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An optimized routing algorithm for vehicle ad-hoc networks

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ABSTRACT

Efficient routing algorithms are essential to guarantee reliable communication in Vehicular Adhoc Networks (VANETs). In this paper, we present a twofold approach entailing the design of a new route metric for VANET communication, which considers important parameters such as the received signal strength; transmit power, frequency and the path loss. We further present an improved genetic algorithm-based route optimization technique (IGAROT) that guarantees better routing in VANETs. We used IGAROT to determine optimal routes required to communicate road anomalies effectively between vehicles in VANETs. The performance of our proposed algorithm was compared with the well-known conventional Genetic Algorithm (GA) route optimization technique under same simulation conditions. Based on the average route results obtained, our findings indicate that IGAROT provided 4.24%, 75.7% and 420% increment over the conventional GA in the low, medium and high car density scenarios, respectively. Our findings suggest that IGAROT improves road anomaly communication among vehicles thus enabling drivers to better navigate anomalous roads with the aim to reduce road-anomaly induced accidents. Further benefits of our system may include the prompt notification of road maintenance agencies concerning persisting road conditions via vehicle to infrastructure communication.

1. Introduction

Vehicular Adhoc Network (VANET) is a technology that uses moving vehicles as nodes in a network to create a mobile network. VANET supposedly turns every participating vehicle into a wireless router or node, allowing vehicles to have a transmission radius between 100 and 300 m. Thus, vehicles within this range can connect and in turn create a network with a wider range [1,2]. VANET comprises of two main components, which are the vehicles and the roadside infrastructures. These components typically establish communication between vehicles described as vehicle-to-vehicle (V2V) communication or between a vehicle and a roadside infrastructure known as vehicle-to-infrastructure (V2I) communication. Usually, the information being communicated are often related to traffic conditions [2,3], road surface conditions [2,4–8], infotainment [2,3,9] among others, towards ensuring the safety of lives and properties as well as providing comfort to drivers and passengers alike.

Despite VANET's promising potentials, a major problem lies in the design of robust communication routing models for route optimization. With so many dynamic factors militating against effective routing in VANET, one pertinent research issue entails constructing an all-encompassing metric that can guarantee reliable routing in VANET. These requirements (including developing both robust route communication metrics as well as effective routing algorithms) are non-trivial problems for VANET developers and contributing in this regard served to motivate the approach proposed in this paper.

It is known that the above limitations can be addressed easily by developing robust VANET communication route metrics and using robust route optimization techniques to determine optimal routes for communication. However, very few metrics exist that consider essential parameters such as the received signal strength, transmit power, frequency and pathloss required for effective communication. Consequently, incorporating as many parameters in a single metric is a critical requirement to develop reliable communication systems for route optimization in VANETs. Furthermore, pertaining to route optimization, a major limitation concerning the use of Genetic Algorithm (GA) for routing lies in its frequent convergence to suboptimal solutions. Consequently, this implies

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that information sent via poorly optimized routes may experience longer delays. These delays may consequently prevent drivers from receiving early warning signals that could potentially prevent possible road accidents. Therefore, it is necessary to improve the performance of the GA optimization technique and design a new comprehensive metric for route optimization in VANET.

Thus, in this paper, we have presented a twofold approach to improve V2I communication. The first entails the development of a VANET communication route metric that factors in its design essential parameters including the received signal strength; transmit power, frequency and path loss. Secondly, an improved genetic algorithm route optimization technique (IGAROT) based on a non-probabilistic selection approach using K-means clustering technique was developed. We applied IGAROT for road anomaly communication in VANETs. Our findings have provided the following contributions:

1) We have developed a new metric for route optimization towards communicating road surface information between vehicles and an infrastructure. This metric incorporates key parameters such as the received signal strength, path loss, transmit power and frequency of communication.
2) We have developed an improved GA based routing algorithm called IGAROT to determine optimal routes for data transmission. Our proposed IGAROT overcomes the challenge of convergence to suboptimal solutions associated with using the conventional GA for route optimization.
3) Our proposed IGAROT and the developed route metric has led to an entirely new routing scheme for V2I communication in VANET.

We organize the rest of the paper as follows: Section 2 presents a brief literature review, our proposed routing algorithm is described in Section 3. The method of analysis is described in Section 4, while Section 5 presents and discusses the findings of this paper. We provide concluding remarks in Section 6.

2. Related works

This section presents an overview of some achievements reported in the literature that motivated this study. Basically, a major limitation with most VANET communication system models is their failure to factor in their design as many essential metrics such as the received signal strength, path loss, transmit power and frequency [10–12]. In this regard, researchers have made several attempts to use different population based meta-heuristic optimization techniques typically inspired by the biological theory of evolution and genetics to optimize communication routes [9,12–14]. In this case, the use of Genetic Algorithm (GA) stands out [14–16]. However, a major limitation with most GA based route optimization approaches lies in their convergence to suboptimal solutions in complex networks (large number of nodes).

A technique that ensures the formation of stable clusters and stability in VANET communications was proposed in [10] alongside a similar approach in [11]. Authors in [10,11] considered vehicular mobility as a factor in their design. Routing paths with smaller number of hops and longer lifetime based on deposited probabilistic pheromone concentration were considered for routing information. In addition, beacon messages specified in the protocol were used to make vehicles aware of information about other vehicles in the same group. This ensured stability and reliability. Results obtained showed an improved performance in terms of routing overhead, end-to-end delay as well as the packet delivery ratio when compared to multicast ad-hoc on-demand distance vector. However, the proposed system does not monitor the quality of multicast tree links nor predict the possible link failures.

Ant Colony Optimization (ACO) algorithms have been applied in several ways to ensure optimum and reliable information routing in VANET [9,12,17]. This entailed developing objective functions to either determine the best route among multiple routes or find an alternative route during link failures. Often, the reported results showed better performance in reducing link failures as well as determining the optimal route among all possible communication routes. However, their model lacked the consideration of essential metrics such as the transmit power, received signal strength, frequency and path loss. Furthermore, the effects of the ACO parameters such as pheromone concentration, pheromone evaporation rate on the performance of the route optimization algorithm were not investigated.

An automatic intelligent method for obtaining optimized QoS parameter configurations in optimal link state routing (OLSR) was analyzed in [18]. Four different meta-heuristic algorithms namely, GA, simulated annealing, differential evolution and particle swarm optimization were considered in [13]. Experimental results showed that the simulated annealing performed better compared to other meta-heuristic algorithms considered. However, the computed paths take longer time when compared to OLSR.

A new alternative route search (ARS) algorithm based on GA was proposed in [14]. A traffic database was created for logging traffic status. This approach dynamically searches for an alternative route based on the current road condition during system malfunctioning or high traffic. Experimental results showed that the proposed technique efficiently searched for the best alternative routes for vehicle navigation. The tuning of the GA optimization parameters to guarantee optimal values was not considered. In addition, the reliability of the alternative search route was not examined.

A new reliability based routing scheme was proposed for VANET in [19] with a similar approach based on evolving graph models presented in [20]. A probabilistic function capable of predicting a wireless link status was used to model the link reliability. It entailed continuous updating and broadcasts of a routing request message from the source node to all other nodes (vehicles). Simulation results showed a better performance in terms of end-to-end delay, packet delivery ratio, link failures and routing requests ratio when compared to the prediction-based routing protocol. However, it is computationally complex. In addition, essential metrics such as path loss, the transmit power and frequency were not considered in their design.

A survey of different bio-inspired approaches proposed for routing in VANET is presented in [21]. It was observed that bio-inspired VANET routing approaches are more robust and capable of adapting to network disruption, thereby ensuring efficient delivery of data packet with low complexity in large scale VANET. The VANET bio-inspired routing approaches were categorized into three namely; the evolutionary algorithm, swarm intelligence and other VANET bio-inspired approaches. Detailed overview of each of the category in terms of complexity, scalability, mobility model, robustness, and QoS routing performance was presented. Analyses showed that the bio-inspired approaches can improved the performance of VANET routing in terms of the mentioned computational metrics. Similarly, a review of different position based routing approaches in VANET was presented in [22]. It was submitted that due to the rapid change in VANET network topology, position-based routing protocols are more suitable. The merit and demerits of each of the position-based routing protocols are highlighted. However, a hybrid protocol was concluded to be the best choice for routing in VANET in both highway and urban environments. This may help address the challenge of local maximum problem because of inaccurate positioning.

The performance of a position-based V2V routing protocols was investigated under different vehicle density and velocity in [23]. It was concluded based on the survey that a number factors such as the distance of source node from the destination, vehicle density, velocity, and direction are crucial for development of different position-based routing protocols. The goal is to improve performance in terms of the routing overhead ratio, packet delivery ratio, and average end-to-end delay. However, there is need to consider more metrics in a single design in order to develop smarter and robust VANET routing protocols. Similarly, the impact of vehicle density and velocity in the development of an intelligent position based VANET routing protocols was investigated and analyzed in [24]. Specifically, two position-based routing protocols namely the Movement Prediction-based Routing (MOPR) and Improved Greedy Traffic Aware Routing (IGyTAR) algorithm were analyzed in terms of the packet delivery ratio, average end-to-end delay, and link failure rate as well as routing overhead. Results obtained showed that the IGyTAR performs better than the MOPR and Greedy perimeter stateless routing (GPSR) in terms of the end-end-delay, routing overhead and packet delivery ratio. While in terms of the link failure detection, the MOPR performed better. Further, a survey of Vehicular Delay Tolerant Networks (VDTN) routing protocols in vehicular environment was presented in [25]. Different protocols were examined to ensure the suitability or not for routing in VDTN. Further suggestions for open research issues towards improving performance of the routing protocols were presented.

