehicles. The transmission range is taken to be 250 meters, vehicle speed is 20 m/s, and the city area is 1 km^2. The simulation is performed 100 times to obtain the required result. For finding the performance, the mean, median, deviation, best, and worst are measured. Comparative studies are done between the two algorithms to find out the best.

Convergence Analysis

Fig. 6 represents the graphs for convergence analysis for the four network models by considering both GA and the LA. In the network with 40 vehicles and 70 nodes, it was found that the convergence is higher in LA than in GA. Initially, both curves overlap between each other and they diverge over the increase in the number of evaluations. The LA curve has the fastest convergence, which shows the reduction in routing cost over GA. The GA curve bends lower than the LA curve but only at a specific point and the deviational difference is high. The cost of routing is estimated as 0.95x10^6, 1.55x10^6, 2.4x10^6 and 3.6x10^6 for LA in network model 1, 2, 3, and 4, respectively. In the network with 50 vehicles and 80 nodes, the LA curve converges steadily with an increase in the number of evaluations and runs parallel to the GA curve. However, in the network with 60 vehicles and 90 nodes, both curves intersect each other at 2.5x10^6 cost of routing. The model with 70 vehicles and 100 nodes has the highest convergence among the four models and the converging point is more at the 10000 evaluations.

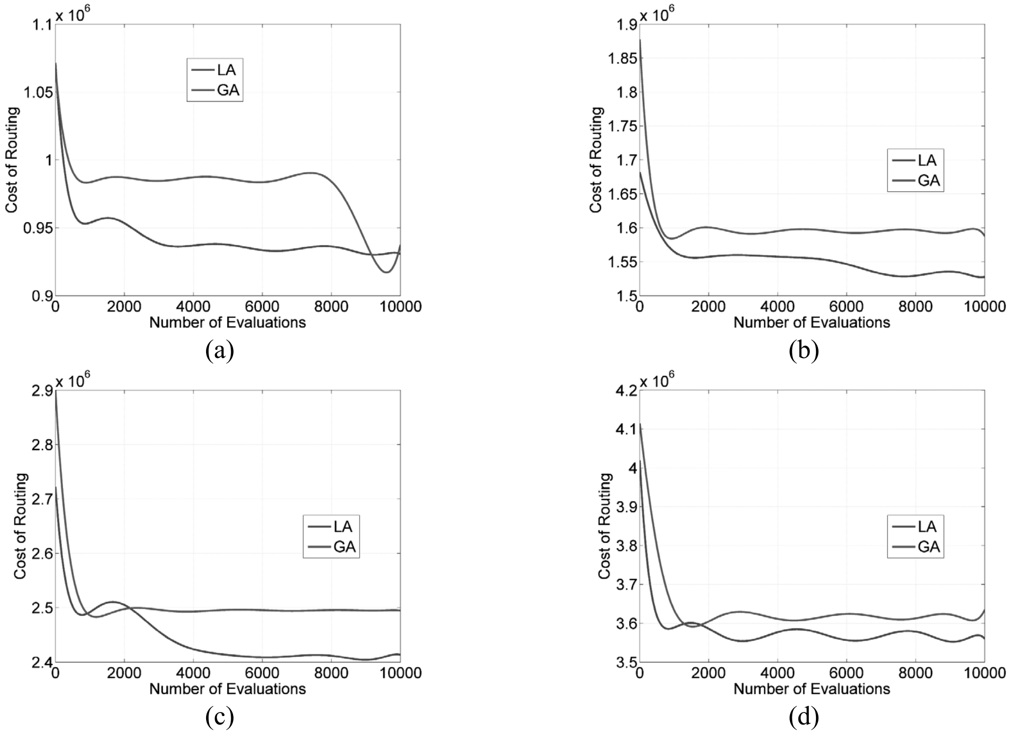
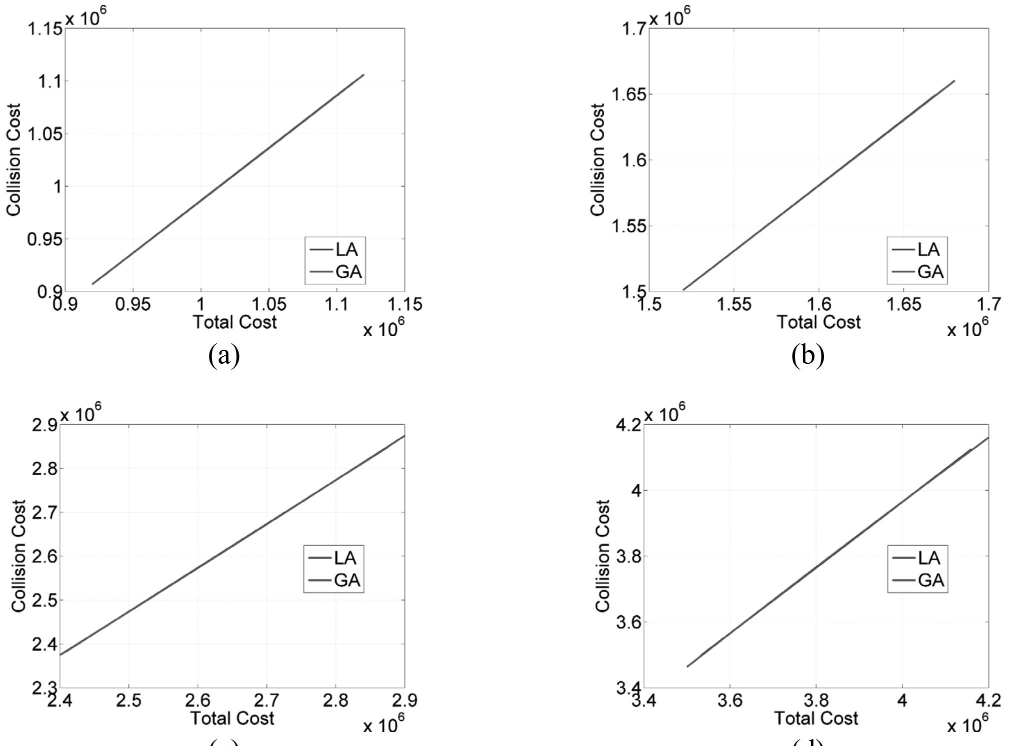
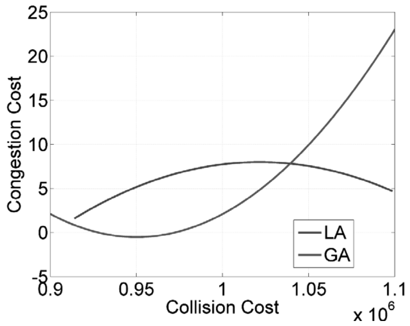
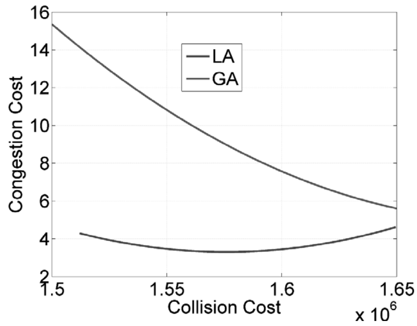


Fig. 7. Convergence on determining the optimal route by LA and GA for network with (a) 40 vehicles and 70 nodes, (b) 50 vehicles and 80 nodes, (c) 60 vehicles and 90 nodes and (d) 70 vehicles and 100 nodes.

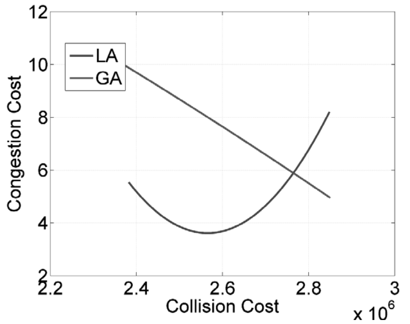



Congestion Cost
Collision Cost
x 10^6
LA
GA

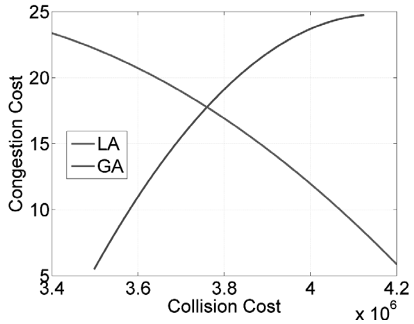
(e)


