Evolutionary Algorithm Based Optimized Relay Vehicle Selection in Vehicular Communication

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ABSTRACT
This paper addresses the broadcasting storm problem by proposing an optimized relay vehicle selection methodology in the vehicular ad-hoc networks (VANETs). A crucial effect observed in the broadcasting storm is the network congestion that is caused by multiple retransmissions generated by the relay vehicles to achieve the desired network coverage. In order to address this problem, we propose an optimized relay selection methodology based on multi-objective genetic algorithm (MOGA) consisting of a novel analytical fitness function. In this paper, we present a detailed study of previous research work and identify the gaps to achieve the optimum performance in terms of network coverage time. We introduce a component-based analytical model containing the proposed MOGA to reduce these performance gaps. A dedicated solver was designed using Python to implement the proposed model in both urban and highway environments. The numerical results obtained by the proposed MOGA are compared with the existing techniques. It is shown that the proposed method performs better in terms of number of retransmissions and network coverage time.

INDEX TERMS
VANETs, broadcasting, genetic algorithm, network coverage, probability of neighborhood.

I. INTRODUCTION
A constant increase in the numbers of vehicles on the road over the years have created new research challenges encountered by transport community, such as providing traffic safety, minimizing congestion and road accidents, and reducing pollution [1], [2]. Therefore, organizations that deal with traffic and road safety issues are on constant lookout for innovative ideas to solve these problems. The most important concept introduced in the recent times is to establish a new type of mobile ad-hoc network for vehicles known as Vehicular Ad-hoc Network (VANET) [3]. Distributed and self-organizing communication networks consisting of highly mobile vehicles are classified as VANETs. A VANET system supports all the types of the communication system including broadcasting. The focus of this research is Broadcast Communication (BC) in VANETs due to its importance in providing solutions to challenges, such as traffic jams, accidents, and delays. Broadcasting is a process of communication that disseminates information from a vehicle to all the vehicles in the network, which may be defined by a certain geographical region.

Although BC is capable of solving many of the challenges encountered by the transport community, however Broadcasting Storm Problem (BSP) is one of the many obstacles faced during the deployment of BC in a real-time VANET environment. The BSP is caused due to retransmissions of the same information packet, $P_{info}$, in a network causing congestion and time delays in dissemination of the information [4], [5]. Removing or constraining retransmissions are the two viable strategies to counter BSP. The removing retransmission strategy works successfully in a one-hop environment, where a vehicle can transmit a $P_{info}$ to all the vehicles in the network in a single transmission. On the other hand, this strategy fails in case of a multi-hop environment, where a single transmission can’t achieve dissemination to all the vehicles in the network. In this case, controlling retransmissions is a better strategy due to the fact that retransmissions are required to guarantee network coverage. In the BC, the network coverage of a $P_{info}$ is achieved when it is received by all the vehicles in the network.

VANET environments, in the most cases, are classified as multi-hop environment due to wireless communication capable On-Board Unit (OBU) hardware have limited communication range, which is approximately around 1000m [6]. A VANET network usually consists of a geographical area covering more than 1000m, therefore a vehicle that resides outside 1000m of a transmitting vehicle is unable to receive the transmission. In this case, network coverage is not...
achieved by a single transmission. In order to achieve network coverage, multiple retransmissions of the $P_{\text{info}}$ is required by using Relay Vehicles (RVs). RVs assist in the retransmissions of the initial $P_{\text{info}}$ that has been transmitted by a Source Vehicle (SV). The initial $P_{\text{info}}$ is transmitted by SV, while all other vehicles in the network can be RVs at that time. In addition to this, vehicles can communicate directly to those vehicles that are in their communication range and are referred to as the neighboring vehicles. Moreover, Figure 1 depicts such a multi-hop environment consisting of an SV in zone 1 that transmits initial information, while, among its neighbors, an RV is selected to retransmit the information in the zone 2 and so on.

In a multi-hop environment, RV plays a crucial role in retransmitting initial $P_{\text{info}}$ to achieving the network coverage. All the vehicles in a network are considered to be potential RVs, and in the absence of a suitable relay vehicle selection methodology, all the potential RVs retransmit the received $P_{\text{info}}$. These blind retransmissions instantiate the BSP due to large number of redundant retransmissions. To control retransmissions, it is essential to have an optimized RV selection methodology to counter the BSP. The optimized relay vehicle selection methodology has to be an effective system capable of reducing the number of retransmissions without compromising network coverage. The efficiency of the system is measured with respect to network coverage time, $N_{CT}$, which is the time interval taken by a $P_{\text{info}}$ to achieve the network coverage. To produce optimized RV selection methodology, we have relied on the Multi-Objective Genetic Algorithm (MOGA) and proposed a novel fitness function that uses an analytical engine to produce optimized results and increase number of generations.

In particular, this paper has following main contributions:

• Proposed design of Multi-Objective Genetic Algorithm (MOGA) consisting of a novel fitness function based on an analytical engine to produce an optimized RV selection methodology.

• Presented a detailed analysis of the analytic model for the proposed design.

• More than 42% decrease in the number of retransmissions exhibited by the proposed MOGA in the vehicular mobile environments compared to previous methodology relying on MOGA called Smart Flooding (SF) [7], [8].

• An average decrease of approximately 99% in the network coverage time required by $P_{\text{info}}$ in the proposed MOGA compared to SF.

• Better performance is shown by the proposed MOGA compared to SF in case of production of the number of generations.

• Proposed MOGA also performs better as compared to other contemporary and latest methodologies proposed in the literature, such as AVED, AddP and Smart Flooding (SF) [7]–[10].

The rest of the paper is organized as follows. Section II contains discussion related to previous strategies in literature tackling the BSP. In addition to this, Section III puts forward the design of the proposed MOGA, whereas Section IV describes the analytical model that is utilized in our contribution. Moreover, Section V presents the numerical results and finally, Section VI concludes the paper.

II. LITERATURE REVIEW

This section contains a detailed review of the literature focusing primarily on review and analysis of previous research studies that present solutions capable of mitigating the BSP in the VANET BC systems. In the literature, the techniques employed for the selection process of RVs are categorized into two distinct areas of sender and receiver driven relay selection broadcasting techniques [11], [12]. The Current Transmitting Vehicle (CTV) selects next RV(s) from its neighborhood in sender driven relay selection broadcasting techniques [12], while, every vehicle contains an independent assessment function based on a selection criterion in relay selection broadcasting techniques [11]. This independent assessment function is capable of establishing the feasibility of a vehicle as an RV. A detailed literature review of these techniques is presented in the following subsections.
A. SENDER DRIVEN RELAY SELECTION TECHNIQUES

In this section, we discuss the information and selection criteria for sender driven relay selection techniques presented in the previous studies. The selection process of RV(s) in the CTV depends on the information available about neighboring vehicles. Based on this information, the CTV should select RV(s) that are at the edge of its transmission range or farthest from it. This selection facilitates maximizing the number of vehicles receiving the transmission by the next RV that is not in the neighborhood of the CTV. On the other hand, it minimizes the chance of transmission to be received by the vehicles in the neighborhood of the CTV.