Other VANET routing protocols, which are non-meta-heuristic based approaches have also been reported in the literature with attention given to the multicast approaches. A review of different multicast routing protocols was presented in [26]. The goal was to examine and classify multicast routing protocols into the geocast and the cluster-based category. It was note that in a dynamic network environment, multicast routing protocols are more suitable and applicable. This protocol minimizes the network power consumption, transmission, and control overhead by utilizing the simultaneous transmission of messages from the source node either to multiple destinations or towards an interested node via flooding, proactive, and reactive technique. Further details on the merits and demerits of each multicast routing protocols can be found in [26]. However, of particular importance is improving the network scalability, throughput and reducing the end-to-end delay. A similar approach that examined different VANET clustering designs with various methods used in electing, affiliating and managing cluster head was presented in [27]. In addition, recent research trends in designing robust cluster-based routing protocols for VANETs as well as open research issues were highlighted in [27]. However, a major limitation in using the cluster-based routing approach is the lack of a realistic vehicular channel model.

An approach that uses VANET cluster scheme (VCS) and VANET multicast routing (VMR) in developing a framework for real time vehicular communication (RTVC) was proposed in [28]. The proposed framework was able to achieve message delivery to multiple vehicles with high throughput. It ensured stable communication between vehicles by harnessing the strength of the VMR and VCS, respectively. The average speed and the direction of vehicle were utilized in the formation of clusters among vehicles in the proposed RTVC framework to achieve message routing stability, while utilizing VMR for packet delivery to the destination vehicle. Results obtained showed that the proposed framework achieved high throughput and low overhead despite the dynamic nature of the network.

In [29], a hybrid of roulette wheel and rank selection technique was used for the development of a new variant of GA with a similar approach proposed in [30]. These variants of GA showed better performance compared to GA with roulette wheel selection. Another variant of GA selection method based on selecting individuals in the HLF chromosomes group was proposed in [31]. Similarly, a variant of adaptive GA for global mathematical test functions and route optimization was presented in [16]. Results obtained demonstrate a better performance compared to GA based on the roulette-wheel selection method.

In [32], a GA approach entailing the selection of weak chromosomes for mating towards introducing diversity into the population was proposed. Simulation results showed better performance compared to GA with roulette wheel or rank selection. A Fluid Genetic Algorithm (FGA) based route optimization technique entailing the replacement of the mutation process in GA with a smart population diversity was proposed in [33]. An improved performance in terms of convergence, speed, and accuracy was reported compared to the conventional GA.

Several GA selection methods viz elitism, roulette wheel and tournament were studied for solving route optimization problems in [34,35] with improved performances reported. Other variants of GA with polygamy selection approaches with improved convergence performance compared to conventional GA were also presented in [15,36,37]. However, a major limitation with these variants of GA selection approaches is their convergence to sub-optimal solutions because of chromosome over fitting [15,33,38]. Furthermore, the performance of these techniques drops when applied to route optimization involving higher number of nodes/cities (more than 10).

3. Proposed routing algorithm

This section presents the methodology adopted to design our proposed optimized routing algorithm. We considered three stages namely, the design of the new route metric, the proposed optimized routing algorithm (IGAROT) and the description of the Vehicle to Infrastructure (V2I) routing protocol that anchors our proposed IGAROT. We summarize this process in Fig. 1 and present detailed description of each stage as follows:

3.1. The route metric

We present a new route metric that determines how suitable a communication link L_w will be to route information between two points $i$and j separated by some distance, d_{ij}. The Global Position System (GPS) coordinates of each vehicle is used to compute the Euclidean distance d_{ij}, expressed as

$$d_{ij} = \sqrt{(y_i - y_j)^2 + (x_i - x_j)^2} \tag{1}$$

where (x_i, y_i) and (x_j, y_j) represent the coordinates of vehicles i and j respectively. The transmission power, P_{tx} of 0 dBm in accordance with the IEEE 802.11p (WAVE) standard is considered in our computations. The IEEE802.11P was used due to its merit of ensuring the successful delivery of the information with low latency within the VANET network [28], therefore satisfying theVANET latency requirement for safety applications [39,40]. The Received Signal Strength (RSS) at the destination infrastructure d_v, and the path loss, PL_w across each link, $L_w$provides a measure for the quality of the communication link. The PL_w is modeled considering free space path loss (in dB) as [41]:

Fig. 1. Design process of the proposed routing system.

$$PL_W = 20\log_{10}(d_{ij}) + 20\log_{10}(f) - 147.55 \quad (2)$$

where f is the signal frequency in Hz, and d_{ij} is the Euclidean distance in meters computed via (1). We used the free space model for the purpose of simplicity because we assumed that the distance between vehicles are often obstruction free and fall within the line of sight. Future works may consider path loss models that are more realistic without necessarily violating the principles of our proposed framework. The RSS at d_v is then computed as

$$RSS_w = P_{tx} - PL_w \quad (3)$$

Hence the route metric r_w, of the individual links L_w, making up a single communication route, P, from vehicle i to j is given by

$$r_w = \frac{\alpha \exp\left[1 - \frac{RSS_w}{RSS_{Th}}\right]}{v_{ij} + \beta} \quad (4)$$

where RSS_{Th} is the maximum received signal strength (a threshold value) above which the link fails, α is a scale parameter computed using the standard deviation of the changing velocity v_{ij} of vehicles logged in the routing table and β is a corrector parameter introduced to guarantee that (4) exists at zero velocity (when a vehicle is stationary). Eq. (4) is a normalized route metric, which we have proposed to evaluate how suitable a route will be for data transmission. Essentially, we constructed this route metric by considering the following relationships: a stationary vehicle is better suited to form a good communication link than a mobile vehicle since mobile vehicles are highly susceptible to fading channel conditions. Consequently, as a vehicle decelerates, it becomes easier to establish a stable communication link. This requirement accounts for the inverse relationship in Eq. (4) between the route metric and the vehicle's velocity. Furthermore, we note that stronger received signal strength (RSS) values at a vehicle's transceiver typically characterizes a good link. This quality thus accounts for the direct relationship between the RSS and the route metric in Eq. (4). However, to ensure that our new metric does not tend to infinity when a vehicle halts (velocity = 0), we have introduced a corrector parameter β in Eq. (4), while we introduced the parameter α to normalized the exponential effect of the RSS. We call α the scale parameter because it simply amplifies the small values typically produced by the exponential function of the RSS. These parameters take up typical values of $\alpha = 10$, and $\beta = 1$. Typically, each vehicle measures its velocity using its speedometer and communicates this velocity value to other vehicles within its transmission range. Furthermore, there is a possibility of having multiple potential routes between the source vehicle s_v and the destination infrastructure, d_v. Thus, K denotes the total number of links, $L_1 = (s_v, n_1)$, $L_2 = (n_1, n_2)\ldots$ $L_k = (n_k, d_v)$ for a given route, P. Therefore, the overall route metric $R(P)$ for a given P is the product of the route metric of all the connected links that form the route:

$$R(P(s_v, d_v)) = \prod_{w=1}^{K} r_w \quad (5)$$

Therefore, the routing task reduces to the choice of a candidate route P^* from within the set of all possible routes $P_n (n = 1, 2, \ldots, M)$ that exists between i and j. Thus, we maximize the objective function as follows:

$$Z(P^*) = \arg\max_{P \in M} \{R(P_n)\}, \ \forall n = 1, 2, \ldots, M \quad (6)$$

where M is the total number of possible routes between the source vehicle s_v and the destination Infrastructure d_v. The ultimate goal is to maximize the route metric given in (6) by using the proposed routing algorithm called IGAROT (to be described next). Our proposed IGAROT together with the formulated new system model in (6) forms a new optimal routing scheme. We present a summary of the process for computing the route metric of each communication link in Fig. 2.

3.2. Proposed optimized routing algorithm (IGAROT)

IGAROT is a variant of GA. In IGAROT, we simply replaced the GA selection method with the K-Means clustering technique leveraging from a similar concept for route optimization presented in [15]. IGAROT uses the number of vehicles involved in a VANET communication scenario to initialize randomly the population of individuals, which serves as the initial solution within the intended search space. To illustrate, if we consider a low-density communication scenario with 10 vehicles, then this leads to a randomly generated 1 by 10 initial population size. The algorithm then forms new generations by selecting the best solutions from the initial population, which evolves after many generations, thus giving better solutions. IGAROT evaluates the fitness of each individual solution using the communication system model presented in (6).

