Reliability-Aware Multi-Objective Optimization-Based Routing Protocol for VANETs Using Enhanced Gaussian Mutation Harmony Searching

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ABSTRACT Vehicular Ad Hoc Networks (VANETs) is an emerging technology that can be applied in intelligent transportation systems. Routing protocols are essential for obtaining reliable VANET networks. This article proposes a novel framework, designated as Reliability Aware Multi-Objective Optimization Based VANETs Routing (RAMO). The framework includes three levels: the first is the simulation of the VANET system; the second is the routing criteria, based on reliability and geometrics; the third level is the routing algorithm. The actual network is the next stage. Furthermore, the framework includes an optimization block that controls the parameters of each of the reliability, geometrical and routing blocks. The optimization is presented under the multi-objective perspective and based on the development of a novel variant of multi-objective harmony searching. This has been designated as Enhanced Gaussian Mutation Harmony Searching (EGMHS), which includes Gaussian mutation, objective decomposition and a harmony memory extraction algorithm. The evaluation was performed based on two levels. The first was the EGMHS evaluation using nine benchmarking mathematical functions, while the second was the RAMO evaluation based on the network simulator. The metrics obtained, including set coverage, delta metric, hyper-volume, packet delivery ratio (PDR) and end-to-end (E2E) delay, demonstrate the superiority over the baseline approaches of both EGMHS and RAMO with EGMHS.

INDEX TERMS Vehicular ad hoc networks, routing, reliability, geometric, multi-objective optimization, firefly.

I. INTRODUCTION

Recently, the emerging technology of vehicular ad hoc networks (VANETs) has developed significantly and many industries are allocating considerable effort to compete in this field [1]. The term VANET refers to mobile vehicles driving on a highway or in an urban environment while connected to each other wirelessly. They utilise an ongoing data exchange between them or with a roadside unit (RSU) for the purpose

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of updating information, guiding infrastructure-less driving and driving assistance [2].

Another aspect of VANETs technology is its integration with a complete intelligent transportation system, ITS [3] for various purposes. The VANETs technology involves different aspects, such as routing [4], reliability analysis [5], message scheduling and medium access [6]. The issue of VANET routing has been regarded as a research problem for several decades. However, it has become more active in recent years for several reasons. Firstly, the rapid development in hardware speeds has made it feasible to incorporate computational algorithms into real-time applications in nature. Secondly,
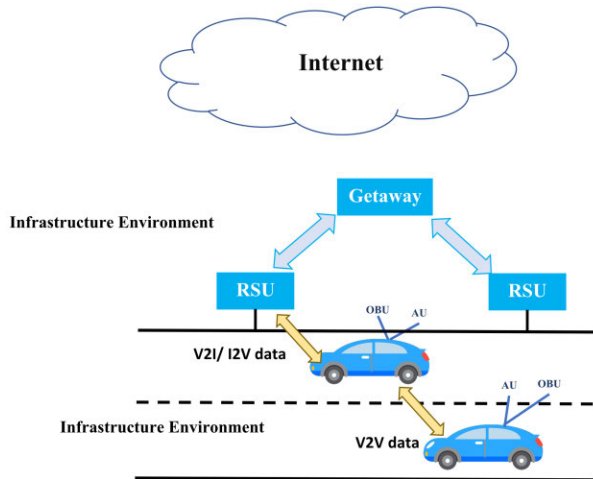
FIGURE 1. Basic Architecture of VANETs [11].

major developments have been made in the field of artificial intelligence and in the ability to produce smart algorithms for creating autonomous systems, including driver-less cars. Thirdly, communication speeds have increased significantly because of the fifth-generation era of technology. All these aspects have enhanced the feasibility of undertaking a significant amount of research in the area of VANETs in general and in the sub-area of routing protocols for VANETs and VANETs clustering in particular [7], [8].

Leveraging global positioning system (GPS) technology, which enables real-time updates on the position of moving nodes or vehicles in VANET, has enabled intelligent routing developments to incorporate a predictive feature of the mobility pattern into the network [9]. The emerging challenge facing VANET routing is the evolution of the complicated structures of the contemporary road environment, with its multi-layers of roads, tunnels and bridges. This makes the recognition of the future direction of nodes highly complex and unpredictable, which then causes the links between the VANETs to rapidly become unstable [10].

Figure 1 depicts the basic design of VANETs [11]. The network design is divided into two parts. The infrastructure-less part deals with ad hoc vehicles, while the infrastructure-oriented half deals with Road Side Units (RSUs) in general. An On-Board Unit (OBU) and a collection of sensors are installed in each vehicle to gather and process data in the form of messages. These are sent to other vehicles (RSUs) when necessary for V2V (vehicular-to-vehicular) or V2I (vehicular-to-infrastructure) communication. A single or many Application Units (AU) are also installed on the vehicles.

II. LITERATURE SURVEY

Various researchers have developed routing protocols for VANETs based on machine learning or meta-heuristic optimization models. Some researchers have adopted reinforcement learning. In the work of [12], a collaborative

learning-based routing scheme for multi-access vehicular edge computing environment. The approach is proactive and it uses end-edge-cloud collaboration to find the routes. In addition, the routes are also preemptively changed based on the learned information to handle the dynamic changes. Similarly, in the work of [13], decentralized moving edge and multi-tier multi-access edge clustering was proposed with an employment of fuzzy logic and Q-learning for route selection. Fuzzy logic was employed to consider multiple inherently contradictory metrics and Q-learning for accomplishing self-evolving capability. In the following sub-sections, we present the usage of multi-objective optimization for various goals of VANETs.

A. MULTI-OBJECTIVE OPTIMIZATION

Some scholars have adopted Multi-Objective Optimization (MOO) for the optimization of the existing routing protocols in Wireless Sensor Network (WSN) [14], as well as to improve their suitability for VANETs [15]. The study of Joshua and Varadarajan [16] reported the use of firefly as MOO for Optimized Link State Routing (OLSR) for VANET based on the developed framework. The developed framework has 3 stages which are i) Scenario generation for the creation of the traffic and road network; ii) weighted cost function formulation, and iii) protocol parameters optimization using the parameters that related to the message holding time, the link status refresh time, the hello message, etc. A 2-Hop routing algorithm was presented by [17], based on the Multi-Objective Harris Hawks Optimization (2HMO-HHO) algorithm with the aim of optimal forwarders selection between the source & destination vehicles. In this approach, two hops selection (rather than multiple hops selection) was aimed at increasing the stability of the selected route to ensure successful data transmission. But the evaluation failed to generate the MOO evaluation measures in terms of the set coverage, number of non-dominated solutions, hypervolume, etc. Several studies have reported the optimization of VANET network using meta-heuristic approaches for different purposes, such as security, MAC layer optimization, and routing optimization.

1) MAC OPTIMIZATION

Regarding the application of a meta-heuristic for MAC layer optimization in VANET, the study by [18] proposed a MOO framework for MAC and physical layer optimization that strives towards optimization of 3 tasks which are latency, throughput, and packet loss. The two layers of the proposed protocol included several parameters. The evaluation of the framework for optimization purposes was based on a Non-dominated Sorting Genetic Algorithm (NSGA-II). Another study by [19] reported the use of a genetic whale optimization algorithm for the selection of the root channel for transmission; the proposed protocol was called Modified Cognitive Tree Routing Protocol (MCTRP). Another application of meta-heuristic in VANET is in data propagation control and broadcast storm prevention. The study by [20]

presented a protocol that aims towards optimization of network life and link stability, as well as reducing the level of obstructions within the selected path. The formulation of the optimization function was done as a single objective function with the inclusion of the two terms. The approach also incorporated the discrete PSO; the approach also included a complexity analysis to improve its feasibility in real-world applications. Meta-heuristic-based optimization has been proposed by many studies for the establishment of multi-cast-based routing in VANETs. Scholars in [21] presented an improved Shuffled Frog-Leaping Algorithm-Based [21] QoS Constrained Multicast Routing (ISFLABMR) as suggested by [20] for optimal sub-tree determination for message dissemination. This selected sub-tree is considered the optimal multicast tree from the available options of the multi-cast tree between the source and the destination. The fitness function formulation was aimed at the optimization of various QoS parameters, especially the jitter, bandwidth, and latency to minimize the cost of transmission of multicast routing.