In [9], an Approximate Vehicular Emergency Dissemination (AVED) methodology is proposed for broadcasting emergency messages in a multi-hop highway VANET environment. Position, velocity, and transmission range of the vehicles in the neighborhood of the CTV are used in the proposed RV selection methodology. Global Positioning System (GPS) is used for calculating position and velocity of the vehicles in the AVED methodology. The transmission process of a $P_{\text{info}}$ is facilitated by the beaconing system, which is a part of IEEE 802.11p protocol. Furthermore, all the vehicles maintain a routing table consisting of their velocities, the distance between vehicles and the stability, and ranking of RVs of neighbors. In addition to this, the selection methodology of RV(s) of AVED consists of assigning wait time to all the potential RVs based on the ranking of the vehicles established by CTV. A vehicle that receives the transmission from SV is a potential RV. After expiry of wait time, the potential RV can retransmit the received $P_{\text{info}}$. The ranking of the vehicles is established by sorting the stability calculated for each of the neighboring vehicles in descending order. Whereas, the stability is formally defined as follows:

$$\text{stability} = \frac{D - R}{D} + (1 - \epsilon) \left(1 - \frac{V}{V_{\text{max}}}\right).$$  \hspace{1cm} (1)$$

where $R$ is the maximum transmission range, while $D$ is the distance between the CTV and its neighbor. Moreover, $V$ is the relative velocity between the CTV and its neighbor, whereas $V_{\text{max}}$ is the maximum relative velocity in the scenario. Finally, $\epsilon$ is a constant in the equation.

Additionally, the AVED simulation results presented in the form of $N_{\text{CT}}$ as delay time(s) and retransmission as forwarding count. These results indicate AVED outperforming other methodologies, such as Flooding, Slotted 1-Persistence, and Weighted P-Persistence methodologies. In addition to this, AVED results are produced for a number of vehicle densities between 20 and 100.

In [10], a reliable multi-hop broadcasting protocol called Adaptive data dissemination Protocol (AddP) is proposed to broadcast emergency messages in multiple VANET environments. The relay selection mechanism in AddP is based on local density and distance from neighboring vehicles. The gain calculated by the CTV for all its neighbors is defined as $G$. The vehicle with the highest $G$ is selected as the next RV.

Mathematically, $G$ is defined below:

$$G = w \frac{D}{Th_D} + (w - 1) \frac{S_D}{Th_{S_D}},$$  \hspace{1cm} (2)$$

where $w$ is the weight that determines the influence of distance and local density. During high-density scenarios, distance is given priority over local density. Moreover, $D$ is the Euclidean distance between the CTV and its neighbor, while $Th_D$ is the distance threshold. In addition to this, $S_D$ is the local density of the CTV, whereas $Th_{S_D}$ is the threshold.

Additionally, GPS system is used to establish accurate distance between the CTV and its neighbors. Furthermore, a disseminated messages monitoring mechanism is implemented to detect retransmission by the selected RV. All the vehicles in the network are part of the monitoring system and are going to transmit after a certain waiting period for the select RV to broadcast. The simulation results of AddP consists of both highway and urban scenarios. However, highway scenario involves RSUs and vehicle densities are considered in the form of vehicles per hour. Since our proposed methodology does not include RSU or vehicle flow, therefore these results are not compared and analyzed. On the other hand, urban scenario results are considered due to the fact that there is no deployment of the RSU and vehicle densities are in the form of vehicles in the network. These result of AddP show better efficiency as compared to other methodologies, such as PG, DOT, and TBN methodologies.

In [13], the selection process of an RV by the CTV requires information about neighborhood vehicle density and inter-vehicular space between neighboring vehicles. The calculation of this information is dependent on GPS system used with OBU in every vehicle. The central concept of the selection process is to select an RV that is farthest from the CTV.

In [14], velocity, density, and antenna height of the vehicles are considered in the selection process used by the CTV. It is assumed in the paper that every vehicle knows its position, velocity, and antenna height, which is shared with neighboring vehicles. The selection process is based on backbone-based data dissemination. In addition to this, efficient broadcasting is increased by using intra-flow and inter-flow network coding.

In [15], a reliable broadcasting Routing Based on Gain Prediction (RB-GP) is proposed for all type of broadcasting in a highway VANET environment. The selection process consisting of a gain function, $G$, uses relative speed and coverage differences of the neighboring vehicles. A vehicle with the biggest gain is select by CTV as the next RV. Computationally, $G$ is defined as follows:

$$G = \alpha G_{\text{Direct}} + (1 - \alpha) G_{\text{Indirect}},$$  \hspace{1cm} (3)$$

whereas

$$G_{\text{Indirect}} = \frac{\mu}{\lambda},$$  \hspace{1cm} (4)$$

and

$$G_{\text{Direct}} = \frac{|N_{\tau} - |N_{\delta}|}{|T_{\tau}|}.$$  \hspace{1cm} (5)
where $G_{indirect}$ is indirect gain due to the selection of a neighbor by the CTV and $\mu$ is the position updating period, which is defined as a regular periodic interval. Finally, $\lambda$ is the time a neighboring vehicle may stay in the transmission range of the CTV. On the other hand, $G_{Direct}$ is known as direct gain, which is the ratio of the coverage difference between the CTV and its neighbor to the current transmitting vehicle’s two-hop vehicle set $T_{2h}$. In addition to this, $N_T$ is set of all the neighbors of the CTV and $N_R$ is the set of all the neighbors of the selected neighbor. The goal of RB-GP is to maximize the coverage area and reduce network coverage time.

In [16], Receiver Signal Strength Indicator (RSSI) voting algorithm is used to improve reliable broadcasting in VANETs. The selection of RV in this paper is based on a voting process consisting of votes from all the vehicles in the neighborhood of the CTV. Every vehicle votes for the highest RSSI level vehicle from their neighborhood and the highest voted vehicle is selected as next RV. Furthermore, during the broadcasting process, the CTV selects RV that has the highest votes, while the selected RV, on receiving the transmission, broadcasts the $P_{info}$ immediately.