A non-probabilistic approach based on K-Means clustering technique selects individual chromosomes for the reproduction process in IGAROT. This technique selects the Good Group Chromosome Cluster (GGCC) in each generation thereby enhancing diversity in the population. The algorithm achieves this by evaluating the fitness of the individual chromosomes and clustering them into two non-overlapping groups based on their fitness value. The reason behind the choice of two groups for clustering is to ensure that

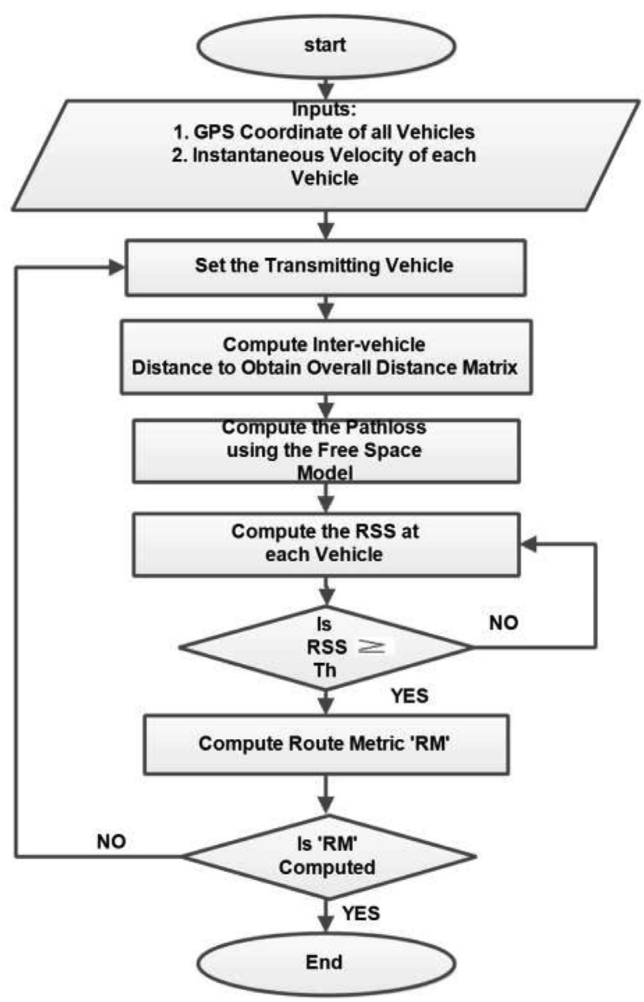

Fig. 2. Flowchart for Computing the Route Metric of a Communication Link.

each chromosome belongs to either GGCC or the Fair Group Chromosome Cluster (FGCC). Essentially, IGAROT uses K-Means during the selection process to group the chromosomes into these two distinct clusters GGCC and FGCC. Here, GGCC contains the fittest chromosomes based on their fitness values, while FGCC contains the weaker chromosomes. Consequently, IGAROT uses this deterministic approach of grouping to filter out weaker chromosomes during the selection process instead of using the probabilistic roulette wheel approach in the generic GA algorithm. This approach interestingly guarantees that stronger chromosomes are passed to subsequent generations implying that better routes with higher route metrics will be computed during the iteration process. Summarily, this explains the relationship between the chromosomes and the route metric since each route metric per link in the network is typically encoded as a chromosome in the IGAROT process.

Furthermore, using K-Means clustering approach increases the convergence speed of the GA process by introducing a high selection pressure and increasing the average fitness value by selecting the cluster of GGCC. The iterative K-Means algorithm minimizes the sum of the distance between each chromosome and its cluster centroid. K-Means moves the chromosomes of individuals in the population into a cluster to group them all appropriately based on their respective distances from the centroid. Mathematically, let T be the total scatter points for a set of N chromosomes in the i^{th}generation expressed as

$$T = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} d(x_i, x_j) \tag{7}$$

where $d(x_i, x_j)$ is the distance between two chromosomes. We express (7) in a general form as

$$T = W(C) + B(C) \tag{8}$$

where $W(C)$ is the within class scattered distance, $B(C)$ is the between cluster distance and C_i denotes the cluster number for the *ith* observation [15].

The algorithm selects the chromosomes in the cluster with larger distances for the maximization operation. We summarize the K-Means clustering algorithm in Table 1. The size of the initial chromosome population typically reduces due to the K-Means clustering process as only the GGCC is selected. This chromosome population in the GGCC typically increases back to the initial population size using the method of elitism selection. This probability replacement ensures that the algorithm randomly selects certain percentage of the fitter individual chromosomes in order to increase the population size in the GGCC. The population then undergoes a two-point chromosome inversion process during crossover in order to produce new offspring. The algorithm then uses a one-point chromosome inversion to ensure diversity in the population in the form of mutation. We introduced elitism to ensure convergence to a global solution. The algorithm forms a new population after the iteration process is completed and the generation counter is increased by one. Our proposed IGAROT with elitism continues to iterate until it satisfies a convergence criterion or a predefined number of generations elapses, which serves as the stopping criterion. We summarize the process of IGAROT with elitism in the flowchart of Fig. 3. The major difference between our proposed IGAROT and the clustering GA with polygamy developed in [15], in terms of the selection process, crossover, mutation and elitism is summarized in Table 2.

3.3. Description of the vehicle to infrastructure (V2I) routing protocol

We developed the V2I routing protocol based on the following assumptions:

1. Each vehicle in the VANET is equipped with a GPS device to be aware of their respective locations.
2. Each vehicle has a transceiver in order to communicate.
3. Each vehicle can measure its instantaneous velocity via its speedometer at any time and can transmit this information via its transceiver to an infrastructure/vehicle.
4. A vehicle transmits road surface information only when it comes to a halt, or when its slows down below a predefined velocity.

We present the illustration in Fig. 4 in order to describe the V2I routing protocol that anchors the proposed IGAROT. In essence, the entire routing process involves a Source Vehicle, s_v, (see Fig. 4) being able to detect the presence of a road anomaly, and being able to send this data to a Destination Infrastructure, d_v, via multiple hops. The destination infrastructure receives the sensed data and hosts it in a database for other vehicles to gain access concerning the road status and for road maintenance agencies to schedule possible maintenance routines. The following steps are involved in our proposed routing protocol:

1. The source vehicle, s_v, that senses a road anomaly sends out a broadcast request to all vehicles within its transmission range to determine the address of the destination infrastructure d_v. In this case (see Fig. 4), all vehicles within the source's transmission range, such as vehicle 1 and 2 in Fig. 4 both receive the request packet. The structure of the broadcast packet is as shown in Fig. 5 with a description of each packet field given in Table 3. The packet contains the Source MAC Address (S_{mac}), Destination MAC Address (D_{mac}), Source GPS (S_{gps}), Source Velocity (S_V) and Generic Destination Flag (GD_F) field.
2. All vehicles within the transmission range of the source vehicle receive the broadcast packet and then examine the "Generic Destination Flag" field to determine if the message is for an infrastructure or not. When the flag is set to 1 (meaning that it is meant for an infrastructure), the vehicles simply append the following information to the header of the packet: Hop MAC Address (H_{mac}), Hop GPS (H_{gps}), Hop Velocity (H_V) as shown in Fig. 6 and then rebroadcast the message for onward transmission towards the infrastructure. During the rebroadcasting process by each hop vehicle, each vehicle examines

Table 1
Summary of the K-Means Clustering Process.

Algorithm 1: K-Means Clustering
1. Randomly Select two chromosome fitness cluster centroid C1 and C2.
2. Compute the distance between each individual fitness value and the cluster centroid.
3. Assign individual fitness value into the appropriate cluster based on the computed centroid distance.
4. Recomputed the two-centroid position after assigning the fitness value of the chromosome to a cluster.
5. Re-iterate step 2 3, and 4 until centroid stability is attained and no change is observed in cluster of chromosome fitness value resulting in the GGCC and FGCC
6. The two centroids are compared, and the one with the higher numerical centroid value is assigned to the GGCC while the other cluster is assigned to the FGCC
7. Terminate the clustering process

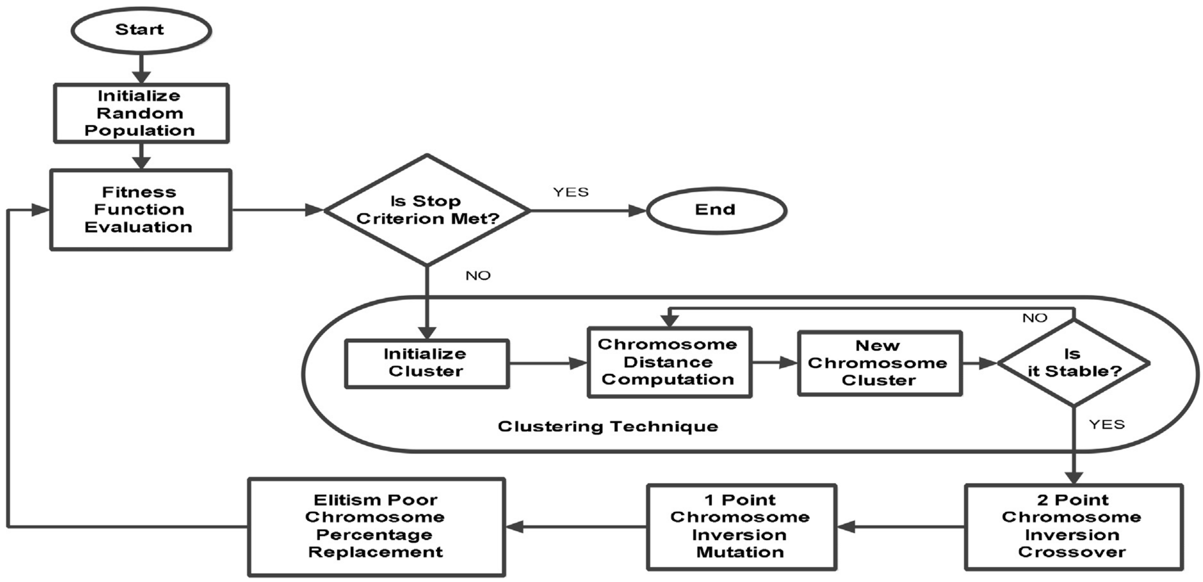

Fig. 3. Flowchart of the Developed IGAROT with Elitism Algorithm.