2) SECURITY OPTIMIZATION

Some studies have also focused on meta-heuristic-based VANET security; for instance, the study by [22] proposed the use of AI-based swarm algorithms to handle routing attacks. Furthermore, a route selection approach based on the fitness values of the routes using Genetic Algorithm GA was proposed by [23]. The greedy approach was used to find the routes while GA was used to select the best route. Despite the superiority of the approach over other comparative routing protocols, it still suffers from slow computation but its hybridization with heuristic can improve its performance.

Authors have also shown concern regarding the speed of GA as reported by [24] where GA was used in both parallel and serial manners; however, the parallel way was reportedly better when using multi-core architecture.

3) ROUTE OPTIMIZATION

Metrics for route optimization have also been developed by some researchers; these metrics include signal strength information, path loss, frequency, and transmit power. The work by [25] proposed an improved GA with additional metrics. A non-probabilistic-based selection method was adopted in the approach based on k-means clustering. The study also suggested further studies on the real-time application of the method. Literature evidence suggests the availability of numerous meta-heuristic-based routing protocols that focused on multi-cast routing and its contribution to network congestion. For instance, the study by [26] reported the use of micro-ABC for multi-cast routing. The purpose of this algorithm is to achieve QoS-constrained VANET with improved network lifetime and reduced delay cost. The algorithm performs bit-based encoding to determine the source-destination route inside a spanning tree. The incorporation of an energy model for electrical efficiency was also proposed. However, only a small portion of the population was considered for the optimization to improve the computational efficiency of the algorithm. A similar approach to meta-heuristic-based multi-cast routing development was proposed by [27] in which improvement to FA using Levey distribution was reported, while path searching was performed using bit string coding; the aim is to achieve the best cost as reflected by low energy consumption, and reduced end-to-end (E2E) delay. An optimized link-state routing protocol has been proposed by [28]. The study proposed an Enhance Harmony Search Optimization (EHSO) algorithm in which the OLSR parameters are configured via a two-stage coupling process. The optimization process using EHSO is based on

TABLE 1. Overview of the various approaches that have been developed for solving the problem of VANETs routing.

Authors	Algorithm	Optimization Improvement	Application	Metric	Solution encoding	Objective function	Limitation
[24]	Genetic	No improvement	route optimization	Route cost	Route encoding	Single objective	it ignores the multi-objective nature
[25]	Improved genetic based routing algorithm was proposed	Uses non-probabilistic selection approach using k-means clustering.	Routing optimization	Signal strength, path loss, transmit power and frequency	Clustering solution	Distance function	real time concern and regarded it as future investigation
[26]	micro-artificial bee colony	Micro population	Multi-cast routing	Achieving QoS-constrained VANET with maximizing network lifetime and minimizing delay cost.	Bit-based encoding for the route between the source and the destination inside a spanning tree	Route length	It ignores packet delivery ratio as an objective in the optimization
[27]	firefly-based searching	Levy distribution	multicast routing	minimizing the energy consumption and E2E delay	binary representation of a route	single objective function	It ignores the multi-objective nature of the problem

the incorporation of two common selection methods in its memory; these selection methods are tournament selection and roulette wheel selection.

III. MOTIVATION

A review of the existing literature found that most approaches that have tackled the problem of routing protocols in VANETs have not considered the multi-objective nature of the problem. The work of [24]–[27] have used single objective optimization with weighted average of the multi-objective. This approach leads to local minima due to the non-convex nature of the optimization surface. In other words, the optimal point of multi-objective is not necessarily the optimal point of each of the separated objectives. Hence, attaining more optimality requires conducting non-dominated optimization for the various parameters of the protocol. For example, one way to increase the packet delivery ratio (PDR) is to accept late packets. Accepting late packets implies higher E2E-delay. On the other side, rejecting old packets implies lower E2E-delay of accepted packets and consequently less PDR [29]. Furthermore, the approaches that have been developed in relation to multi-objective based meta-heuristic searching have not concentrated on the exploration aspect in the solution space nor the non-domination of the searched solutions [27], [24].

Multi-objective harmony searching optimization has been used extensively as a potential approach to solving random based searching problems of a multi-objective nature. Meanwhile, the majority of approaches to developing an online criterion for probing the exploration while performing the search in the space have been unsuccessful.

The goal of this article is to develop a routing protocol for VANETs based on multi-objective optimization by using two aspects of the network, namely, the geometrical and the reliability. An enhanced multi-objective harmony searching was developed by adding various mechanisms for supporting and balancing exploration and exploitation.

Examining the meta-heuristic-based routing protocols reveals an increasing trend in the use of such approaches. However, the majority of meta-heuristic-based routing algorithms have relied on single objective-based optimization, which is inadequate due to the multi-objective nature of the problem, i.e., the implicit conflict between one objective and the other. For example, decreasing the E2E delay of the transmission might conflict with the increasing packet delivery ratio (PDR). Another aspect of using such algorithms is the concern about the speed of the approach, considering the need to generate a significant number of candidate solutions and evaluate them. This leads to a trade-off between capturing the optimization surface behaviour and falling into non-convergence.

Furthermore, it has been observed that each approach has focused on a certain metric or multi-metrics but ignored others. Another observation, as shown in Table 1, is the need to adapt or improve the meta-heuristic approach to make it better suited to the nature of the problem, instead of using it

as a direct application. For example, [25] improved genetics with k-means clustering, while [26] converted an artificial bee colony to micro to make it feasible from the time execution perspective. Two categories of routing applications were considered in developing meta-heuristic-based routing. The first category is general routing protocols, such as in [25] [26], while the second category is multi-cast routing, such as in [26], [30], [20] and [20]. Another observation was the variation of the metrics used between one approach and another. For example, while [30] focused on minimizing the energy consumption and delay, [20] formulated an optimization model for optimizing the QoS, i.e., the PDR and E2E delay, and the jitter. Moreover, a review of all the approaches revealed that none used multi-objective optimization in the literal meaning; instead, most combined the multi-objective functions as a multi-term in a single objective function, which leads to a deviation from the optimal solution in the non-convex optimization type of surface. More specifically, previous researchers have addressed the multi-objective aspect of the routing problem by combining the objectives in one weighted sum equation, which is subject to deviation from the optimal point due to the addition of non-homogenous terms. This would be expected in the optimization of routing protocols due to the non-linearity of the problem. A prudent development would be to conduct MOO-based routing and select the operating point of the Pareto front based on various heuristics derived from the nature of road environments and the current state of the network. Another observation was that despite the numerous approaches that address VANETs routing, few have considered path reliability as a metric for the optimization of path purpose. This claim is supported in the article by [26].

The remainder of the article is organised as follows. In section IV, we present the contributions. Next, the methodology is developed in section V. The experimental works and results are outlined in section VI. Lastly, the conclusion and future work are presented in section VII.

IV. CONTRIBUTION

This article provides the following contributions:

It formulates the routing problem in networking as a multi-objective mathematical optimization problem, based on geometry and reliability parameters as the solution space, and E2E delay and PDR as the objective space variables.

1) It proposes a novel routing optimization framework, named Reliability Aware Multi-Objective Optimization Based VANETs Routing (RAMO). The framework includes three levels: the first is the simulation of the network of VANET which is responsible of calculating the objective values of the optimization decision variables; the second is the criteria of routing, which are based on reliability and geometrics; and the third level is the routing algorithm.

2) It improves an existing multi-objective optimization algorithm based on harmony searching by incorporating

Gaussian mutation, the probabilistic management of harmony memory based on crowding distance, and objective decomposition. This was designated as Enhanced Gaussian Mutation Harmony Searching (EGMHS).