Research studies proposed in [11], [12], and [17]–[19] also consist of RV(s) selection process that are categorized as sender driven selection technique. All of the research methods proposed in sender driven selection techniques require a number of information parameters to be available to the CTV. These information parameters have to be correct and are usually calculated from the information shared by vehicles in the neighborhood. This calculation requires powerful processors as well as time for actual number crunching depending on the complexity of the proposed analytical engine. In any case, time is an important factor especially for VANETs due to mobility associated with vehicles. The time used by an analytical engine to produce results also changes the network situation over time. Hence, the results are ineffective because they are based on old information and RV selected may no longer be the right candidate or may no longer exist in the current neighborhood of the CTV.

Moreover, among the information needed by the CTV, the vehicle position plays an important part in the selection process. This information is required to be accurate enough for sender driven selection techniques to work effectively. Most of the previous research studies depend on GPS system, which is accurate in the most cases. However, the GPS system is not quite efficient in case of urban environments consisting of high rising buildings.

**B. RECEIVER DRIVEN RELAY SELECTION TECHNIQUES**

An independent selection criterion is part of all the vehicles, considered as potential RVs, in receiver driven relay selection techniques. The independent selection criterion establishes credentials of a vehicle for the purpose of RV selection process. Although the selection criteria are independent, however, there is still a requirement for these vehicles to observe surrounding environment to collect useful information for analysis during the selection process. Therefore, it is important that a proposed methodology establishes a process of observing environment as well as identify relevant information parameters for the selection process. We have categorized these methodologies into following two subsections based on the process of identifying information parameters.

1) **NON - OPTIMIZATION TECHNIQUES**

This section discusses and analyses related to the previous research studies that have proposed non-optimization techniques. A technique lacking optimization criteria to solve broadcasting storm falls under non-optimization techniques. Predefined information parameters are used to replace optimization phase to solve broadcasting storm in the non-optimization techniques. Lack of effectiveness of these techniques can be questioned, however, these techniques can be implemented in a real-time system as compared to optimization techniques due to the difference in system complexities.

In [20], a distributed position-based protocol is proposed for emergency messages broadcasting in VANETs for both highway and urban scenarios. The selection process of multi-hop environments in this proposed model is based on the position, speed as well as the direction of potential RVs from the CTV using GPS. Based on the direction of the potential RV, a flag, $FL$, is set to 1 or −1 to facilitate wait time, $WT$, calculation. A potential RV can retransmit $P_{info}$ after the expiry of $WT$. The $WT$ is determined using following equation:

$$WT = -\frac{D}{R} WT_0 + m(1 - a^{-FL})WT_0,$$

where $D$ is the distance between the CTV and its neighbor, while $a$, $m$ and $WT_0$ are constants consisting of values 1.15, 0.6 and 400 $\mu$s respectively. Finally, $R$ is defined as the communication wireless radius. In addition to this, the simulation results are collected for different vehicle densities and are compared with another methodology known as UV-Cast. However, the parameters of retransmissions and network coverage time are not present in the performance section. Therefore, it is not possible to compare and established efficiency of the proposed methodology.

In [21], an urban broadcast mechanism in VANET environment is proposed based on road layout. It is assumed that road layout information is already available to all the vehicles in the network. The selection process in the proposed methodology is based on the difference of position between the CTV and the potential RV. The goal is to facilitate retransmission by the farthest vehicle from the CTV. Therefore, a Forwarding Timer, $FT$, of a potential RV is determined by inversely proportional to its distance from the CTV. After $FT$ expires, the vehicle can retransmit making it the selected RV. On the other hand, remaining potential RVs terminate retransmission process when they receive the transmission. In addition to $FT$, Intersection Forwarding Timer, $IFT$, is also introduced for vehicles that are either approaching an intersection or at
the vehicle is between $W$. A vehicle establishes its credential as an RV if the vehicle is in the transmission range and approaching intersection, where $IFT_{\max}$ is maximum timer value, while $WT_{\text{MAX}}$ is maximum waiting time. Additionally, $D_{\text{vrc}}$ is the distance from the center of the intersection to the potential RV and $c$ is half of the diagonal length of the intersection area. Due to chances of collisions in the network, the CTV retransmits again if it is unable to receive the transmission from an RV. In addition to this, when the intersection is a possibility, a vehicle will retransmit after $IFT$ expires, if it is unable to receive a transmission from the intersection. It is important to mention that authors does not establish any criteria for the vehicle to calculate its current position. In addition to the previously proposed game theory models, a geographic-based broadcast suppression mechanism suggests the farthest vehicle from the CTV as the next RV. A candidate RV has to independently determine whether it is the farthest to the CTV in the transmission range and assign itself a $WT$. To calculate a $WT$, the proposed analytical engine is required to first calculate a contention window $CW$ using below mentioned formula:

$$CW = \left( \frac{R_{\text{max}} - D}{R_{\text{max}}} \times (CW_{\text{max}} - CW_{\text{min}}) \right) + CW_{\text{min}},$$

(8)

where $R_{\text{max}}$ is maximum transmission range of a vehicle, while $CW_{\text{max}}$ is the maximum value of contention window and $CW_{\text{min}}$ is the lowest value of contention window.

In addition to this, based on $CW$ a random $WT$ is calculated. RV transmits the packet after the expiry of the $WT$.

There are existing research studies to provide solutions for one hop VANET broadcasting scenarios which are not in the scope of this paper due to our focus on the multi-hop environment. Due to our focus on the multi-hop environment, these studies are ignored. In addition to this, a major advantage of the non-optimisation techniques is their capability of being feasible for the implementation in a real-time environment. However, the working of the non-optimization requires accurate information, such as density, speed, and position of the vehicles, for efficient performance. Most of these techniques are dependent on not so reliable GPS, while remaining techniques do not clarify the issue of gathering reliable information. Another problem is the time required by the non-optimization techniques to gather relevant information that has to be further evaluated through a complex analytical process. This issue creates inefficiency due to outdated information caused by the dynamic nature of the VANETs.

2) OPTIMIZATION TECHNIQUES

The BSP is considered an NP-Hard problem in the previous research studies [7], [8]; therefore optimization techniques are used to solve the BSP in the VANETs. In the optimization techniques, information related to the parameters are collected and analyzed with the help of optimization process. Consequently, an optimization phase is introduced in the selection process to evaluate information required for the purpose of providing efficient solutions. This section contains discussion and analysis related to the previous research studies that have proposed optimization techniques.