Table 2
Comparison of the Clustering GA and the proposed IGAROT for Route Optimization.

S/NO	GA Processes	Clustering GA	IGAROT
1.	Initialization	Yes	Yes
2.	Fitness Evaluation	Yes	Yes
3.	Selection	K-Means with Less Fit Chromosome Cluster (LFCC) Discard	K-Means with Selection Probability Replacement
4.	Crossover Method	Polygamy and Population Control	Two-Point Chromosome Inversion
5.	Mutation	Bit Reversal or String Reordering	One-Point Chromosome Inversion
6.	Elitism	Offspring Parent Replacement	Poor Chromosome Percentage Replacement

S_{mac}	D_{mac}	S_{gps}	S_V	GD_F	...

Fig. 4. An Illustration of a Broadcast Request Sent out from the Source Vehicle.

S_{mac}	D_{mac}	S_{gps}	S_V	GD_F	H_{mac}	H_{gps}	H_V	...

Fig. 5. Broadcast Packet sent from the Source Vehicle.

the hop fields of each packet in order to determine whether the originating hop address already exists in the packet or not. If it exists, the hop vehicle simply discards the packet; else, it appends its own hop information before onward transmission. This mechanism helps to prevent the problem of broadcast flooding within the network. Furthermore, it ensures that the message from the source vehicle always proceeds toward the destination infrastructure without looping through the network.

3. Based on a defined maximum number of hops, the source message is transmitted through multiple hops (for example, through vehicles 1–5 in Fig. 4) to the destination infrastructure (see Fig. 4). During this process, the initial source packet arrives at the destination infrastructure along with the different hop information appended to it.

Table 3
A Description of the Packets Field.

Field	Description
Source MAC Address (S_{mac})	To identify the source vehicle
Destination MAC Address (D_{mac})	To identify the destination infrastructure
Source GPS (S_{gps})	To determine the coordinates (Position) of the source vehicle
Source Velocity (S_V)	To record the instantaneous velocity of the source vehicle
Generic Destination Flag (GD_F)	To identify the target destination node, which can either be Infrastructure or Vehicle depending on the Generic Destination Flag (1 = Infrastructure, 0 = Vehicle)
Hop MAC Address (H_{mac})	To identify the hop vehicle within the transmission range which received the broadcast, examined it and rebroadcast to the next hop towards the destination infrastructure
Hop GPS (H_{gps})	To determine the coordinates (Position) of the hop vehicle
Hop Velocity (H_V)	To record the instantaneous velocity of the hop vehicle

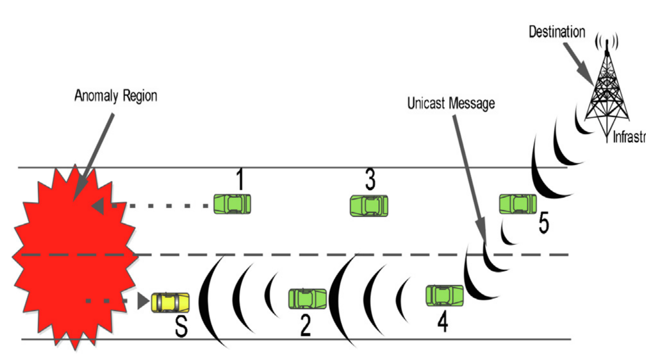

Fig. 6. Broadcast Packet sent from the Hop Vehicle.

4. At the destination infrastructure, the infrastructure extracts the information within the packet. The destination infrastructure then uses the information within the packet to develop a complete routing table of the entire network as illustrated in Table 4.

Table 4
Network Routing Table.

Source Vehicle GPS (Sgps)	Generic Destination Flag (GD_F)	Hop GPS (H_{gps})	Hop Velocity (H_V)	Destination (G_{gps})

5. Based on the acquired information about the entire network, the destination infrastructure uses IGAROT to compute the optimal path back to the source vehicle as shown in Fig. 7.
6. The infrastructure sends an acknowledgement back to the source vehicle using the optimally computed path, for example, through vehicle 5, 4, and 2 to the source vehicle in Fig. 7.
7. The source vehicle then uses the optimal path placed within the acknowledgement packet to send the sensed road anomaly data back to the infrastructure as illustrated in Fig. 8. The data is stored in the infrastructure's database and regularly updated for future access by other vehicles or by road maintenance agencies.
8. After convergence has occurred within the network, the infrastructure's database is considered updated based on the current condition of the entire road network. Consequently, drivers plying or intending to ply the road network can easily query the closest infrastructure database to obtain the status of the road in order to improve driving experience/decision.

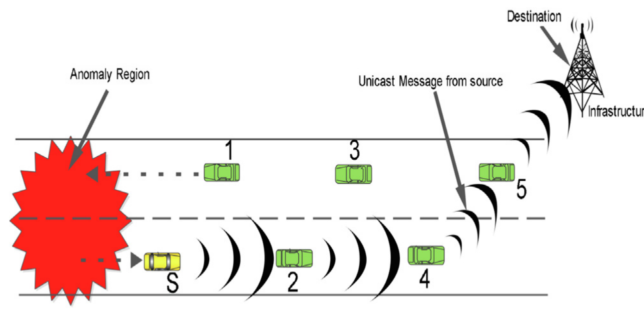

Fig. 7. An Illustration of the Optimally Computed Path by the Infrastructure.

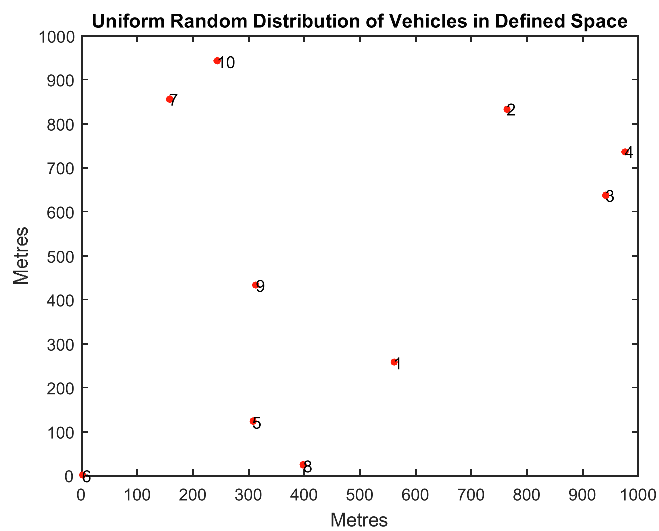

Fig. 8. An Illustration of the Optimally Path for Sending the Sensed Anomaly to the Infrastructure.

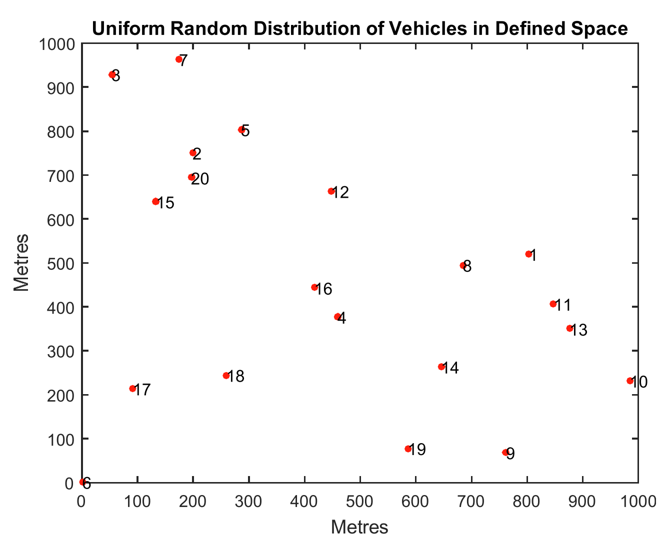

Fig. 9. Low Density VANET Communication Scenario.