3) This study evaluates the developed EGMHS algorithm based on multi-objective benchmarking mathematical functions using MOO evaluation metrics, and VANET simulations using the RMOOR framework and networking evaluation metrics.

V. METHODOLOGY

This section presents the methodology developed for the purposes of this study. It starts by presenting the Enhanced Gaussian Mutation Harmony Searching (EGMHS) in sub-section 4.1. Next, the framework of Reliability Aware Multi-Objective Optimization Routing (RMOOR) is outlined in sub-section F.

A. ENHANCED GAUSSIAN MUTATION HARMONY SEARCHING (EGMHS)

The developed Gaussian harmony searching model is presented in this section. Sub-section (1) presents the general algorithm and its pseudocode. Afterwards, details of the Gaussian mutation are provided in sub-section (2), while details of the extraction of the new harmony memory are outlined in sub-section (3). Lastly, the objective decomposition is presented in sub-section (4).

1) GENERAL ALGORITHM

The algorithm of the developed harmony searching multi-objective optimization is provided below as Algorithm 1. The inputs were the initial harmony memory (HM), harmony searching consideration rate ($HMCR$), pitch adjustment rate PAR, control probability PC, global search switch GSS, bandwidth (bw), Gaussian mutation parameter Pgm), sigma and damping parameter of bandwidth ($dampingBW$). The output of the algorithm is the modified harmony memory ($newHM$). Initially, the algorithm builds the probability density function based on the existing harmony memory objective values in line 1. Next, it processes the harmony memory element by element, using the first index h, before going through the dimensions of each element one by one, using the other index j, as given in lines 2 and 4. It performs either the creation of a new value in the corresponding element and dimension, or its replacement with another random element and dimension, which is selected using a random number, as shown in the condition statement in line 5. The control parameter for this is the memory consideration rate (HMCR). The new value is stored in a separate variable and used to affect the subject element and dimension using the pitch adjustment rate (PAR), which is referred to in line 15. The effect is performed using a control variable that changes according to the current iteration.

The exploration is made adaptive with respect to the current stage of searching. The initial stage is more explorative

than the previous searching stages. This is provided by the value of $e^{1-10\frac{t}{tMax}}$, where t denotes the current iteration number and *tMax* denotes the maximum number of iterations. Hence, a higher number of iterations is equivalent to a less aggressive exploration. The usage of objective decomposition to change the solution is given in line 19. In line 18, a roulette wheel is used to select a solution based on the selected objective. Next, the algorithm uses the new value to influence the subject value according to the mutation parameters in line 29. In addition, the bandwidth changes iteratively with respect to the damping factor in line 33.

Algorithm 1 General Enhanced Gaussian Mutation of Multi-Objective Harmony Searching Optimization

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Inputs:
HM // harmony memory
$HMCR$//harmony memory consideration rate
PAR//pitch acceptance rate
bw//bandwidth
PC,//probability constant
GSS
Pgm /probability gaussian mutation
$sigma$, //standard deviation constant
$dampingBW$
Outputs:
$newHM$
Start
  1: Create pdf for each objective:
  2: for h=1: HMS
  3:   Xnew = []
  4:   for j=1: solDim
  5:    if rand < HMCR
  6:     if rand < Pc
  7:      randIdx=round (unifrnd(1, HMS))
  8:      Xnew(j)= HM (randIdx,j)
  9:     else
10:      Xnew(j)= HM(h,j)
11:     end
12:    else
13:     Xnew(j)=unifrnd(LB(j),HB(j))
14:    end
15:    if rand< PAR
16:     if rand< Pbw
17:      obj=randi(gmhs.nObj)
18:      r1= roulette_wheel (pdf (:, obj))
19:      Xnew(j) = Xnew(j) + rand∗(HM(r1)-Xnew(j))
20:     else
21:      if rand<0.5
22:      Xnew(j) = Xnew(j)+rand∗bw;
23:      else
24:      Xnew(j) = Xnew(j)-rand∗bw;
25:     end
26:      end
27:    end
28:   end % end for j
29: Xnew=GaussianMutation(Xnew,Pgm, sigma)
30: Xnew=CheckBounds(Xnew, LB, HB);
31: newHM(h,:)=Xnew;
32: update pdf
33: bw= bw ∗ dampingBW
34: sigma = sigmadampingBW
35: end // end for h
End

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2) GAUSSIAN MUTATION

The Gaussian mutation is presented in Algorithm 2. The input of the algorithm is the solution before mutation Xnew, the standard deviation Sigma, the probability of Gaussian mutation Pgm and the range of the solution, as determined by the lower and upper bounds. The output is the mutated Xnew. The Gaussian mutation concept is to modify the current solution value to a new value using the probability density function from the Gaussian distribution, the expected value as the current solution and the standard deviation as the input Sigma, as given in line 3. This is achieved using the probability of changing the solution Pgm, as given in line 2.

Algorithm 2 Gaussian Mutation of the Developed EGMHS Optimization

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Input:
Xnew // generated solution
Sigma //standard deviation constant
Pgm //probability gaussian mutation
LB, UB //lower bound and upper bound
Output:
Xnew //mutated solution
Start:
1: For j=1: Dim
2:   If rand<Pgm
3:     Xnew(j)=normrnd(Xnew(j),sigma)
4:     Xnew(j)=checkBound(Xnew(j),LB,HB)
5:   else
6:     Xnew(j)=Xnew(j)
7:   end
8: end
End

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3) EXTRACTION NEW HM PSEUDOCODE

The environmental selection is an algorithm that receives an existing harmony memory of double the typical size. It selects from the memory subset of solutions with the same harmony memory size.

As observed in Algorithm 3, it iterates over the memory solutions, as given in line 3 and selects the solution that has the highest crowding distance, as given in line 3. From this, it selects the solution with the maximum fitness values according to a pre-defined grid, as given in line 4 and selects from these the solutions that have the highest solution space distance, as given in line 6. The algorithm is useful for reducing the number of choices and enabling three solution selection criteria from the harmony memory: (i), higher crowding distance; (ii), a higher solution space distance; and (iii), higher fitness values of the grid in the solution space.

4) OBJECTIVE DECOMPOSITION

The role of objective decomposition is to use one selected objective from a uniform distribution as the criterion for selecting a solution as the leader and then to use the probability density function of the selected objective, with respect to all solutions, as a model for generating the leader. This approach plays an important role in the exploration of the

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Algorithm 3 Environmental Selection of Solutions From the Harmony Memory

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Inputs:
newHM // new harmony memory
Outputs:
HM //final harmony memory
Start:
1: For sols in the last rank
2:   idx = find max (crowding Distance)
3:   if length(idx) >1 // if there are more than one solution have the best crowding distance
4:     idx = find max(gridFitness(idx)) // select based on grid occupancy
5:     if length (idx) >1 // if there are more than one solution have the best grid fitness
6:       idx = find max(solSpaceDist(idx)) // select based on solutions space distance
7:     end
8:   end
9: end
End

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solution space as well as the exploitation of the fitness values with respect to the objectives. This concept is shown in the algorithm of the general algorithm in lines 1, 17 and 18.

5) COMPLEXITY ANALYSIS

The computational complexity of one iteration of the algorithm $O(HMS \times solDim)$, where HMS denotes the memory size and $solDim$ denotes the length of the solution. The real complexity depends on the size of the first rank as a percentage of HMS.

B. FRAMEWORK OF RELIABILITY AWARE MULTI OBJECTIVE OPTIMIZATION BASED VANETs ROUTING RAMO

The first development stage is to propose the RAMO framework, which is depicted in Figure 2. As observed, the framework combines several separate blocks for controlling the simulation scenarios of vehicle mobility and their data exchange in the environment. Blocks include: (1) The data generator, which is responsible for generating the packets in each node and deciding their final destination; (2) The mobility model, which is responsible for calculating the mobility variables of the vehicles in the environment; (3) The driving model, which is responsible for controlling the decision to change the mobility state based on the decision expected of the driver; and (4) The road model, which is responsible for controlling the highway area by incorporating length, width, the number of lanes and directions, and the speed limit.