In [26], an Adaptive Distributed Dissemination (ADD) protocol is proposed to perform efficient data dissemination in the VANETs. It is designed to operate in the urban scenario for diverse road traffic conditions without using roadside infrastructure. The relay selection of ADD is based on two previously proposed game theory models, namely Asymmetric Volunteer’s Dilemma and Forwarding Games. In these game theory models, a $WT$ is assigned to all the potential RVs, which is calculated based on information about roads, intersections as well as physical location, velocity and moving direction of the vehicles. A vehicle can transmit after the expiry of the assigned $WT$, however, a vehicle cancels transmission if it receives the same $P_{\text{info}}$. 

$$IFT = \begin{cases} \frac{WT_{\text{MAX}} \times D_{\text{vrc}}}{c}, & \text{if vehicle is not in intersection} \\ IFT_{\text{max}}, & \text{if interaction within transmission range and approaching intersection,} \end{cases}$$

(7)

where $D_{\text{vrc}}$ is maximum transmission range and $c$ is half of the diagonal length of the intersection area.
In [7] and [8], a Smart Flooding (SF) methodology is proposed to provide solutions to counter the BSP in the VANETs. SF is based on Multi-Objective Genetic Algorithm (MOGA) and consists of three distinct components: evolutionary algorithm, real-time simulator, and log analyzer. The MOGA proposed in the SF initially employs a random function to generate population for first-generation and forwards them to fitness evaluation process. This fitness evaluation process consists of two steps, which are performed by the real-time simulator and log analyzer. In the first step, real-time simulator, such as NS-2 [27], facilitates in evaluates each individual of the population by simulating the solution proposed by that individual and creates log files. While in the second step, log analyzer is employed to extract information from these files to assign a fitness value to each individual and report back the information to the evolutionary algorithm component. After receiving the log files, a reproduction function is called to select best-suited individual for the purpose of reproduction activities to generate next generation. These steps are repeated until the termination criteria are invoked.

The optimization techniques are quite expensive in terms of processing power and time consumed compared to other types of techniques. On the other hand, the results produced by these techniques are far more efficient. Therefore after evaluating a number of techniques proposed in the previous research studies, we decided to propose an optimized technique capable of solving the BSP in both urban and highway environment for all types of information. In addition to this, we also use pattern identification to facilitate implementation of the proposed model in the real-time environment.

**C. GENETIC ALGORITHM IN VANET BROADCASTING**

Genetic Algorithm (GA) is a heuristic search algorithm that is based on the evolutionary computing branch of Artificial Intelligence (AI) [28]. The concept of GA is derived from the biologically evolutionary process of organisms exhibited in nature. The evolutionary process is essential to counter external environmental factors, otherwise organisms are in danger of being extinct. The GA follows similar concepts where external factors are predefined according to the desired problem. In addition to this, a selection criterion is used by both the biological evolutionary process as well as the GA to determine best-suited individual, which are more adapted to survive. A population of an organism is evolved by providing better reproduction or mutation opportunities to these individuals. The biological evolutionary process is open-ended, while the GA always has termination criteria for termination of this process [29]. In addition to this, the parameter of interest with respect to the desired problem are usually encoded in bits. Individual of populations consists of a single variant of these parameters. The first generation is created randomly, while best individuals are selected based on fitness criteria. New individuals of subsequent generations are generated by the exchange of bits between best-selected individuals determined by the fitness criteria. In additions to this, mutation is used to change bits of individuals to introduce diversity into the population to avoid local minima [29].

In VANETs, GA is used to produce optimized RV methodologies/solutions capable of evaluating potential RVs that facilitate in minimizing retransmissions. For this purpose, each individual in the GA is a possible solution to the BSP. Best individuals are capable of achieving network coverage with the minimum number of retransmissions. These individuals are selected to reproduce and create individuals with better-optimized solutions. This process facilitates the GA to produces thousand of permutations of different solutions in the VANETS assisting the search for optimized solutions.

**III. PROPOSED MULTI-OBJECTIVE GENETIC ALGORITHM**

Multi-Objective Genetic Algorithm (MOGA), a variant of GA, is proposed to optimize solutions capable of countering the BSP in the VANETs. The proposed MOGA is shown in figure 2 and related pseudocode is put forward in Algorithm 1. In addition to this, MOGA have been used, instead of the GA, due to its capability of handling more than one objectives/parameters at a time interval. There are two parameters that are optimized by the proposed MOGA, namely number of retransmissions, $N_R$, and network coverage time, $N_{CT}$. The proposed MOGA produces the best configuration of wait time, $WT$, for optimized $N_R$ and $N_{CT}$ for different values of probability of neighborhood, $P_{NC}$. The $WT$ is defined as the time a vehicle waits before retransmitting an information packet, $P_{info}$. While the probability of neighborhood, $P_{NC}$, is determined by all the vehicles, $N_{VP}$, that have received this information, and all the vehicles in the neighborhood, $N_{VH}$, of that vehicle. Mathematically, $P_{NC}$ is

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**Algorithm 1 Pseudocode of MOGA**

1: function MOGA($TTL, V_N, M_{RULES}$)
2:   $\{L_N, L_0, G_X, G_O\} \leftarrow \emptyset$
3:   isTerminate $\leftarrow$ false
4:   $T_M \leftarrow \{L_N, L_0, G_X, G_O, isTerminate\}$
5:   $G_C \leftarrow$ RANDOMGENERATION()
6: while $T_M[\text{isTerminate}] = \text{false}$ do
7:     $f \leftarrow \{G\}$
8:     for $i \leftarrow 0$ to Length of $G_C$ do
9:         $f[i] \leftarrow$ FITNESSFUNC($G_C[i], TTL, V_N$)
10:    end for
11:   $G_S \leftarrow$ SORTSOLUTIONSFUNC($f, G_C$)
12:   $T_M \leftarrow$ TERMINATIONFUNC($f, G_S, T_M$)
13:   $G_C \leftarrow$ REPRODUCEBYCROSSOVERFUNC($G_S$)
14: if $G_N = 10$ then
15:     $G_N \leftarrow -1$
16: else
17:     $G_C \leftarrow$ MUTATIONFUNC($G_C, M_{RULES}$)
18: end if
19: $G_N \leftarrow G_N + 1$
20: end while
21: return $T_M[G_O]$
defined as follows:

\[ P_{NC} := \begin{cases} 0, & \text{if } N_{NP} = 0 \\ 1, & \text{if } N_{VH} = 0 \\ \frac{N_{NP}}{N_{VH}}, & \text{otherwise}, \end{cases} \]  

(9)

where, the \( N_{VH} \) is based on neighborhood databased \( L_{V} \), which is collected by using the beaconing mechanism of IEEE 802.11P. A more detail design, discussion as well as usage of \( L_{V} \) is put forward in Section IV. On the other hand, another parameter required for successful broadcasting is network coverage, \( N_{C} \), which is not handled as an optimization parameter. It is considered as a decision parameter and is implemented by discarding any individuals of a population that is unable to achieve it irrespective of their \( N_{R} \) and \( N_{CT} \).