4. Method of analysis

We analyzed IGAROT and compared its performance to the known conventional GA routing algorithm. We considered three different possible car density scenarios that may exist in a typical VANET. These are: (1) low car density, (2) medium car density and (3) high car density scenarios each comprising of 10, 20 and 30 vehicles respectively. These were generated using the uniform random distribution and deployed within a 1000 by 1000 m defined physical network space. Our overall goal was to determine the optimal communication route based on the developed model presented in (6) based on IGAROT and comparing its performance to the conventional GA. We show different distributions of car nodes in Figs. 9–11 respectively in order to demonstrate our concept. Observe how the car density increases in each scenario thus warranting more cars being involved in the communication process. More communicating cars in the network typically complicate the routing process, which we seek to investigate by our new methods.

We fine-tuned IGAROT and the conventional GA in order to determine the most suitable parameter values for better solution and convergence to routes with optimal route metric. The parameters of IGAROT tuned are the Crossover Probability (Pc), Mutation Probability (Pm), Elitism Probability (Pe), Poor Chromosome Selection Replacement Probability (Ps) as well as the Population Size (Popsize) and Number of Generation (Numgen). While the GA parameters tuned are the Pc, Pm, Popsize as well as the influence of the Numgen on its performance. In fine-tuning IGAROT, the Pc, Pm, Pe, Ps. Popsize, and Numgen were set to 0.4, 0.01, 0.3, 0.6, 100 and 1000 respectively. We tuned the conventional GA using the same initial values for IGAROT. The Pc was varied in the range of 0.1–1 with an increment of 0.1, Pm was varied from 0 to 0.1 with an increment of 0.01, Popsize within 20–100 with an increment of 10, Numgen was varied from 100 to 1000 with an increment of 100, Pe and Ps were varied incrementally from 0 to 1 with an increment size of 0.1. In tuning these routing algorithms, we conducted 100 independent simulations based on the parameter ranges earlier stated. We present in Table 5 the best parameter values averaged over 100 independent simulations. We used these parameter settings for both IGAROT and the conventional GA in order to optimize the route metric model in (6). This determines the best

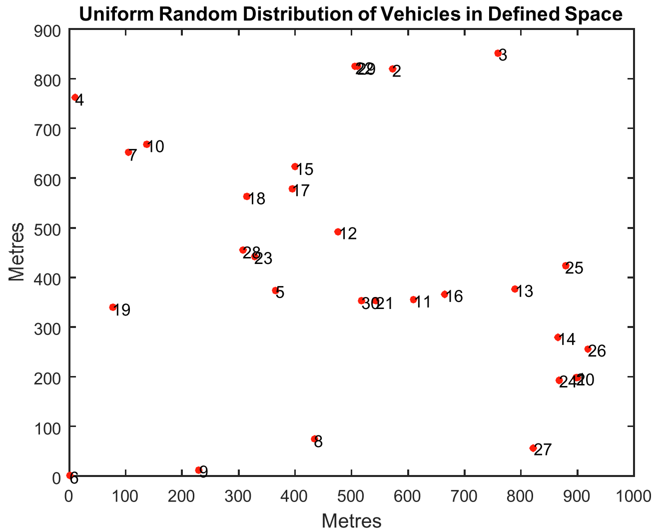

Fig. 10. Medium Density VANET Communication Scenario.

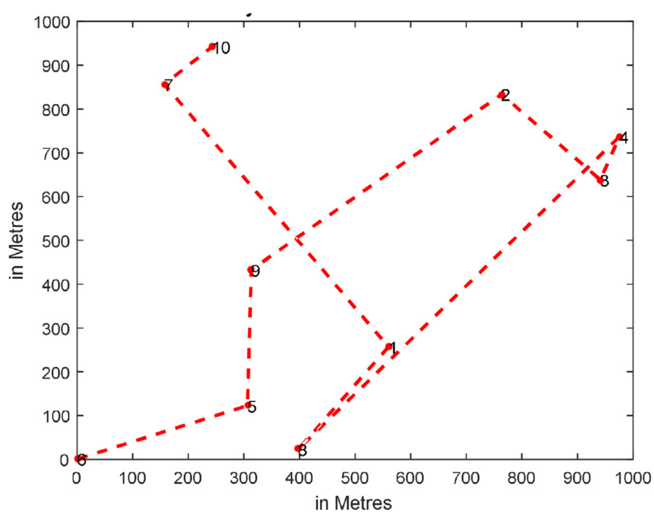

Fig. 11. High Density VANET Communication Scenario.

reliable communication route to send road anomaly data from the transmitting vehicle (node) to the destination infrastructure (V2I).

Observe in Table 5 that optimal Pc values of 0.2, 0.4 and 0.6 were obtained for IGAROT for the low, medium and high car density scenarios, respectively. These values are smaller compared to the optimal values of 0.5, 0.6 and 0.7 obtained for the conventional GA for the low, medium and high-density car density scenarios, respectively. This may be attributed to the statistical nature of these algorithms. Similarly, it is seen that the best Pm values for each of the communication scenario for IGAROT increases as the number of vehicles increases. A constant value of Pm = 0.03 across the three scenarios considered was obtained for GA. It can be inferred that the denser the communication network, the higher the mutation probability required by the proposed IGAROT. This introduces diversity in the population to ensure better convergence to optimal solutions. We note that a best Popsize of 60 was obtained for both the proposed IGAROT and GA for the low-density scenario, which is lower compared to that of the medium and high-density scenarios with 80 Popsize. A possible reason may be that the smaller number of vehicles (10) in the low-density scenario is sufficient to provide the appropriate search space while the medium density and high-density scenarios are higher due to the increased number of vehicles involved in the V2I communication. Furthermore, 200 and 600 Numgen values were obtained for the GA and IGAROT respectively for the low-density scenario; this may be attributed to the smaller number of vehicles involved in the communication process. However, we note that the algorithms typically require higher Numgen values in order to converge at global optimum values in the medium and high-density communication scenarios. One reason may be that the algorithms tend to lean towards exploring more of the search space than exploiting. The elitism probability values obtained to improve the performance of IGAROT are 0.2, 0.3 and 0.4 for the low, medium and high-density scenarios, respectively. Observe that these values increase steadily as the communication network becomes denser with more vehicles involved in the network. A logical explanation may be the need to replace poorer sets of chromosomes in the algorithm as the network becomes denser. We evaluated both algorithms based on the parameters of this section and we report our findings in the next section.

5. Results and discussion

In this section, we present and discuss results based on the application of both GA and IGAROT for V2I route optimization problems.

5.1. Application of GA for V2I route optimization

GA with optimal parameter settings as stated in Table 5 was used to optimize the route metric communication model in (6), towards determining the most reliable route. An initial solution for each of the V2I communication scenarios is presented in Figs. 12–14 for the low, medium and high-density scenarios, respectively.

Obviously, the routes formed by GA in the initial solution for all simulations carried out are not optimal. The total route metric after the first iteration for the low density was 3.3754e−5, while that of the medium density was 3.2598e−10. These are visualized in Figs. 12 and 13, respectively. Similarly, after the first iteration for the high-density scenario, the total route metric obtained using

Table 5
Tuned Optimal IGAROT/GA Parameters for each V2I Communication Scenario.

GA Parameter	Low Density		Medium Density		High Density	
	IGAROT	GA	IGAROT	GA	IGAROT	GA
Crossover Probability (Pc)	0.2	0.5	0.4	0.6	0.6	0.7
Mutation Probability (Pm)	0.01	0.03	0.02	0.03	0.04	0.03
Population Size (Popsize)	60	60	80	80	80	80
Number of Generation (Numgen)	600	200	900	900	1000	900
Elitism Probability (Pe)	0.2	NR	0.3	NR	0.4	NR
Poor Chromosome Selection Replacement Probability (Ps)	0.5	NR	0.5	NR	0.5	NR

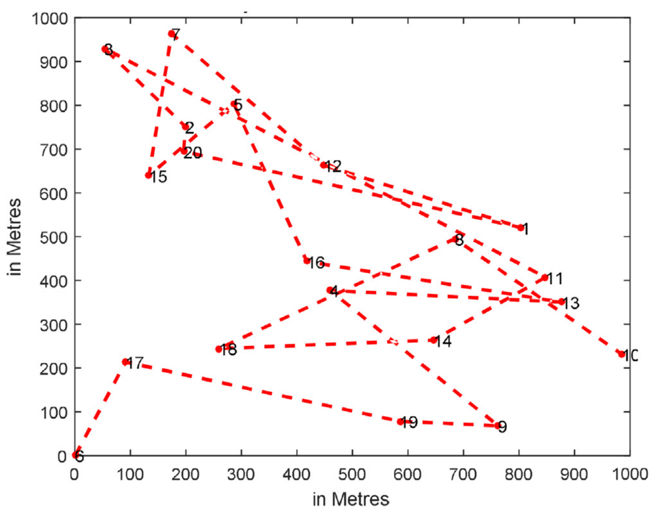

Fig. 12. Initial GA Solution for V2I Route Optimisation Low Density.