Congestion Cost
Collision Cost
x 10^6
LA
GA

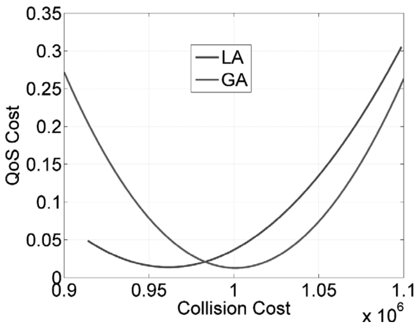
(f)


Congestion Cost
Collision Cost
x 10^6
LA
GA

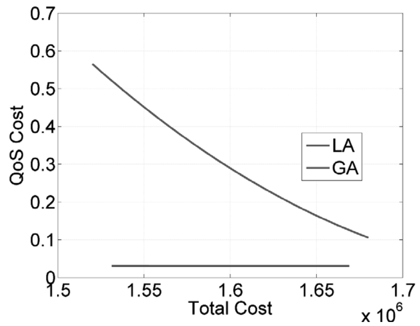
(g)


Congestion Cost
Collision Cost
x 10^6
LA
GA

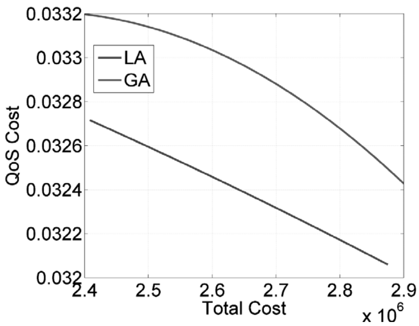
(h)


QoS Cost
Collision Cost
x 10^6
LA
GA

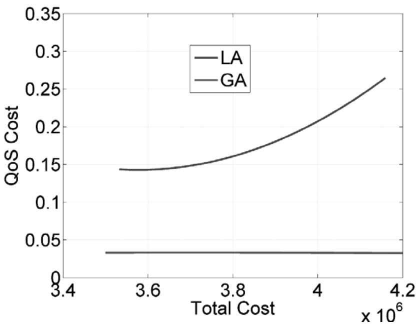
(i)


QoS Cost
Total Cost
x 10^6
LA
GA

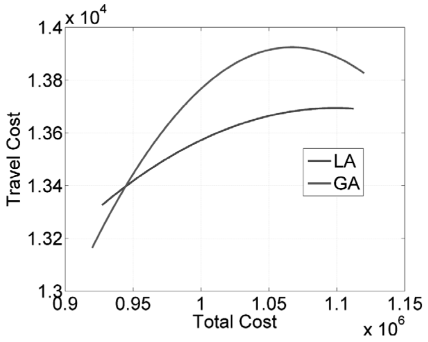
(j)


QoS Cost
Total Cost
x 10^6
LA
GA

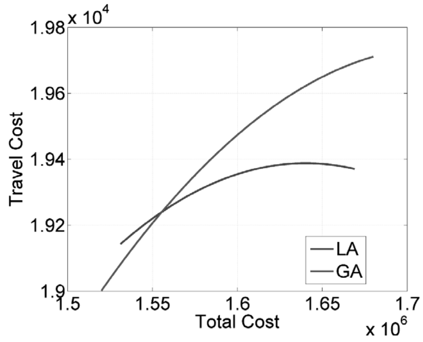
(k)


QoS Cost
Total Cost
x 10^6
LA
GA

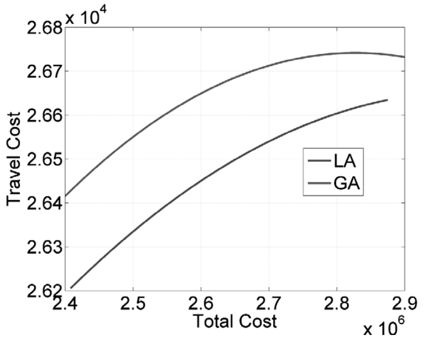
(l)