Moreover, a solution, also called a chromosome, is an individual RV selection methodology in the proposed MOGA comprising of \( WT \). The binary encoding system is used for encoding chromosomes, similar to the previous studies [7], [8]. In addition to this, the values of \( WT \) for 0 and 1 of \( P_{NC} \) are not encoded in chromosomes. Therefore, in the proposed MOGA, a vehicle \( v \) initiates the retransmission process immediately when \( P_{NC} = 0 \). On the other hand, a \( v \) stops transmission if \( P_{NC} = 1 \). Due to predefining of these values, there is no requirement for these two values to be encoded in the chromosome. Following is an example of a chromosome encoding corresponding to the information provided in Table 1.

00000001, 00000001, 00000010, 00000010, 00000011, 00000011, 00000100, 00000100, 00000101

**TABLE 1. An example of chromosome information.**

<table>
<thead>
<tr>
<th>( P_{NC} )</th>
<th>0.1</th>
<th>0.2</th>
<th>0.3</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.7</th>
<th>0.8</th>
<th>0.9</th>
</tr>
</thead>
<tbody>
<tr>
<td>( WT )</td>
<td>1.0</td>
<td>2.0</td>
<td>3.0</td>
<td>4.0</td>
<td>5.0</td>
<td>6.0</td>
<td>7.0</td>
<td>8.0</td>
<td>9.0</td>
</tr>
</tbody>
</table>

Additionally, the proposed MOGA consists of three essential functions, namely fitness, reproduction and termination.

**A. FITNESS FUNCTION**

The quality of an individual RV selection methodology is defined by a fitness value, \( x \), that determines the worth of an individual as a possible solution or a parent for next generation. The fitness function, \( f(x) \), determines \( x \) of all the individuals in a generation and is based on an analytical engine. The analytical engine consists of an iterative evaluation process, which is mathematically defined as following:

\[ f(x) := [N_{R} \ N_{CT}], \]  

(10)

\[ N_{R} := \sum_{i=1}^{N_v} \alpha_i, \]  

(11)

\[ \alpha := \sum_{i=1}^{N_{VH}} \alpha_i, \quad \text{if } TTL - TI > 0 \]

\[ \alpha := \frac{N_{NP}}{N_{VH}}, \quad \text{if } TTL - TI = 0, \]  

(12)

\[ \alpha^d_{II} := V(N_{R}, P_{NC}, WT, TTL, L_{V}, s), \]  

(13)

\[ \alpha^d_{IU} := V(N_{R}, P_{NC}, WT, TTL, L_{V}, M), \]  

(14)

where the \( f(x) \) is a vector consisting of \( N_{CT} \) and \( N_{R} \). In addition to this, \( TTL \) is time to live, which is the period of the lifespan of an \( P_{info} \). Therefore any individual with \( N_{CT} \) greater than \( TTL \) indicates \( N_{C} \) is not achieve.
Moreover, $\alpha$ defines properties of $v$ facilitating in resolving $N_R$ iterative equation. There are two types of $\alpha$ defined in our system namely: $\alpha^d_H$ and $\alpha^d_U$. The $\alpha^d_H$ is used in case of highway scenarios requiring only $s$ parameter, whereas, the $\alpha^d_U$ is used for urban scenario requiring the $M$ defined in equation 16.

### B. REPRODUCTION FUNCTION

The reproduction function, $z(x)$, facilitates the creation of new generations with the help of existing generation. The two independent individual functions, known as mutation function, $mt(x)$, and crossover function, $c(x)$, are parts of the $z(x)$. The $mt(x)$ is defined as a process of mutation to diversify current genetic pool. In the proposed MOGA, the $mt(x)$ selects 10% individual in the current generation randomly and changing their 48 bits from random locations. The mutation values selected for this study is due to the fact that a higher value of mutation rate does not increase the rate of evolution, whereas lowering value slows down this rate.

Moreover, the $c(x)$ is defined as a process of exchanging genetic materials between two individuals to produce better-optimized individuals. The best-optimized individuals, based on minimized $N_{CT}$ and $N_R$ of the individuals of the current generation, are selected to reproduce next generation. The selected individuals swap arbitrary bits from various unique locations to create new individuals during the process of the $c(x)$.

### C. TERMINATION FUNCTION

The proposed MOGA keeps track of an individual that has the best fitness value, $x$, among all individuals of generations. The strategy encoded in this individual is the best-optimized RV selection methodology/solution, which is denoted as $G_O$ and its fitness value is denoted as $G_X$. The global parameters $G_O$ and $G_X$ are compared and replace with local parameters $L_O$ and $L_X$, if $L_X$ is better then $G_X$. In addition to this, when $L_X$ for last 24 hours of $T_H$ is unable to force a change in $G_X$, then the $(x)$ is invoked. The functionality of terminating simulation and recording best possible optimized RV selection methodology/solution at that time is performed by the $t(x)$, which is formally defined as following:

$$t(x) := \begin{cases} 
    \text{True} , & \text{if } T_H = 24, \ L_X > G_X \\
    \text{False} , & \text{otherwise} 
\end{cases} \quad (15)$$

### IV. ANALYTICAL MODEL

The complete model utilized in this paper consists of three distinct components namely: physical, communication and algorithmic. These three components are interrelated with each other and form an integral part of the analytical model as shown in figure 3. The model has been designed to investigate BC strategies for the ad-hoc vehicular network in both urban and highway environments. A detailed discussion regarding the working of these components are provided in following sections:

#### A. PHYSICAL COMPONENT

The physical component is composed of two models known as object and mobility models. Object model facilitates the creation of physical objects, such as roads and vehicles, while mobility model helps in establishing movements of vehicles.

1) OBJECT MODEL

The functionality of object model is related to the creation of physical structures or objects, which are either a road, $\omega$ or a vehicle, $v$. $\omega$ and $v$ are the only two physical structures required for the purpose of this study. Therefore, the object model supports the requirement of the analytical model by creating $\omega_n$ number of roads such that $\omega = 1, \ldots, \omega_n$ as well as $V$ number of vehicles such that $v = 1, \ldots, V$.
2) MOBILITY MODEL

Mobility model facilitates the movement of vehicles within the confines of a road, \( \omega \). For the purpose of movement, each \( v \) in an urban scenario is assigned a set of movement parameters \( M \), whereas a parameter \( s \) representing the speed of a vehicle is introduced in highway scenario. In addition to this, \( M \) also includes \( s \) as well as \( \theta_{rd} \) and \( \theta_{ld} \). The \( \theta_{rd} \) is the distance covered in a straight line after which the \( v \) is allowed to turn right, whenever there exists a possibility of a right turn. On the other hand, the \( \theta_{ld} \) is the distance after which the \( v \) is allowed to turn left, whenever possible. Moreover, in the analytical model, the \( \theta_{ld} \) is given priority over the \( \theta_{rd} \) and the value of the \( s \) ranges between 60 and 100 km/h. Formally \( M \) is defined as follows:

\[
M := \{ s, \theta_{rd}, \theta_{ld} \}.
\]

B. COMMUNICATION COMPONENT

The communication component consists of two communication modules namely: protocol and broadcasting modules. In the proposed model, the protocol module supports communication between vehicles also known as V2V communication, which is the focus of this paper. On the other hand, broadcasting module establishes a system of information broadcasting based on a RV selection methodology/strategy provided by the algorithmic component consisting of the proposed MOGA. Following sections contain a detail discussion related to modules of the communication component.