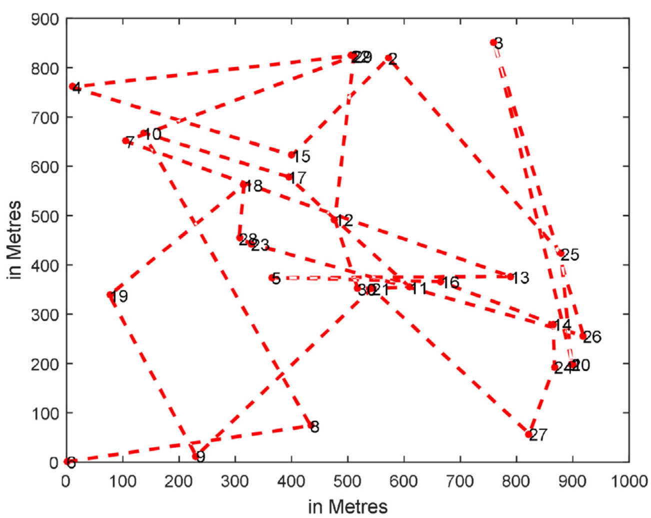

Fig. 13. Initial GA Solution for V2I Route Optimization Medium Density.

the GA algorithm as the initial solution was 1.0967e−14 with the suboptimal route shown in Fig. 14. It is generally observed that the total route metric obtained using GA decreases as the

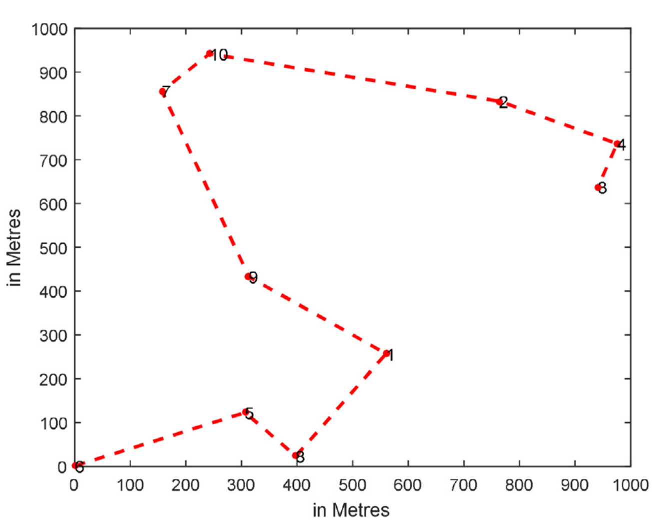

Fig. 14. Initial GA Solution for V2I Route Optimization High Density.

communication scenario becomes denser with higher number of vehicles. It is noted that 100 different independent simulations were conducted using the same GA optimal parameter settings and the best, average and least fitness route metric obtained are summarized in Table 6.

The best, average and the least fitness route metric values for the low-density communication scenario obtained was 4.6944e−5, 4.3921e−5 and 4.2272e−5 respectively (See Table 6). This high best fitness route metric compared to the medium density of 1.4246e−9 and 0.8209e−13 for high density may be attributed to the small number of vehicles (10 nodes) involved in the V2I communication as compared to 20 and 30 vehicles involved in the medium and high density V2I scenarios, respectively. A plot of the optimal best reliable route formed by GA is shown in Fig. 15, while Fig. 16 shows the least reliable communication route for the low-density scenario. The best and least fitness route metric plots for the medium scenario is shown in Figs. 17 and 18, respectively, while the high-density scenario is shown in Figs. 19 and 20. Road anomalies were communicated to the destination infrastructure using either a single-hop or multi-hop route.

5.2. Application of IGAROT for V2I route optimization

We present in this section the results obtained for IGAROT using the optimal parameter settings given in Table 5. Figs. 21–23 present the initial solutions by IGAROT for the low, medium and high-density scenarios, respectively. Observe generally that the initial solution formed after the first iteration by IGAROT converges to a suboptimal solution. The total route metric obtained after the first iteration by the algorithm is 3.4156e−5 for low density in Fig. 21, 3.4457e−10 for medium density in Fig. 22 and 6.9059e−14 for high density presented in Table 7.

The best route metric fitness values of 4.6944e−5, 4.5782e−5 and 4.2822e−5 were obtained for the low-density communication scenario (See Table 7). Figs. 24 and 25 present the least and best communication routes for the low-density scenario.

The initial solution formed by IGAROT has higher total route metric with improved performance compared to the GA. We conducted 100 different independent simulations using IGAROT with the optimal parameter settings in Table 5. The best, average and least route metric fitness values obtained for the low scenarios are attributed to the small number of vehicles (10 nodes) involved in the V2I communication as opposed the 20 and 30 vehicles involved in medium and high-density V2I communication, respectively. The best fitness value for the low density reflects the exploration of the search space by IGAROT as compared to GA. We show in Fig. 24 the least reliable result obtained with suboptimal solution by the IGAROT for the low-density case. The least and best fitness route metric plots for the medium scenario is shown in Figs. 26 and 27, respectively. While Figs. 28 and 29 present the least and best reliable communication routes for the high-density case. A close observation of the initial solution of Fig. 23 and the best fitness reliable route for high density presented in Fig. 29 shows a tremendous improvement in the initial suboptimal solution. The routing protocol used the reliable communication route to route the sensed road anomalies information from the transmitting vehicle to the destination infrastructure via multihops.

Table 6
GA Best, Average and Least Fitness Reliability for Several Simulations.

Fitness Value	Low Density	Medium Density	High Density
Best Fitness	4.6944e−5	1.4246e−9	1.1150e−13
Average Fitness	4.3921e−5	1.1797e−9	0.9757e−13
Least Fitness	4.2272e−5	1.0348e−9	0.8209e−13

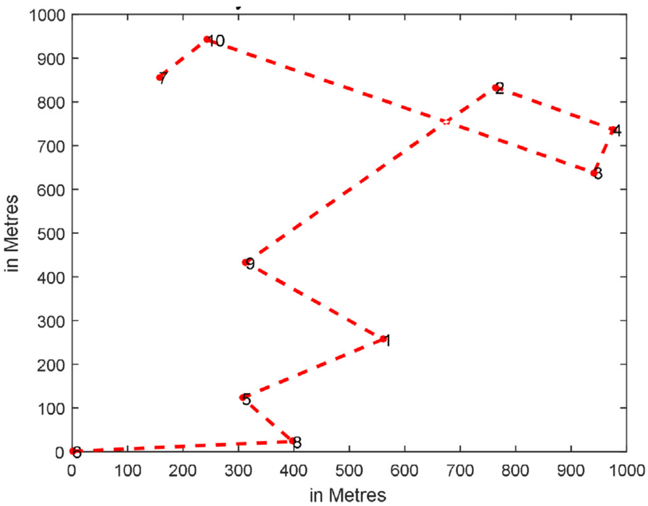

Fig. 15. Best Fitness Reliable Communication Route Low Density (GA).

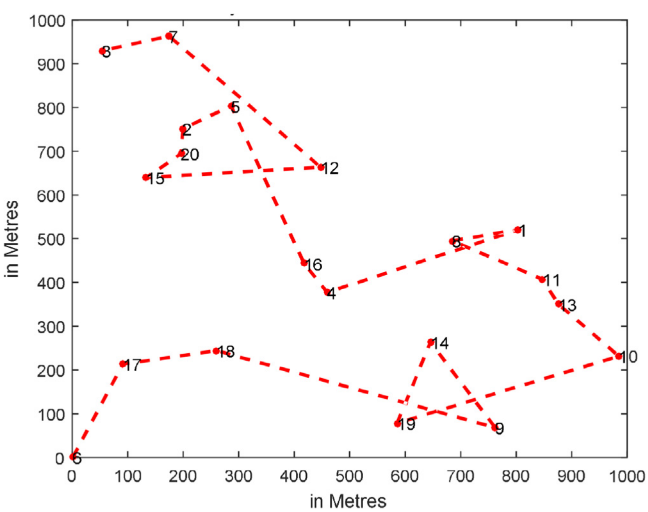

Fig. 16. Least Fitness Reliable Communication Route Low Density (GA).

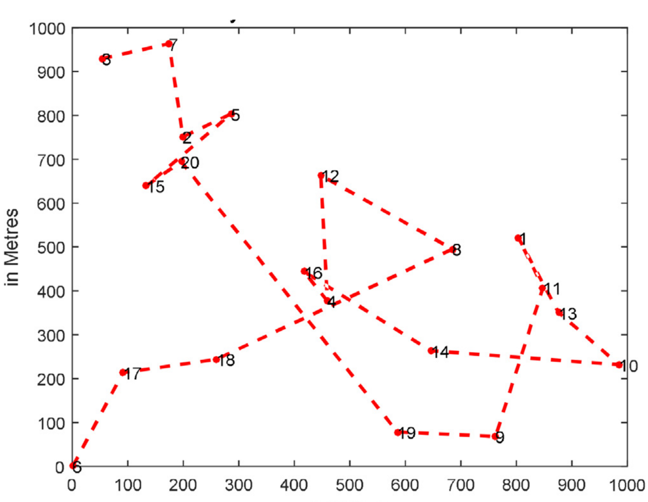

Fig. 17. Best Fitness Reliable Communication Route Medium Density (GA).