Next, the routing model provides the framework core and is combined with the reliability model that is responsible for deciding the link weight based on its reliability. In addition, the geometric model analyses the vehicle location and locations of other vehicles using the exchanged location information and considers this state in the routing. Both the geometric and reliability models feed their information to the routing algorithm, which then fuses the information and uses
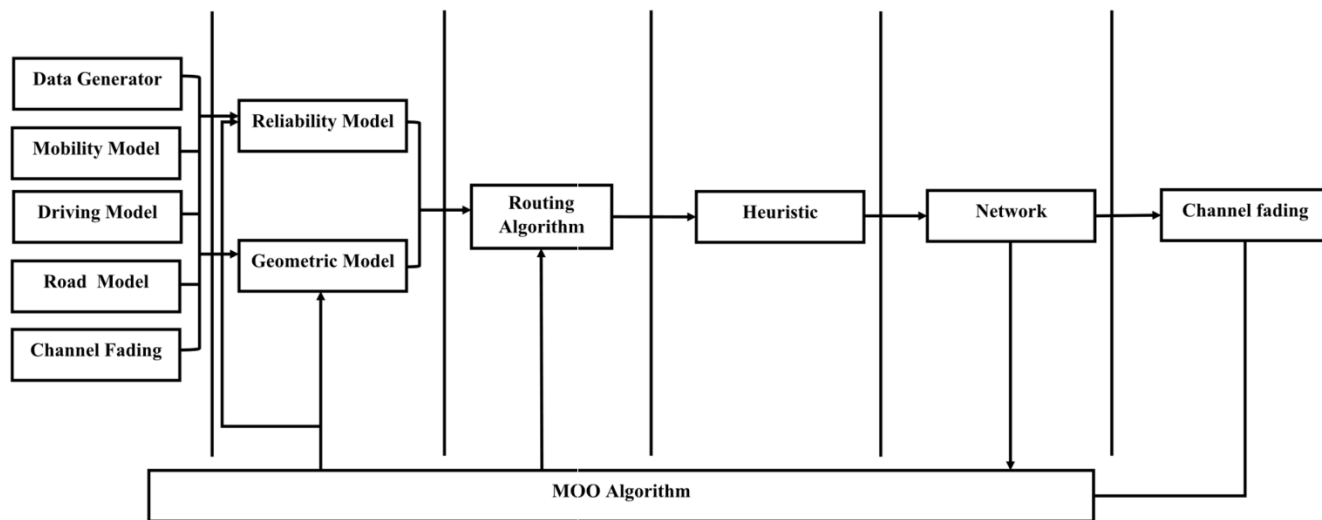
FIGURE 2. Reliability Aware Multi Objective Optimization Based VANETs Routing RAMO.

various internal criteria to decide the best next-hop routing. The result of this is a routing path that passes from one source node to another destination node in a reactive manner. Next, the performance metrics, namely, PDR and E2E delay, are provided from the network to the multi-objective optimization MOO algorithm. This is responsible for changing the internal parameters of the reliability model and the geometric model to search for the best set of parameters that provide the optimal solutions, in the form of a set of non-dominated solutions. Next, the application decides which non-dominated solution to use to operate the protocol, according to a set of preferences.

1) DATA GENERATION MODEL
The data is generated using two probabilistic models. The first is the normal distribution, which is used to generate the expected number of packets, as shown in Equation (1). The second model is the exponential distribution, which is used to generate the time interval between one packet and the next, as shown in Equation (2).

$$P(n) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(n-\mu)^2}{2\sigma^2}} \tag{1}$$

$$P(T) = \begin{cases} \lambda e^{-\lambda T}, & T \geq 0 \\ 0, & T < 0 \end{cases} \tag{2}$$

2) MOBILITY MODEL
To ensure the VANET model has a practical nature, we adopt a realistic mobility model that captures the vehicles' mobility dynamics [31]. The mobility model is based on the acceleration generated from the driving behaviour model. After generating the acceleration, the velocity is calculated based on integration which is discretized by summation, while the distance is generated based on an integration of the velocity, as shown in Equations (3) and (4) and it is

also discretized by summation. Two parameters control the driving behaviour (DB) of Equation (5), namely the aggressiveness factor AGG and the probability factor pr. It was assumed that the granularity of the model is T_u

$$v_t = v_{t-1} + T_u a_t \tag{3}$$

$$x_t = x_{t-1} + T_u v_t \tag{4}$$

$$a_t = DB(AGG, pr) \tag{5}$$

3) DRIVING BEHAVIOR MODEL
Another realistic aspect of the VANET model is the driving behaviour. The model is responsible for generating the driving acceleration. In this model, acceleration can be positive or negative; negative acceleration indicates deceleration. Acceleration is determined as a random portion of A_{max}, which indicates the maximum permitted acceleration in the model. Meanwhile, deceleration is determined as a random portion of the minimum deceleration permitted in the model, or $(-1)D_{max}$. There is also the possibility of generating zero acceleration, which indicates a fixed velocity. The change between the three cases relates to the probability factor pr and the two calculated variables $acci$ and $dacci$, each of which relates to the aggressiveness factor AGG, as depicted in Equations (6) (7) and (8).

$$a_i(t) = \begin{cases} R_2 A_{max}, & if\ R1 < acci + pr \\ R2(-1)D_{max}, & if\ (acci + pr < R1 \\ & < acci + dacci + 2pr) \\ 0, & otherwise \end{cases} \tag{6}$$

$$acci = \begin{cases} R_4(1-2pr) & if\ R3 < 3\frac{AGG}{4} \\ 0 & otherwise \end{cases} \tag{7}$$

$$dacci = \begin{cases} R_4(1-2pr) & if\ 3\frac{AGG}{4} < R3 < AGG \\ 0 & otherwise \end{cases} \tag{8}$$

4) HIGHWAY MODEL

The road model combines several variables. The first is the number of lanes N_L, the second is the width of the highway W, the third is the length of the highway L, the fourth is the direction of the lanes on the highway d_i and the last is the speed limit on the lanes v_i. A combination of the five variables provides the description of the highway used in the framework.

5) URBAN MODEL

The urban model is simulated as a set of junctions, whereby each junction combines four connected roads. The roads run east-west and north-south. Each road has two directions and a traffic sign for synchronising the vehicle movements on the road. Also, the traffic sign uses two systems. First, one sign is green at a certain time and the remainder are red. Hence, exiting vehicles can take one of three directions, forward, right or left, with respect to the road. In the second system, two signs are green at one time and the vehicles can go forward or left with respect to the road movement (British system).

6) CHANNEL FADING MODEL

Simulating the channel fading also enables a realistic evaluation of the VANETs. The Nakagami distribution was developed by Nakagami in 1940 and is given by the formula in Equations (9),(10) and (10).

$$p\,(r) = \frac{2m^m r^{2m-1}}{\Gamma\,(m)\,\Omega^m} \exp\left(-\frac{mr^2}{\Omega}\right) m \geq \frac{1}{2} \qquad (9)$$

$$k = \frac{m - \sqrt{m^2 - m}}{\sqrt{m^2 - m}} \qquad (10)$$

$$p(s) = \left(\frac{m}{s}\right)^m \frac{s^{m-1}}{\Gamma(m)} \exp\left(-\frac{ms}{s}\right) \qquad (11)$$

7) LINK RELIABILITY MODEL

It was assumed that the probability of a successful data exchange between one vehicle and another is an indicator of the link reliability. Hence, it was assumed that AT and L are (respectively) the association time, data exchange time and total link duration. Then, $P_s = \text{Pr}\{A + T_s \leq L$ is the probability of a successful data exchange because, for any successful data exchange, the association time added to the data exchange time must be lower than the total transmission time. The total time to transmit a given message of size S is calculated as shown in Equation (12):

$$T_s = \frac{S}{D_r} \qquad (12)$$

where:

S denotes the size of the message

D_r denotes the data rate

$$P_s = \min(1, \frac{\frac{D_{i,j}}{v_{rel}}}{A + \frac{S}{D_r}}) \qquad (13)$$

$D_{i,j}$ denotes the relative velocity between vehicle i and vehicle j

v_{rel} denotes the relative velocity between vehicle i and vehicle j

Each message has a certain size, which implies a different value of link reliability.