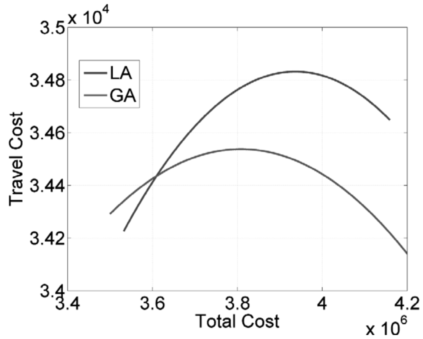
(m)



(n)



(o)



(p)

Fig. 8. Mutual relationship exists between the total cost and the other costs such as collision cost, congestion cost, QoS cost and travel cost. (a), (e), (i) and (m) are the results from the network with 40 vehicles and 70 nodes. (b), (f), (j) and (n) are from the network with 50 vehicles and 80 nodes, (c), (g), (k) and (o) are from the network with 60 vehicles and 90 nodes, and (d), (h), (l) and (p) are from the network with 70 vehicles and 100 nodes.

Cost Analysis

The mutual relationship exists between each of the routing costs under LA and GA; performance is illustrated in Fig. 7-10. In fig. 7, while comparing the total cost with QoS cost, the total cost is increased with the increase in QoS cost under both LA and GA operations for the network configurations 1 and 4 and configuration 1, respectively. It remains constant under LA and GA operations for network configurations 2 and 4, respectively, and decreased under LA and GA operations for network configuration 3. The collision costs produced by LA and GA operations overlap between each other in all models and increase over the increase in the total cost. The total cost is increased with the increase in the congestion cost under LA and GA operations for configurations, 1, 2, 3, and 4 and 1, respectively. The congestion cost is decreased under GA operation for the network configurations 2, 3, and 4.