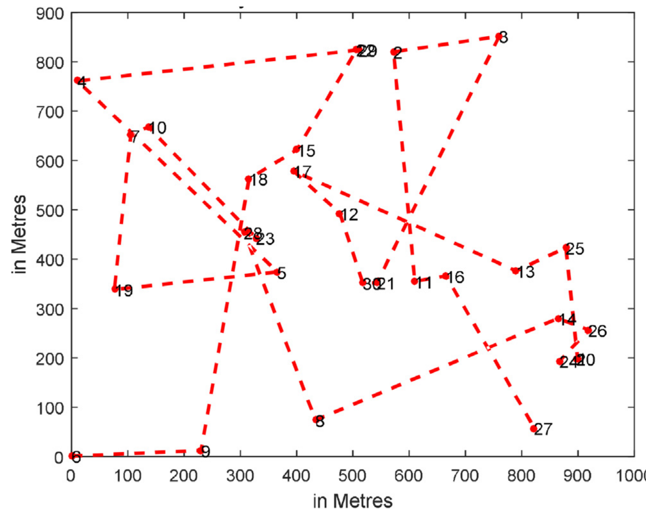

Fig. 18. Least Fitness Reliable Communication Route Medium Density (GA).

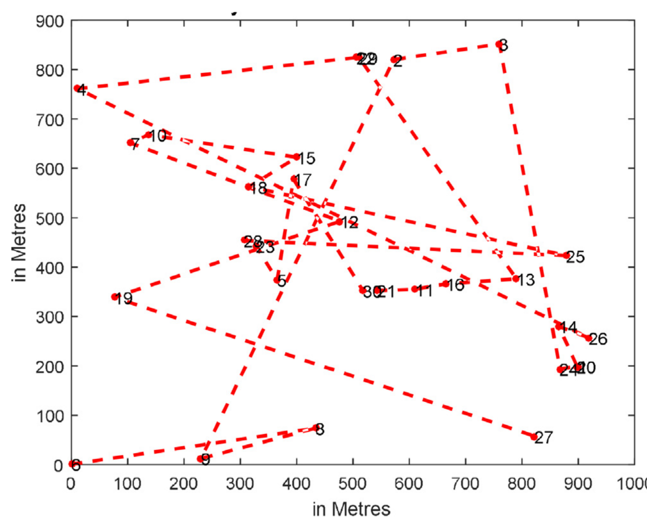

Fig. 19. Best Fitness Reliable Communication Route High Density (GA).

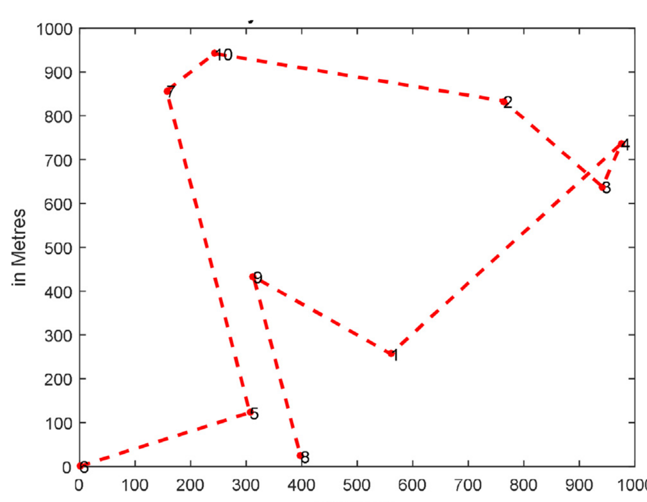

Fig. 20. Least Fitness Reliable Communication Route High Density (GA).

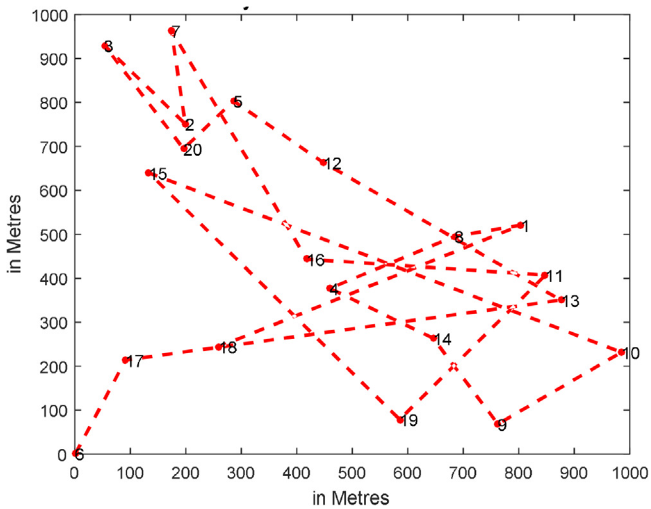

Fig. 21. Initial IGAROT Solution for V2I Route Optimisation under low car density scenario.

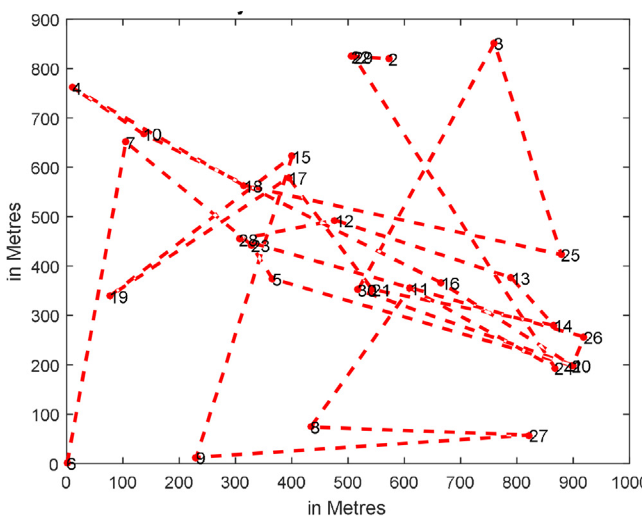

Fig. 22. Initial IGAROT Solution for V2I Route Optimisation under medium car density scenario.

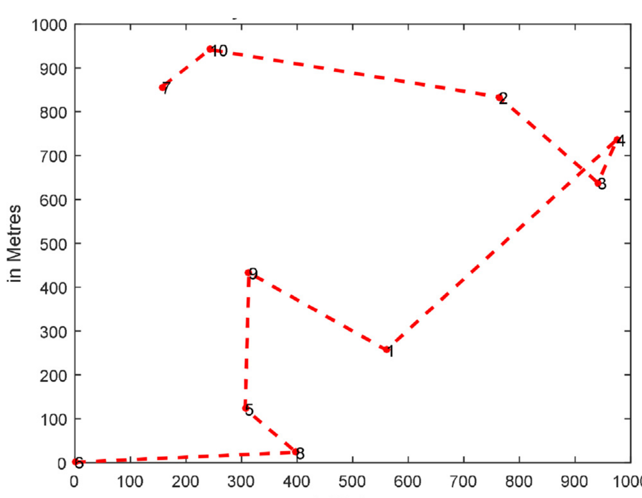

Fig. 23. Initial IGAROT Solution for V2I Route Optimisation under high car density scenario.

Table 7
IGAROT Best, Average, and Least Fitness Reliability for Several Simulations.

Fitness Value	Low Density	Medium Density	High Density
Best Fitness	4.6944e−5	2.1714e−9	5.7750e−13
Average Fitness	4.5782e−5	2.0729e−9	5.0821e−13
Least Fitness	4.2822e−5	1.9818e−9	4.3167e−13

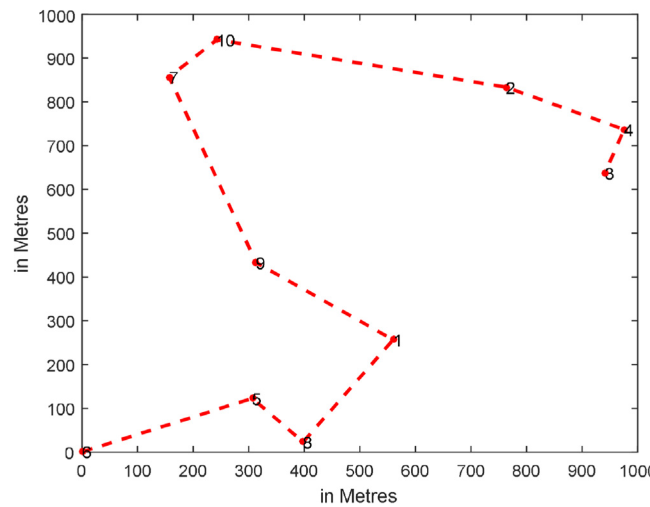

Fig. 24. Least Fitness Reliable Communication Route Low Density (IGAROT).

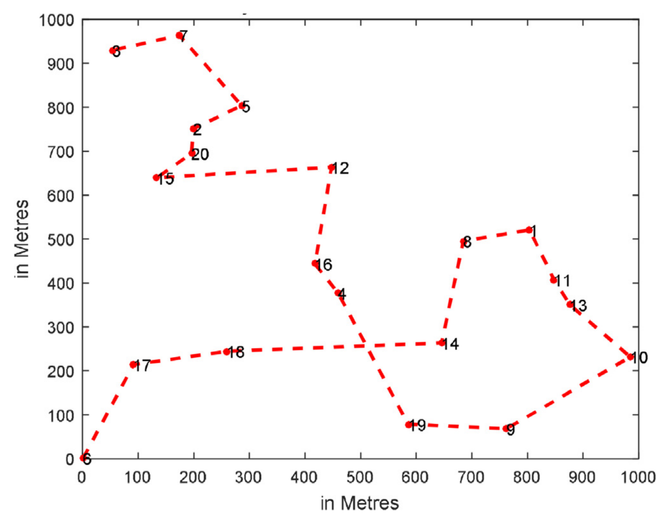

Fig. 25. Best Fitness Reliable Communication Route Low Density (IGAROT).