8) THE GEOMETRICAL BLOCK

This block is responsible for re-ordering the nodes in a priority list of next-hop based on the location of the final destination node, with respect to each node in the candidate node of next-hop. Each message has a certain destination, which implies a different order of geometrical priority.

9) ROUTING ALGORITHM

The routing algorithm is responsible for fusing the geometric and reliability to provide the optimal route for the messages. This will be achieved by ordering the candidate nodes to route the request message, based on the reliability information provided by the reliability block and the geometrical information provided by the geometrical block.

The fusion between the two criteria is made using the probabilistic approach. The highest percentage was selected as $PR_{next-hop}$ from the candidate next-hop in the neighbour updated zone using the parameter of fusion α. This is achieved by generating a random number between 0 and 1. If the number is higher than α, then the highest priority with respect to reliability is chosen. Otherwise, the highest priority with respect to the geometrical model is selected.

This process is repeated until the $PR_{next-hop}$ nodes have been selected from the candidate nodes. The process of route discovery is triggered if the neighbour zone is updated with a percentage of γ or upon receiving a route error message from the last discovered route.

The goal of the neighbour zone update process is to collect the mobility information from each node about its neighbour.

This cycle is done periodically in each $[+T_{nzu}]$. The information is collected from a hello message. The transmitted information is the position, velocity and acceleration. Hence, each vehicle can calculate the relative distance, relative velocity and relative acceleration with respect to its neighbours.

10) MOO OPTIMIZATION

The goal of the optimization is to select the best parameter values that optimize the performance metric, namely PDR, E2E-delay and over-head. The solution space was selected to include $x = (PR_{next-hop}, \alpha T_{nzu}\gamma) \epsilon R^4$ The optimization problem is formulated as Equation (14).

$$x^* = argmax(PDR\frac{1}{E2EDelay}, \frac{1}{Overhead}) \qquad (14)$$

In order to select one of the Pareto front solutions, sorting is conducted in descending order using Equation (15)

$$f\,(x) = w_1 PDR + w_2 \frac{1}{E2EDelay} + w_3 \frac{1}{Overhead} \qquad (15)$$

where:

$w = [w_1 w_2 w_3]$ denotes a reward vector and we select the solution at the top.

11) MOO METRICS

The multi-objective optimization measures are a combination of the set coverage, hyper-volume, number of non-dominated solutions, delta measures and generational distance. They are provided in Table 2. As the table illustrates, each measure has a role in evaluating the MOO performance. Basically, there are three aspects of performance: the domination, which is measured by the set coverage; the spread, which is measured by the hyper-volume; the richness of the solutions, which is measured by NDS; the diversity, which is measured by delta; and the error which is measured by the generational distance

VI. EXPERIMENTAL WORKS AND RESULTS

This section presents the experimental work and the analysis of the results. For the experimental evaluation, MATLAB environment 2019b was used. Each experiment was repeated ten times to generate a boxplot representation of the results and to address random behaviour.

The section is composed of two sub-sections: the first is the MOO optimization, described in (A), while the second is the simulation-based evaluation, outlined in (B).

A. MOO OPTIMIZATION

This sub-section provides the multi-objective optimization (MOO) evaluation of EGMHS and its comparison with the benchmarks, namely GMHS [32], NSGA-II [33] and MOHS [34]. MOO evaluation involves a multi-objective evaluation and is based on the following metrics: the set coverage, hyper-volume, number of non-dominated solutions, delta metric and generational distance.

Here, the MOO evaluation metrics for two mathematical functions, namely KUR and ZDT3, are presented. The remaining mathematical functions are provided in the appendix.

The first metric presented is the set coverage, as presented in Figure 3. It is given as a boxplot visualization because each algorithm was run ten times for the function to enable a statistical evaluation. The boxplot is given as an adjacency matrix of sub-figures where the row i and column j represents the set coverage of method in row i over method in column j. We are interested in top row which shows the domination of EMGS over other methods and its comparison with furthest right column which shows the domination of other methods over EMGS. Obviously, EMGS has shown higher domination over other methods as it is observed. As illustrated in Figure 3, the domination of EMGHS over GMHD, MOHS and NSGA-II is greater than the domination of the three benchmarks over EMGHS. The set coverage of EMGHS over NSGA-II has reached the median value of 0.75 compared with near zero of NSGA-II over EMGHS. Similarly, the set coverage of EMGHS over GMHS and MOHS is nearly 0.5 compared with near 0 for GMHS and MOHS over EMGHS.
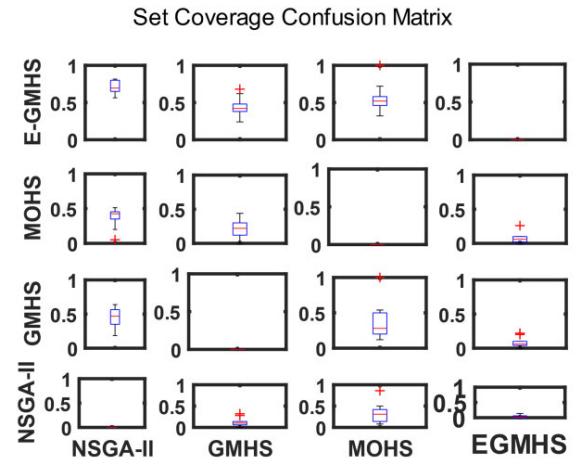

FIGURE 3. Set coverage of EMGHS comparing with the benchmarks GMHS, MOHS, and NSGA-II for KUR function.
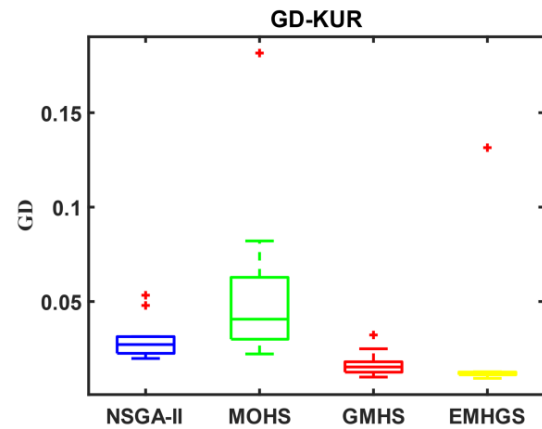

FIGURE 4. Generational distance of EGMHS comparing with the benchmarks MOHS, GMHS and NSGA-II for KUR function.

This indicates that the GMHS developed was capable of providing more dominant solutions than the benchmarks.

The second metric generated is the generational distance for the approaches, based on the KUR function, as shown in Figure 4. As indicated in this figure, EGMHS provided the lowest value of generational distance. This suggests better optimization performance, considering that the generational distance indicates the distance between the found Pareto and the true Pareto. This interpretation used the three features that exist in EGMHS, namely Gaussian mutation, environmental selection (extracting a new HM) and objective decomposition.

The third metric generated is delta, which indicates two aspects at the same time, namely the domination and the equal distribution of solutions on the Pareto. Like the generational distance, EGMHS was capable of providing the lowest value of delta, as shown in Figure 5, which is an indicator of its superiority with respect to this metric.