1) PROTOCOL MODULE (PM)

This module defines the protocol that governs communication in our model. The architecture of the PM is based on IEEE 802.11p protocol that is a wireless protocol standard belonging to the family of IEEE 802 and is created specifically to support mobile vehicular communication networks [30], [31]. There are many different features and protocols contained in IEEE 802.11p making it a dominant protocol in the field of vehicle communication networks. Among these important features, the two most significant features concerning this research are known as Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) and beaconing system [32].

The CSMA/CA perform the functionality of packet collision management, which employs pre-emptive methodologies to avoid data packet collisions [33]. Vehicles attempting to transmit \( P_{info} \) at the same time in a neighborhood are going to cause \( P_{info} \) collision. To avoid such scenario, the CSMA/CA uses a unique transmission process. In this transmission process, a vehicle before transmitting the \( P_{info} \) inspects channel to verify its available for immediate transmission. A channel is available if there are no other transmissions by any other vehicles in the neighborhood. In the case of availability of the channel, the vehicle transmits immediately; otherwise, the vehicle is assigned a random wait time. After expiry of this wait time, the vehicle inspects channel availability to perform transmission or assign wait time due to channel unavailability. The vehicle continues with this process until the completion of the transmission. Due to the existing of the CSMA/CA, which is implemented in our system, we will not consider any other collision avoidance algorithm.

Additionally, the beaconing system is a process consisting of transmitting a packet by every vehicle at a fixed time interval [34], [35]. This facilitates a vehicle in announcing itself to all the vehicles in its neighborhood. The information of this vehicle is recorded in a neighborhood database by each vehicle that receives the transmission. This database is one of the most important information set used in the proposed MOGA to evaluate as well as establish an effective optimized RV selection methodology.

2) BROADCASTING MODULE (BM)

A vehicle consults BM at the start of broadcasting, which provides a wait time \( WT \) different to the wait time of the CSMA/CA. Broadcasting can resume after \( WT \) expires. \( WT \) values are provided by the algorithmic component and are based on the \( P_{NC} \).

C. ALGORITHM COMPONENT

The algorithm component contains an appropriate algorithm to calculate wait time \( WT \). In this study, the algorithm component contains the proposed MOGA put forward in Section III.

V. RESULTS AND ANALYSIS

This section contains results that are collected from simulation models of urban as well as highway environments developed in Python. There are dedicated solvers/applications available for implementing both the VANET scenarios as well as the proposed MOGA. However, to the best of our knowledge, we were not able to find a solver/application that can accommodate implementation of both the proposed MOGA in the VANET environment. In addition to this, in order to keep the computational complexity to an optimum level, simulations are conducted on supercomputer Raijin, located in Canberra, Australia [36]. The machine is equipped with state-of-art Fujitsu high-performance processor and has distributed memory cluster that facilitated in achieving overall lower simulation complexity. Multi and parallel processing is supported by the supercomputer, which is based on Unix system. Additionally, Table 2 put forwards all the simulation parameters, while Table 3 contain all the symbols and notation used in this paper.

Moreover, we conducted several different experiments to verify the analytical concepts discussed in the paper above. The range of vehicle densities is between 5 and 500 vehicles traveling on either highway or urban scenario. The highway scenario consists of 3 lanes comprised of vehicles traveling in only one direction with a safety distance of 70 to 120 meters. On the other hand, urban scenarios consist of six roads connected to each other at different points enabling vehicles to turn left or right. The number and connection of roads with each other are established dynamically. All the roads in the
TABLE 2. Simulation parameters.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulation Area</td>
<td>Variable</td>
</tr>
<tr>
<td>Frequency</td>
<td>5.9 GHz</td>
</tr>
<tr>
<td>Type of Scenarios</td>
<td>Highway and Urban</td>
</tr>
<tr>
<td>Highway Lane</td>
<td>4</td>
</tr>
<tr>
<td>Vehicle Safety Distance</td>
<td>70-120 meters</td>
</tr>
<tr>
<td>Urban Roads</td>
<td>9 different roads</td>
</tr>
<tr>
<td>Vehicle Densities</td>
<td>5, 10, 20, 40, 50, 100, 150, 200, 250, 300 350, 400, 450, 500 vehicles</td>
</tr>
<tr>
<td>Speed(s)</td>
<td>between 60 and 100 km/h</td>
</tr>
<tr>
<td>Protocol</td>
<td>IEEE 802.11p</td>
</tr>
<tr>
<td>Transmission Range</td>
<td>1000m [6]</td>
</tr>
<tr>
<td>Mutation Rate</td>
<td>10%</td>
</tr>
<tr>
<td>Mutating Bits</td>
<td>48</td>
</tr>
<tr>
<td>Mutation Period</td>
<td>10&lt;sup&gt;th&lt;/sup&gt; generation</td>
</tr>
</tbody>
</table>