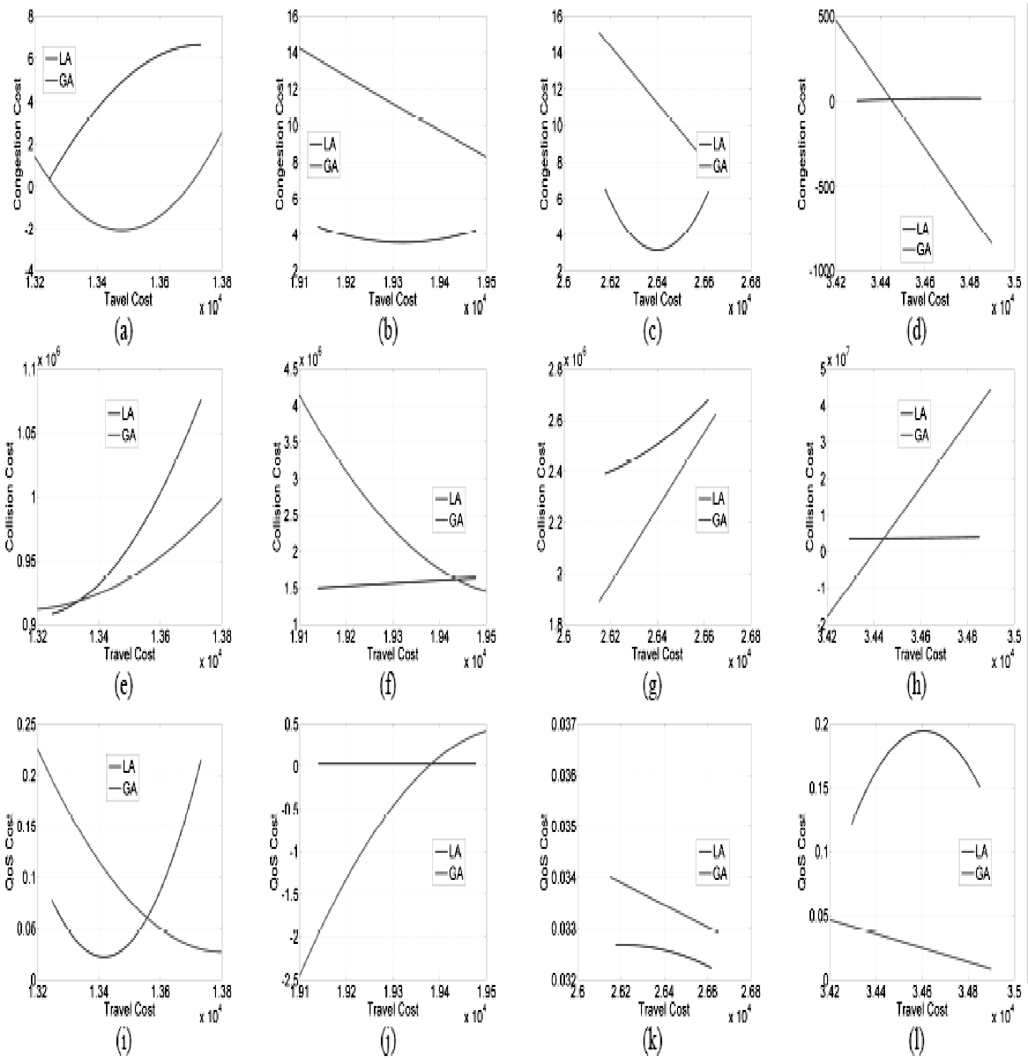


Fig. 9. Mutual relationship exists between the travel cost and the other costs such as collision cost, congestion cost and QoS cost. (a), (e) and (i) are the results from the network with 40 vehicles and 70 nodes. (b), (f) and (j) are from the network with 50 vehicles and 80 nodes, (c), (g) and (k) are from the network with 60 vehicles and 90 nodes, and (d), (h) and (l) are from the network with 70 vehicles and 100 nodes.

In fig. 8, the congestion cost is increased with the increase in the travel cost under both LA and GA operations for network configuration 1. In contrast, the congestion cost is decreased under LA and GA operations for network configurations 2 and 3, respectively. For network configuration 4, the congestion cost remains constant under LA operation. The comparison of travel cost against collision cost reveals that the travel cost is greatly increased under LA and GA operations for all network configurations except configuration 2 under GA operation. When comparing the QoS cost with travel cost, it decreases with the increase in the travel cost under LA operation for network configurations 2, 3, and 4 and increases for configuration 1. In contrast, the QoS cost decreases over increasing travel cost for network configurations 1, 3, and 4, and increases over increasing the travel cost for configuration 2, under GA operation. The congestion cost approximately increases for increasing travel cost for all the network configurations, except configuration 1 in which the opposite occurs.

In fig. 9, while comparing the collision cost with congestion cost, the LA shows slightly increased congestion cost with the increase in the collision cost of about 5 for configuration 1. However, under the GA operation, the congestion and collision costs are much higher. According to configuration 2, both GA and LA show inversely proportional relationship between collision and congestion costs. The congestion cost is decreasing with increasing collision cost under GA operation for configuration 3, whereas under LA operation, the collision cost also increased up to 2.9×10^6 at higher congestion cost. As per network configuration 4, the cost characteristics of both algorithms intersect with each other. The GA convergence shows increased collision cost with the increase in the congestion cost and LA convergence shows decreased congestion cost with increased collision cost.

Table 2. Computing time incurred by LA and GA.

Configuration	**GA**	**LA**
40 vehicles, 70 nodes	263.4403	98.9077
50 vehicles, 80 nodes	346.8884	115.7794
60 vehicles, 90 nodes	447.7318	134.142
70 vehicles, 100 nodes	560.5515	153.164