In addition, the hyper-volume is shown, which indicates the volume allocation of the solutions in the objective space. This is an indicator of the flexibility provided to the
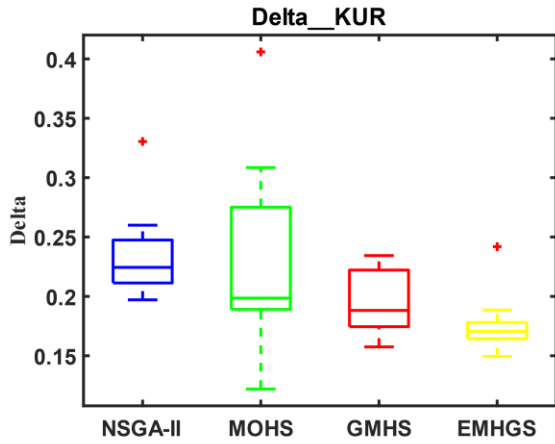
FIGURE 5. Delta of EMHGS comparing with the benchmarks MOHS, GMHS and NSGA-II for KUR function.
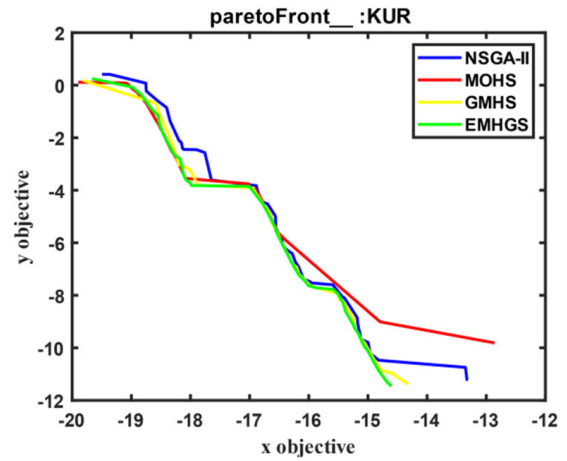

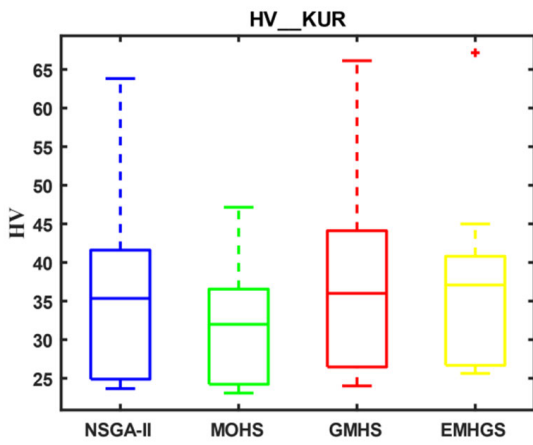**FIGURE 7.** Pareto front of EMGHS comparing with the pareto front of the benchmarks for KUR function.

FIGURE 6. Hyper-volume of EMHGS comparing with the benchmarks MOHS, GMHS and NSGA-II for KUR function.
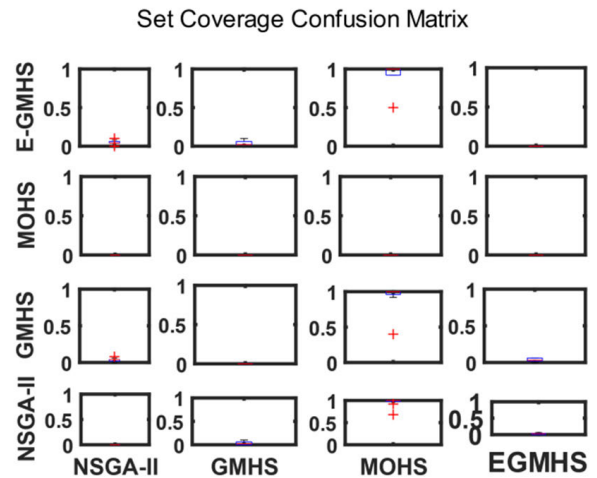

FIGURE 8. Set coverage of EMGHS comparing with the benchmarks GMHS, MOHS, and NSGA-II for ZDT3 function.

decision-maker, based on the generated solutions from the optimization algorithm. As observed in Figure 6, EGMHS was capable of providing the highest hyper-volume value from a statistical perspective. Hence, it is not only superior in terms of domination but also in the exploration of the solution space.

Lastly, the Pareto fronts found by EGMHS and the benchmarks are presented in Figure 7. This shows the minimisation performance achieved by the algorithms and how EGMHS

was capable of reaching more optimal or fewer solutions, compared with the benchmarks.

Like KUR, the evaluation metrics of ZDT3 are presented in Figures 8 to 11. The results reveal a similar superiority of EGMHS, compared with the benchmarks, for almost all metrics. Furthermore, the algorithm was capable of providing not only greater domination but also an equivalent hyper-volume, which indicates the flexibility of the choices available to

TABLE 2. MOO evaluation measures.

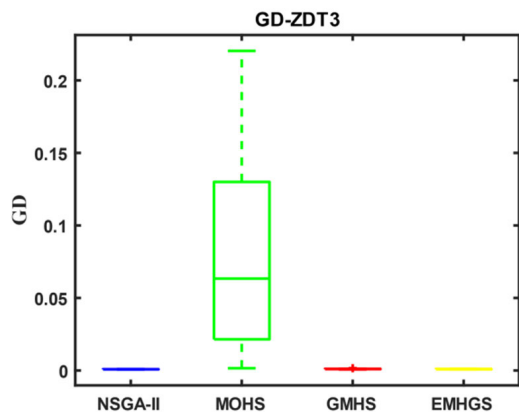| Measure Name	Equation		Role
Set coverage	$C(P_{s1}, P_{s2}) = \frac{|\{y \in P_{s2} \mid \exists x \in P_{s1} : x \succ y\}|}{|P_{s2}|}$	(16)	Domination
Hyper volume	$HV = Volume(\underset{x \in Ps}{\cup} Hyper\ cube(x))$	(17)	Spread
Number of non-dominated solutions	$NDS(N) = |P_s|$	(18)	Rich decision set
Delta measure	$\triangle = \frac{d_f + d_l + \sum_{i=1}^{N-1}(d_i - \overline{d})}{d_f + d_l + (N-1)\overline{d})}$	(19)	Diversity
Generational distance	$GD(P_s, P_T) = \frac{(\sum_{i=1}^{|P_s|} d_i^2)^{\frac{1}{2}}}{|P_s|}$	(20)	Optimality

FIGURE 9. Generational Distance of EGMHS comparing with the benchmarks MOHS, GMHS and NSGA-II for ZDT3 function.
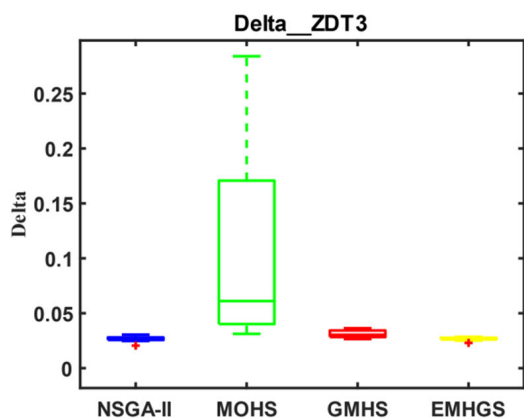

FIGURE 10. Delta metric of EGMHS comparing with the benchmarks MOHS, GMHS and NSGA-II for ZDT3 function.
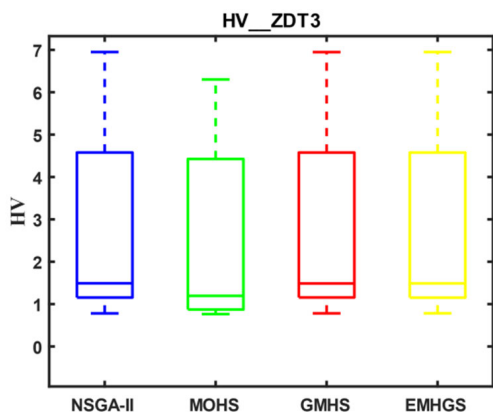

FIGURE 11. Hyper-volume of EMHGS comparing with the benchmarks MOHS, GMHS and NSGA-II for ZDT3 function.

the decision-maker, based on the results provided by the algorithm.