TABLE 3. Symbols and notations.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>P&lt;sub&gt;info&lt;/sub&gt;</td>
<td>Information Packet</td>
</tr>
<tr>
<td>N&lt;sub&gt;R&lt;/sub&gt;</td>
<td>Number of Retransmissions</td>
</tr>
<tr>
<td>N&lt;sub&gt;CT&lt;/sub&gt;</td>
<td>Network Coverage Time</td>
</tr>
<tr>
<td>N&lt;sub&gt;V&lt;/sub&gt;</td>
<td>Number of Vehicles initiating transmission Packets</td>
</tr>
<tr>
<td>N&lt;sub&gt;C&lt;/sub&gt;</td>
<td>Network Coverage</td>
</tr>
<tr>
<td>f(x)</td>
<td>Fitness Function</td>
</tr>
<tr>
<td>z(x)</td>
<td>Reproduction Function</td>
</tr>
<tr>
<td>t(x)</td>
<td>Terminal Function</td>
</tr>
<tr>
<td>e(x)</td>
<td>Cross-Over Function</td>
</tr>
<tr>
<td>m(x)</td>
<td>Mutation Function</td>
</tr>
<tr>
<td>WT</td>
<td>Wait Time</td>
</tr>
<tr>
<td>AWT</td>
<td>Average Wait Time</td>
</tr>
<tr>
<td>TTL</td>
<td>Time To Live</td>
</tr>
<tr>
<td>P&lt;sub&gt;NC&lt;/sub&gt;</td>
<td>Probability of Neighborhood Coverage</td>
</tr>
<tr>
<td>N&lt;sub&gt;NP&lt;/sub&gt;</td>
<td>Number of vehicles that have received the transmitted packet</td>
</tr>
<tr>
<td>N&lt;sub&gt;VH&lt;/sub&gt;</td>
<td>Number of neighboring vehicles in the neighborhood</td>
</tr>
<tr>
<td>z&lt;sub&gt;1&lt;/sub&gt;</td>
<td>Equation representing highway scenarios</td>
</tr>
<tr>
<td>z&lt;sub&gt;2&lt;/sub&gt;</td>
<td>Equation representing urban scenarios</td>
</tr>
<tr>
<td>M</td>
<td>Set of movement parameters</td>
</tr>
<tr>
<td>L&lt;sub&gt;N&lt;/sub&gt;</td>
<td>Set of Neighborhood Vehicles</td>
</tr>
<tr>
<td>G&lt;sub&gt;O&lt;/sub&gt;</td>
<td>Best optimized solution</td>
</tr>
<tr>
<td>G&lt;sub&gt;X&lt;/sub&gt;</td>
<td>Fitness of the best optimized solution</td>
</tr>
<tr>
<td>L&lt;sub&gt;O&lt;/sub&gt;</td>
<td>Best local optimized solution</td>
</tr>
<tr>
<td>L&lt;sub&gt;X&lt;/sub&gt;</td>
<td>Fitness of the best local optimized solution</td>
</tr>
<tr>
<td>T&lt;sub&gt;H&lt;/sub&gt;</td>
<td>Simulation time</td>
</tr>
<tr>
<td>M&lt;sub&gt;R&lt;/sub&gt;</td>
<td>Mutation rules</td>
</tr>
<tr>
<td>V&lt;sub&gt;N&lt;/sub&gt;</td>
<td>Vehicle density</td>
</tr>
<tr>
<td>d&lt;sub&gt;1&lt;/sub&gt;</td>
<td>Distance covered in a straight line after which v is allowed to turn right</td>
</tr>
<tr>
<td>d&lt;sub&gt;2&lt;/sub&gt;</td>
<td>Distance covered in a straight line after which v is allowed to turn left</td>
</tr>
<tr>
<td>G&lt;sub&gt;C&lt;/sub&gt;</td>
<td>Current generation</td>
</tr>
<tr>
<td>G&lt;sub&gt;N&lt;/sub&gt;</td>
<td>Generation number</td>
</tr>
<tr>
<td>M&lt;sub&gt;RULES&lt;/sub&gt;</td>
<td>Mutation Rules</td>
</tr>
<tr>
<td>V&lt;sub&gt;N&lt;/sub&gt;</td>
<td>Total number of vehicles</td>
</tr>
</tbody>
</table>

urban scenario have two lanes occupied by vehicles traveling in opposite directions.

Additionally, each of the seven experiments consists of a source vehicle that initiates the process of retransmitting by transmitting initial P<sub>info</sub>. The neighboring vehicles receiving the P<sub>info</sub> from the source calculate WT based on P<sub>NC</sub> and retransmit when their WT expires. The process of retransmission continues until TTL of the P<sub>info</sub> is expired, or N<sub>C</sub> is achieved. The results of these experiments are presented in following subsections:

A. NUMBER OF RETRANSMISSIONS

In the first experiment, we explore the number of retransmissions exhibited by the optimized solutions produced from the proposed MOGA and compare it with SF, AVED, AddP and [21]. The experiments of MOGA for each vehicle density are repeated at least ten times. The average number of retransmissions for different vehicle densities are compared with existing techniques, and shown in Figure 4. For detail individual discussions of the simulation environment, Figure 4 is divided into following two scenarios:

1) HIGHWAY SCENARIO

The optimized solutions of the proposed MOGA in the highway scenario are compared with the SF and the AVED. In case of the SF, 50 vehicles are used with an inter-vehicle distance of 100m on highway scenario with 15 generations to produce the resultant number of retransmissions [7], [8]. On the other hand, AVED produces approximately five number of retransmissions for 20 to 100 vehicles in 1km area, therefore it can be deduced that AVED produces five transmissions per km. Based on this assumption as well as the inter-vehicle distance of about 90m, we recalculated and obtained results show in Figure 4.

The results show that the proposed MOGA performs better for 50 vehicles as compared to the SF. The SF produces about 85 retransmissions, while the proposed MOGA produce an average of 13.29 retransmissions. Due to the fact that the SF does not implement the CSMA/CA, a RV has to retransmit more than once for successful transmission; therefore the number of retransmissions are quite high. Even when we implement CSMA/CA in the SF, it would require approximately 24 retransmissions to obtained the required network coverage, which is still higher compared to the proposed MOGA. The number of retransmissions calculated in
the previous statement for the SF is based on our understanding that on average a vehicle transmits at least three times in a retransmission process of a $P_{\text{info}}$.

Moreover, the AVED methodology uses IEEE 802.11p protocol, therefore it employs the CSMA/CA. The performance of the proposed MOGA is also better than AVED. In case of 100 vehicles on the road with an inter-vehicle distance of 900 meters, the AVED requires 45 retransmissions, while the proposed MOGA requires an average of 32.9 retransmissions to achieve the network coverage. In case of 450 vehicles, the AVED requires 205 retransmissions, on the other hand, the proposed MOGA needs 160 retransmissions. The proposed MOGA and the AVED use similar approaches, however, the AVED does not use an optimization algorithm to optimize its parameters, causing it to be outperformed by the proposed MOGA.

2) URBAN SCENARIO

The optimized solutions of the proposed MOGA in the urban scenarios are compared with SF, AddP and [21]. In case of the SF, 134 vehicles are used with an inter-vehicle distance of 100m in an urban scenario with 15 generations to produce the resultant retransmissions [7], [8]. On the other hand, the AddP contained results for 50 to 600 vehicles in an urban environment, while the [21] consists of simulation scenario of 2000 vehicles at 43.2 vehicles per km with speed of each vehicle between 20 and 30 km/h. Therefore we calculated transmissions based on vehicles per km for 500 vehicles.

The results show better performance related to the number of retransmissions of optimized solutions produced by the proposed MOGA compared with the SF for 134 vehicles. The proposed MOGA produces 24.5 transmissions, while the SF produces 80 retransmissions. In addition to this, if we take into consideration the implementation of the CSMA/CA in the SF, the numbers of retransmissions are reduced to 23.34 depending upon the fact that all vehicle in SF retransmits at least three times as a prerequisite to achieving network coverage. The SF, in this case, performs a little better, however, that result is based on the assumptions.