5.3. Comparative performance analysis of the techniques for VANET route optimization

We present here a comparative performance analysis of GA and IGAROT based on the model in (6). The average of 100 different independent simulations are reported in Table 8 using the optimal parameter settings obtained for each algorithm in Table 5. We subjected both algorithms to the same uniform distribution of nodes (vehicles) in the physical network space. We recorded and analyzed the performance of each algorithm based on the best, average and least route metric fitness values. Table 8 summarizes the performance of each algorithm.

Observe that both algorithms converged to the same best fitness value of 4.6944e−5 for the low-density V2I communication scenario (See Table 8). A logical explanation may be the small

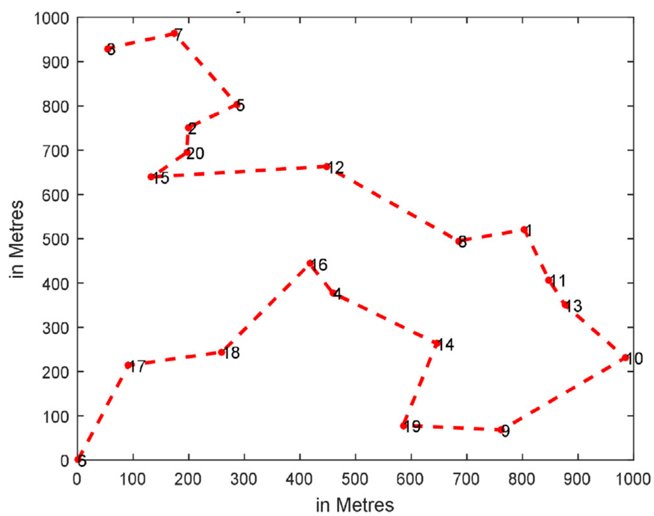

Fig. 26. Least Fitness Reliable Communication Route Medium Density (IGAROT).

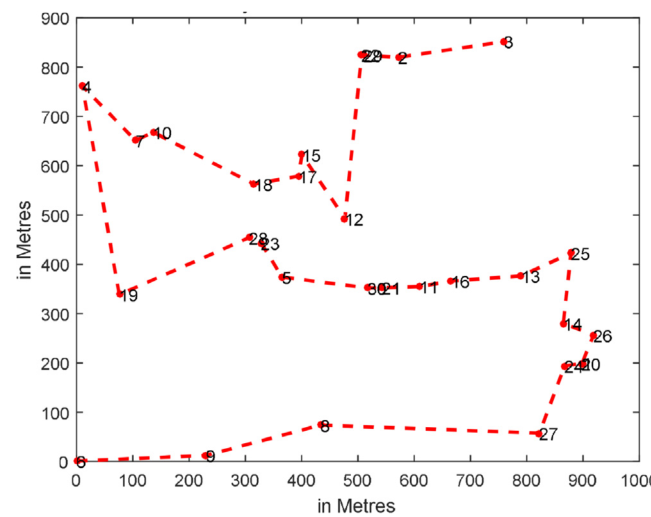

Fig. 29. Best Fitness Reliable Communication Route High Density (IGAROT).

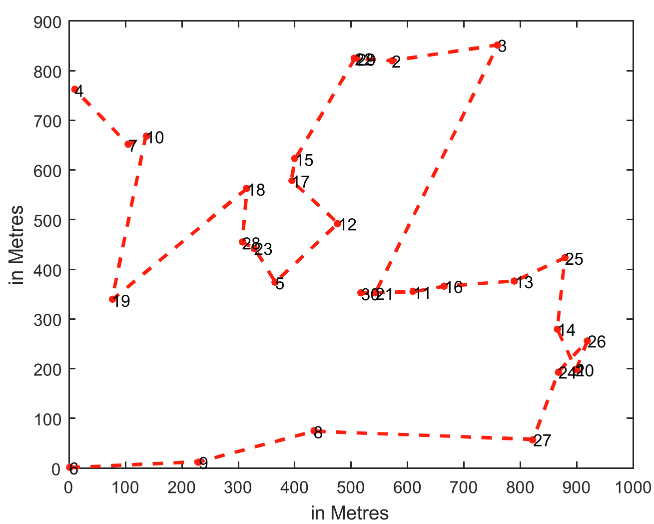

Fig. 27. Best Fitness Reliable Communication Route Medium Density (IGAROT).

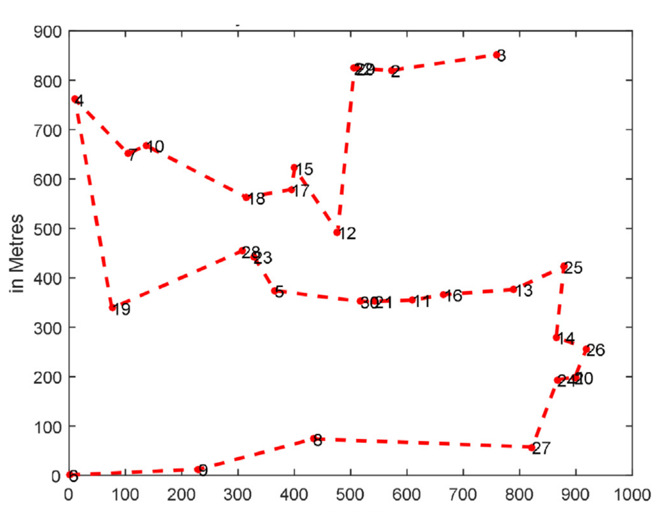

Fig. 28. Least Fitness Reliable Communication Route High Density (IGAROT).

Table 8
Comparative Performance Analysis of GA and the Proposed IGAROT for V2I Route Optimisation.

Optimization Technique	Least Fitness	Average Fitness	Best Fitness
Low Density Communication Scenario			
GA	4.2272e−5	4.3921e−5	4.6944e−5
IGAROT	4.2822e−5	4.5782e−5	4.6944e−5
Medium Density Communication Scenario			
GA	1.0348e−9	1.1797e−9	1.4246e−9
IGAROT	1.9818e−9	2.0729e−9	2.1714e−9
High Density Communication Scenario			
GA	0.8209e−13	0.9757e−13	1.115e−13
IGAROT	4.3167e−13	5.0821e−13	5.775e−13

number of nodes (10 vehicles) involved in the network. This implies that both GA and the proposed IGAROT performed well and are capable of handling data routing in low-density V2I communication scenarios. However, on the average performance, IGAROT with a 4.5782e−5 route metric value performed better compared to GA having a fitness value of 4.3921e−5. Similarly, IGAROT converged to a more reliable communication route with a fitness value of 2.1714e−9 compared to the 1.4246e−9 of GA for the medium density scenario. Also, on the average, IGAROT with a fitness value of 2.0729e−9 performed better than GA with a fitness of 1.1797e−9. Furthermore, IGAROT performed better in terms of the least fitness value for both the low and medium density scenarios. Observed for the high-density scenario that IGAROT performed better in terms of best, average and least fitness with values 5.775e−13, 5.0821e−13 and 4.3167e−13 respectively, as compared to GA with 1.115e−13, 0.9757e−13 and 0.8209e−13 best, average and least fitness value respectively. Essentially, IGAROT exhibited an improved performance in routing information based on the three different simulated V2I communication scenarios considered.

6. Conclusion

This paper has presented a route metric model that incorporates in its design essential parameters such as the received signal strength, path loss; transmit power and the frequency of communication. We have addressed the challenge of determining the most reliable communication route in a V2I VANET. In addition, we have developed an improved GA technique called IGAROT to ensure improved route selection in VANET. Our proposed IGAROT clusters chromosomes into two non-overlapping groups using iterative K-Means algorithm. The algorithm then updates the size of the good chromosome cluster in the initial population size using an elitism selection probability. We compared IGAROT to the conventional GA route optimization algorithm based on the design of a robust communication route metric. From our findings, IGAROT demonstrated improved convergence performance over the conventional GA. Based on the average route metric results obtained in Table 8, IGAROT provided 4.24%, 75.7% and 420% increment over the conventional GA in the low, medium and high car density scenarios, respectively. In future works, we intend to analyze the design complexities associated with our proposed scheme. In addition, we shall look at other interesting issues concerning how to implement IGAROT in real time VANET communication systems. IGAROT presents greater potentials for use across diverse fields including data transmission in wireless sensor networks, information routing in wide body area networks, data classification, robot route optimization and other applications. These areas can be explored in future works.

7. Appreciation

We are immensely grateful to the esteemed reviewers of our paper for their tremendous contributions towards making our manuscript better. We thank you all!

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