B. SIMULATION BASED EVALUATION

The evaluation was performed based on the experimental parameters depicted in Table 3. As shown in the table,

TABLE 3. Simulation parameters used for conducting the evaluation after training.

Parameter	EGMHS	GMHS	MOHS	NSGAII
Number of Iterations	25	25	25	25
Number of Solutions	100	100	100	100
Size of External Archive	100	100	100	-
HM Consideration Rate	0.9	0.9	0.9	-
Cross Probability	0.5	0.5	0.5	-
Global Searching Probability	0.9	0.9	0.9	-
Initial Pitch Adjustment Rate	0.9	0.9	0.9	-
Damping Ratio for Bandwidth	1	1	1	-
Mutation Probability	0.1	0.1	0.1	0.1
Alpha	-	-	70	-
Phi	-	-	2	-
Psi	-	-	4	-
Initial Pitch Adjustment Rate	-	-	0.1	-
Initial Gamma1	-	-	0.1	-
Initial Gamma2	-	-	0.1	-
Mutation Shrink	-	-	-	0.5

we selected the highway because it is more challenging for routing protocols because the vehicles move faster and have more sparsity. This makes the routing link subject to breaking and a reliable routing algorithm is required to address this.

As shown in the table, the same values were used for the common parameters of the four approaches to ensure the evaluation was objective. Basically, the four algorithms used the same number of iterations and solutions, which were set to 25 and 100, respectively. The external archive size is a specific parameter of the HS family and was set to 100.

Similarly, the HM consideration rate, cross probability, global searching rate, initial pitch adjustment rate, damping ratio for bandwidth and mutation probability were set to 0.9, 0.5, 0.9, 0.9, 1 and 0.1, respectively. The MOHS involves a longer list of parameters that includes Alpha, Phi, Psi, Initial Pitch Adjustment Rate, Initial Gamma1, Initial Gamma2 and Mutation Shrink as 70, 2, 4, 0.1, 0.1 and 0.1. For NSGA-2, a mutation shrink of 0.5 was used. The parameters used took the best values according to the mathematical evaluation presented earlier.

For the simulator, we performed the optimization in an environment consisting of two-lane roads on each side, as illustrated in Figure 12. The messages were generated at random vehicles and had random vehicles as destinations (these scenarios were considered routing scenarios).

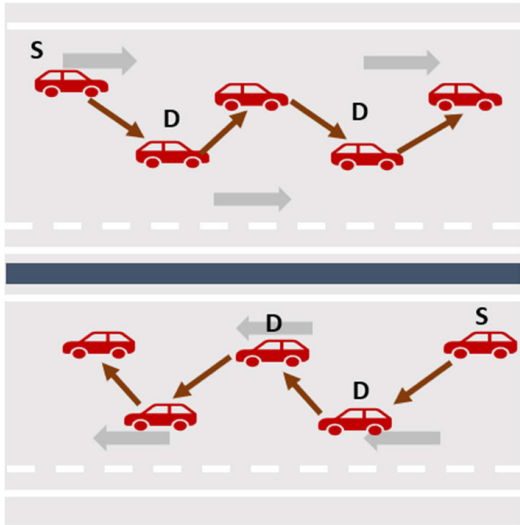The parameters of the simulation are provided in Table 4

FIGURE 12. A conceptual diagram that represents a snapshot of the simulation environment.

TABLE 4. The parameters of the simulation for conducting the optimization.

Parameter	EGMHS
Road length	10 km
Lane width	3.25 m
Total number of vehicles	250
Transmission range	300 m
Expected Incoming Vehicles	5 Vehicles
Expected Time Interval	8 sec
Experiment time	100 sec
Data Packet Lifetime	5 sec
Packet inter arrival Time	1.5 sec
Data Packet Generation Mean	2 packets
Average size of packet	80 bytes
Data Buffer Size	150 packets
Minimum velocity	36 km/h
Maximum velocity	110 km/h
Maximum acceleration	2 m/sec^2

The reader is reminded of the use of the solution representation $x = (PR_{next-hop}, \alpha T_{nzu} \gamma)$ After conducting the optimization based on the simulation, the best solutions for the parameters were obtained, as provided in Table 5. As the table shows, each algorithm has different metrics values.

Figure 13 shows the set coverage values of the solutions conducted by the optimization algorithms on the network simulator. It will be observed that each approach provided different set coverage values, with the least successful

TABLE 5. The best solutions as provided by each of the optimization algorithms.

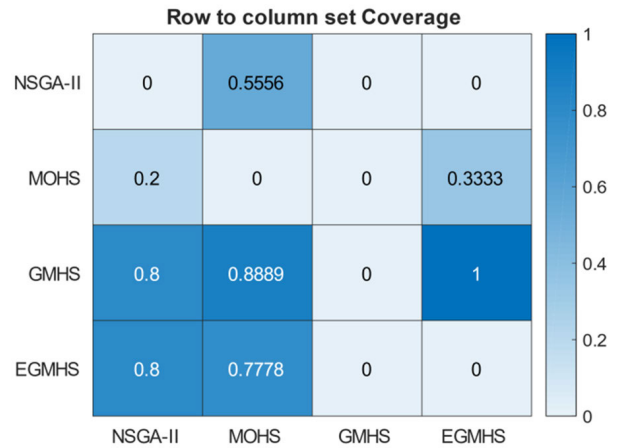| Algorithm\solution component	*alpha*	*gamma*	*pathsNum*
NSGAII	0	0.772	3
MOHS	0.015	0.670	4
GMHS	0.080	0.821	8
EGMHS	0.116	0.977	9

FIGURE 13. Set coverage values of comparing NSGA-II, MOHS, GMHS and EGMHS in RAMO.

performances being those of NSGA-II and MOHS, and the most competitive performance being between GMHS and EMGHS. The domination of GMHS over EMGHS was due to the difference between the mathematical functions and the nature of the simulation in terms of randomness.

The evaluation of the mathematical functions is included in addition to the set coverage hyper-volume. This indicates the flexibility of the choices available to decision-makers as the solutions will cover a higher hyper-volume and a wider range in the objective space. As shown in Figure 14, the hyper-volume of GMHS was the highest, NSGA-II and EGMHS provided similar hyper-volumes, while the lowest performance level was observed for NSGA-II.

After performing the simulation, the implementation was performed on a simulator using the parameters provided in Table 6. As presented in the table, the simulator had two bounding velocities: the minimum was equal to 36 KM/h and the maximum was equal to 110 KM/h. The buffer size was selected to accommodate 150 packets at a time. The data packet lifetime was selected as 8 seconds. The parameters of the packet generation models were set to 1.5 seconds and 2 packets for the expected time interval between two packets and the expected number of packets, respectively.

For further elaboration, the packet delivery ratio and the E2E delay of two randomly selected solutions from the Pareto front for each algorithm are presented; these were tested in the simulator. As presented in Figures 16 and 17, EMGHS
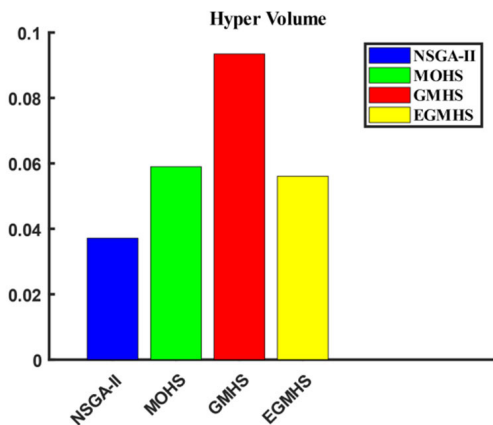
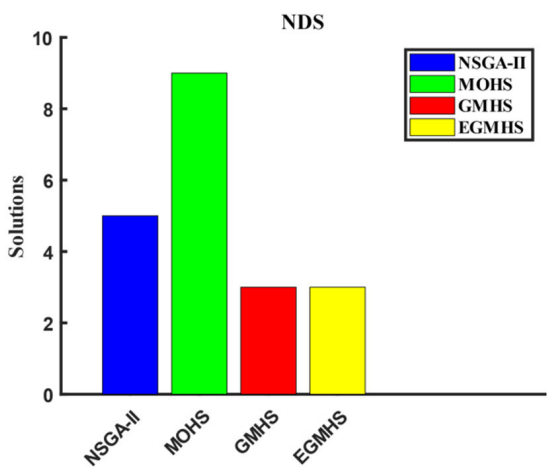**FIGURE 14.** The hyper-volume comparison between our developed EGMHS and the benchmarks.