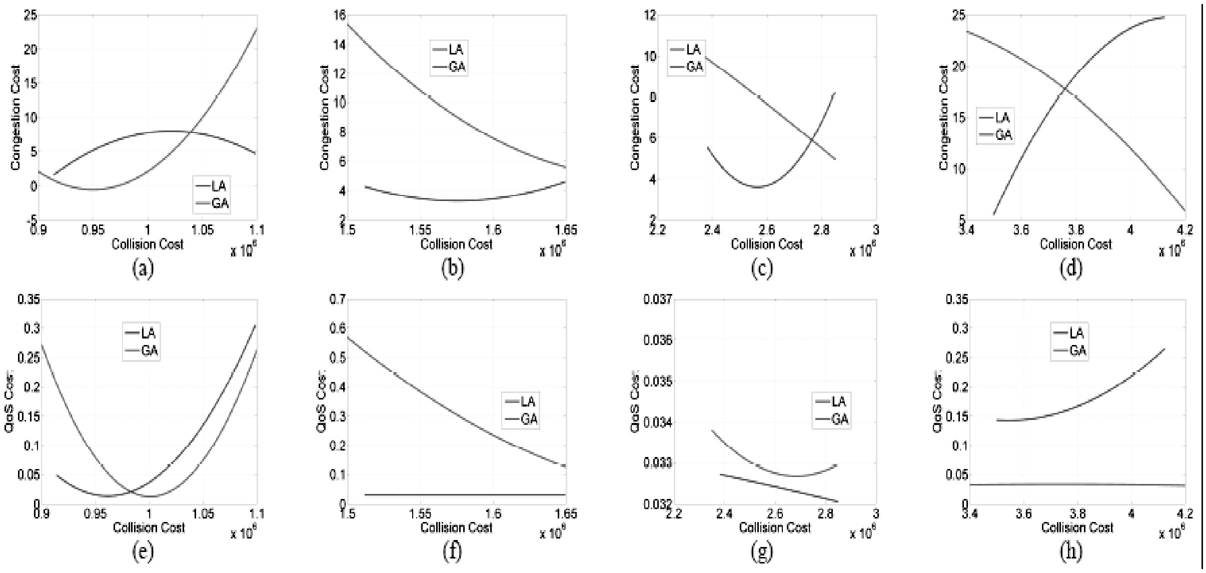


Fig. 10. Mutual relationship exists between the collision cost versus congestion cost, QoS cost and travel cost. (a) and (e) are the results from the network with 40 vehicles and 70 nodes. (b) and (f) are from the network with 50 vehicles and 80 nodes, (c) and (g) are from the network with 60 vehicles and 90 nodes, and (d) and (h) are from the network with 70 vehicles and 100 nodes.

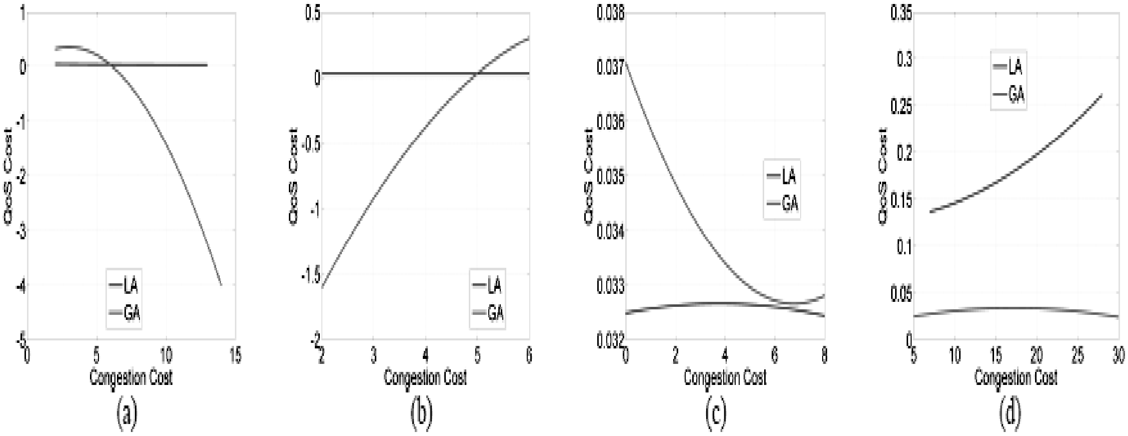


Fig. 11. Mutual relationship exists between the congestion cost and QoS cost for the network configuration (a) 40 vehicles and 70 nodes, (b) 50 vehicles and 80 nodes, (c) 60 vehicles and 90 nodes, and (d) 70 vehicles and 100 nodes.

Comparing the collision cost with QoS cost, the collision cost increases with the increase in QoS under LA operation for configurations 1 and 4. Both curves intersect at $0.98x10^6$ collision cost. However, under GA operation, the QoS cost is decreased for configurations 2, 3, and 4. In fig. 10, the QoS cost remains constant for varying congestion cost under LA operation for network configurations 1, 2, and 3. Under GA operation, the constant QoS is observed for network configuration 4, but the QoS cost decreases and increases for configurations, 1, 3 and 2, 4, respectively.

Computational Overhead

Table II details the computational time incurred by LA and GA to determine the optimal route for various network configurations. The results confirm that the computational time is greatly decreased for all the network models while using LA. The LA records at least 60% (approximated) reduction of computing time to determine the optimal route over the GA. To a maximum, LA reduces 70% of the cost incurred by GA for determining the route for network configuration 4.

CONCLUSIONS AND FUTURE WORK

This paper addressed the multiple objective constraints required for solving a vehicle routing problem for VANET. For this, a vehicle routing problem model had been proposed that mainly depends on the collision, congestion, travel, and QoS cost. The QoS based cost function had been derived using the fuzzy inference system. LA has been exploited for solving the routing model and the computational time is calculated along with the cost and convergence. The performance of LA is demonstrated by comparing the results with the GA using renowned analyses such as convergence analysis, complexity analysis, and cost analysis. The experimental results show that the computational time taken by the LA is about 72% lesser than the time taken by GA. Specifically, the convergence rate is high for the LA with 2.2% difference from the GA and the cost of collision, congestion, and QoS have been decreased when the LA is used. From the results, it has been confirmed that the LA significantly reduces the computational complexity. The proposed cost model and the algorithm produced encouraging results. In the future, the obtained results will be experimentally compared against the conventional routing protocols using network simulators such as NS2 or NS3.

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اختيار الطريق الأمثل لشبكات الفانيت (VANET) باستخدام خوارزمية الأسد

***موكوند واغ وجوماثي ن**
*قسم هندسة الحاسوب، كلية سينجاد للهندسة، بيون، ماهاراشترا
الجامعة التقنية، أفادي، تشيناي

الخلاصة

تُعد شبكات الفانيت (VANETs) من الشبكات المهمة جداً في مجال نظام النقل الذكي (ITS) لتعزيز سلامة الطرق، وستتم تغطية الاتصالات بين المركبات اعتماداً على تلك الشبكات. توجد أعمال بحثية عديدة في مجال تطوير شبكات VANET، ولكن تكمن المشكلة العامة في تحقيق مقاييس جودة الخدمة متعددة القيود. ولحلِ هذه المشكلة، يقترح هذا البحث خوارزمية لاكتشاف الطريق الأمثل للمساعدة في عملية التوجيه في شبكات VANET. أولاً، يستمد هذا البحث نموذج التكلفة لمشكلات توجيه المركبات من خلال النظر في مقاييس جودة الشبكة مثل تكاليف السفر، الاصطدام، الازدحام والوعي بجودة الخدمة (QoS). تم دمج الوعي بجودة الخدمة في نموذج التكلفة ليكون ضمن إجمالي تكلفة التوجيه. ونظراً لأن نموذج تكلفة التوجيه هو دالة تصغير، تم استخدام خوارزمية تحسين مستوحاة من علم الاحياء تم طرحها مؤخراً تسمى خوارزمية الأسد (LA) لحل الدالة. تم فحص الأداء باستخدام ثلاثة تحليلات شهيرة مثل تحليل التقارب وتحليل التكلفة وتحليل التعقيد. تمت مقارنة نتائج المحاكاة التي تم الحصول عليها باستخدام MATLAB مع الحل القائم على الخوارزمية الوراثية الحالية (GA). ووُجد أن خوارزمية الأسد تعمل بشكل أفضل من الخوارزمية الوراثية مع انخفاض في تكلفة التوجيه وتعقيده.