FIGURE 15. Number of non-dominated solutions comparison between our developed EGMHS and the benchmarks.

TABLE 6. The parameters of the simulator that is used for conducting the evaluation after training.

Parameter	Value
experiment time	100 second
Number of Vehicle	25
Max velocity	110 KM/h
Min velocity	36 KM/h
Data buffer size	150 packets
Data packet life time	8 second
Packet inter arrival time	1.5 seconds
Data Packet Generation Mean	2
Seed	1:5
$w = [w_1\ w_2\ w_3]$	[1/3 1/3 1/3]

achieved a higher PDR with a lower E2E delay in the two solutions, compared with the other algorithms. In addition to
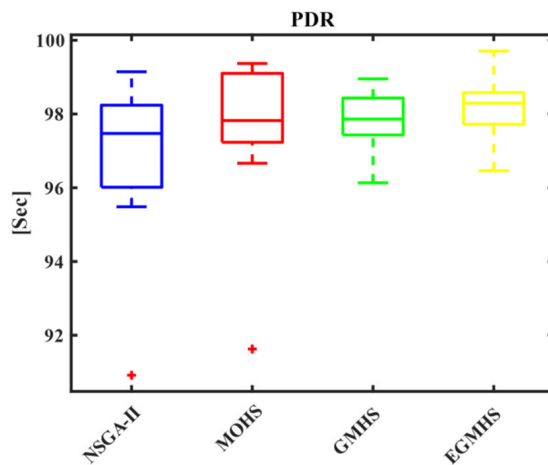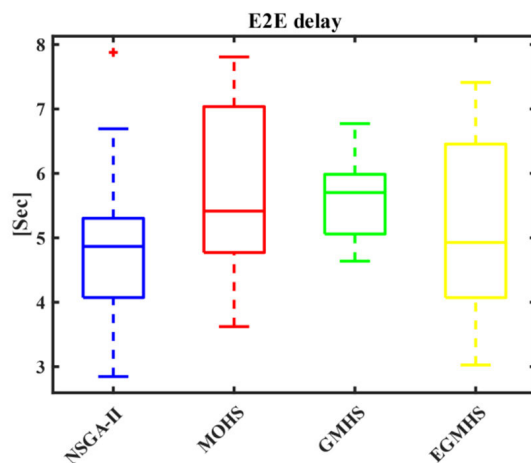

FIGURE 16. Overall PDR for solution 1.

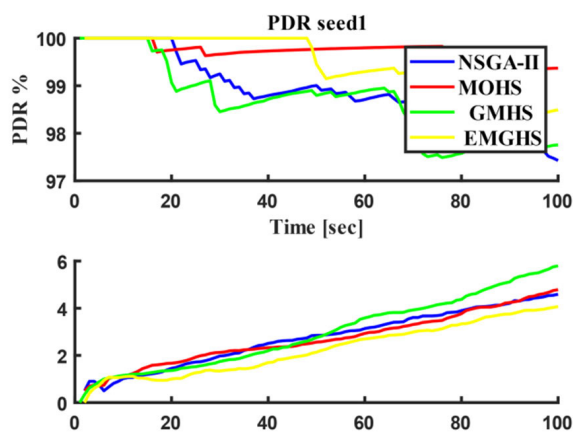
FIGURE 17. Overall E2E delay for solution 5.

FIGURE 18. Time series PDR and E2E delay for solution 1.

the average values, the time series of the metrics are presented in Figures 18 and 19. The results show that EMGHS was capable of maintaining its level of PDR and E2E delay for the entire experiment, compared with the other benchmarks.
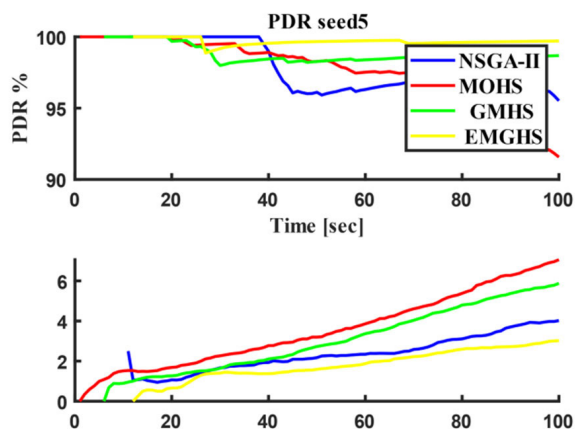
FIGURE 19. Time series PDR and E2E delay for solution 5.

The interpretation was that this occurred because of the more effective search in the solution space conducted by EMGHS, compared with those of the other benchmarks. This was due to the various features that were added to this algorithm, as presented in the previous section.

VII. CONCLUSIONS AND FUTURE WORK

This article has presented a solution to an active research problem in vehicular ad hoc networking, that of finding the best route to send messages towards a destination node. For route selection, many factors, such as E2E delay and packet delivery ratio, contribute to the route quality; this is reflected in the final network metrics. The article has proposed a novel framework, designated as Reliability Aware Multi-Objective Optimization Based VANETs Routing (RAMO). The framework includes three levels: the first is the simulation of the VANET network; the second is the routing criteria, which are based on reliability and geometrics; the third level is the routing algorithm. The next stage is the actual network. Moreover, the framework includes an optimization block that controls the parameters of each of the reliability, geometrical and routing blocks. The optimization is presented from the multi-objective perspective. Considering that the literature on multi-objective meta-heuristic optimization contains a wide range of algorithms, the research developed one of the fastest and most effective algorithms, based on the concept of harmony searching optimization, before incorporating it into the RAMO framework. The development of the multi-objective optimization harmony searching was based on incorporating Gaussian mutation, the management of harmony memory and objective decomposition. The multi-objective harmony searching was designated as Enhanced Gaussian Mutation Harmony Searching (EGMHS). After their development, both EGMHS and RAMO were compared with three benchmarking algorithms, namely traditional multi-objective harmony searching (MOHS), Gaussian mutation harmony searching (GMHS) and the non-dominated sorting genetic algorithm NSGA-II. The new algorithm was evaluated using a nine-function set of multi-objective mathematical functions with a known Pareto front and a highway type VANET environment. The metrics generated included a set coverage for investigating the domination percentages; the relative generational distance; the hyper-volume, for investigating the flexibility of choices for the decision-maker; the number of non-dominated solutions; and the delta metric, which indicated equal distributions of the solutions in the objective space. In addition, the developed EGMHS was incorporated into the RAMO framework and evaluated based on a networking simulator for road types and environments. The results were compared with various optimization benchmarks. The results demonstrate that the new algorithm outperformed the others in terms of both MOO and networking metrics. In terms of MOO metrics, EGMHS could accomplish a higher set coverage than the other approaches, which means providing more dominating solutions. This was consistent with the simulation results, where EGMHS was capable of providing higher PDR and lower E2E delay. This makes it more suitable for VANETs routing. The study contains some limitations. First, it considered routing in a 2D environment; however, many urban areas and cities include 3D road architecture, such as various levels of bridges or tunnels, which require a special type of treatment. In addition, the optimization based on meta-heuristic searching requires a considerable computational capacity to guarantee coverage of a wide range of candidate solutions in the solution space and adequate time for evaluating the generated solutions.

Future work will extend the developed RAMO framework to include a 3D routing optimization, in addition to a 2D-based routing optimization.

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