Moreover, the results depicted by AddP show that the number of retransmissions is significantly higher as compared to the proposed MOGA retransmission. The AddP also uses the CSMA/CA of IEEE 802.11p protocol; therefore the considerably higher values could be attributed to the formula for calculating $V$ as well as lack of deploying optimization techniques. In addition to this, [21] produced approximately 61.5 retransmissions for 450 vehicles, while the proposed MOGA produces an average of 53.7 retransmissions. The difference in the number of retransmissions can be attributed to the lack of using optimization technique.

Additionally, the results show variation in the number of retransmissions generated by the proposed MOGA for urban and highway scenarios. These variations are attributed to the number of vehicles per km$^2$ indicating that there are more vehicles in the transmission range of a vehicle in an urban scenario as compared to a highway scenario. Therefore a single transmission in the urban scenario can cover a larger region and a higher number of vehicles as compared to the highway scenario. This effect causes better performance of the proposed MOGA optimized solutions in the urban scenario as compared to the highway scenario.

B. NETWORK COVERAGE TIME

The second phase of experiments investigates network coverage time of the proposed MOGA in highway and urban scenarios as well as comparing them with other methodologies shown in Figure 5. The results are divided into two scenarios, namely highway, and urban scenarios, which are discussed below:

1) HIGHWAY SCENARIO

The network coverage time, $N_{CT}$, of the proposed MOGA in highway scenarios are compared with AVED. Due to the fact that the network coverage time results in Figure 4 of SF are of urban scenarios only, we are unable to compare it with the proposed MOGA optimized solutions of highway scenarios. On the other hand, the AVED results are calculated and reproduced based on the fact that it takes 30ms for the propagation of $P_{\text{info}}$ inside a 1km area with a safety distance of 20m irrespective of vehicle density. The calculation required a change in safety distance to 90m, which is an average safety distance in the highway scenarios of the proposed MOGA.

The implementation of IEEE 802.11p and the criteria set forward for selecting RV consists of similar parameters for both AVED and the proposed MOGA, however, the results show a significant difference of $N_{CT}$ between both methodologies. The primary reason for this difference is due to the lack of deployment of optimization techniques in AVED.
2) URBAN SCENARIO
The results of urban scenarios of the proposed MOGA with respect to $N_{CT}$ are compared with SF, AddP, and [21]. The $N_{CT}$ of SF is collected for vehicle densities of 50, 134 and 350. Due to the higher values of $N_{CT}$, we had to create a right side margin. In the absence of the right margin, the differences in $N_{CT}$ of the other methodologies of AddP and [21] could not be clearly viewable. In addition to this, the analytical analysis is used to produce [21] results of $N_{CT}$ for 450 vehicles.

The results depict a significant difference between $N_{CT}$ of the SF and the proposed MOGA in urban scenarios. The multiple transmission combined with continues blind transmissions until the TTL of the packet expires caused the SF to exhibit higher values of $N_{CT}$. The availability of neighborhood information facilitates the proposed MOGA to limit its transmissions giving other vehicles time to retransmit the same $P_{info}$. The availability of the opportunity to retransmission for a vehicle in a VANET system is essential for the reduction in the $N_{CT}$ and achieving the network coverage. Similarly, the proposed MOGA show significantly better performance when compared to AddP and [21]. Primarily unavailability of the optimization techniques in AddP and [21] provides an edge to the proposed MOGA.

C. GENERATIONS
In this experiment, an illustration as well as comparison are presented for the number of generations produced by the evolutionary algorithms, namely the proposed MOGA and the SF. The evolutionary nature of these algorithms dictates an evolutionary process producing a number of generations to come up with the best-suited individuals for the prevailing environmental conditions. The fitness criteria of the SF is dependent on NS2 simulator, which increases overall the complexity of the system. Hence, the complexity of the system has a direct relationship with reproduction cycle, therefore, an increase in complexity also increases the time for producing a new generation. Due to the complexity of the SF fitness engine, the optimized solutions collected by only 15 generations. On the other hand, the methodology used in the proposed MOGA consists of the analytic engine for fitness function, which decreases complexity. The decrease in complexity helps in generating greater numbers of generations to obtain better-optimized solutions as shown in Figure 6. The effect of the number of generations is observable on the difference in the results of the number of retransmissions and network coverage time of the proposed MOGA and the SF.

D. AVERAGE WAIT TIME
Moreover, the number of generations produced by the proposed MOGA in highways and urban scenarios should have few minor difference. However, this assumption is not supported by the results collected for both of the scenarios. The primary reason for the difference in results is due to varying simulation complexities of the scenarios. The simulation
The complexity of urban scenarios is higher compared to highway scenarios owing to increase in the number of parameters, such as $\theta_{rd}$ and $\theta_{ld}$. However, the complexity of highway and urban scenarios come close to each other with the increase of vehicles, consequently showing minor differing in the number of generations.

The complexity of the proposed MOGA is very high, therefore it is not possible for it to be deployed in the real-time environment with currently available computing resources. To implement the resultant optimized solutions in real-time VANET environments, we are required to identify and understand patterns in these solutions. In this experiment, we have put forward average wait time, $AWT$, of both highway and urban scenarios in Figure 7. The results illustrate the close association of data against the $P_{NC}$. The close association of data indicates the fact that although the number of vehicles per square meter is different, the values of $AWT$ produces minor fluctuations in the $N_{CT}$ and $N_{R}$ in both scenarios. For the purpose of further experiments to establish the applicability of $AWT$ and to avoid confusion, we have to name $AWT$ of highway and urban environments as strategy $S_1$ and strategy $S_2$ respectively.

### E. IMPLEMENTATION OF STRATEGIES IN HIGHWAY SCENARIO

This experiment consists of applying the $AWT$ with respect to the $P_{NC}$ of strategies $S_1$ and $S_2$ to highway scenarios. The results showing $N_{R}$ as well as $N_{CT}$ are shown in Figure 8 and 9 respectively. It can be seen from both of the figures that there are minor differences between the average highway
results of the optimization techniques produced from the proposed MOGA and, strategies $S_1$ and $S_2$. In addition to this, the results produced by both of the strategies are very closely related suggesting any of the strategies can be used for the urban environment, hence eliminating the need to identify the urban environment.

The similarity of the results for both the strategies $S_1$ and $S_2$ is attributed to the fact that there can be more than one optimized strategies available in the search domain of the solutions. Hence, it is not unusual for the proposed MOGA to find solutions capable of satisfying multiple optimized parameters for different environments, such as urban and highway environments in our case. Moreover, we conclude that the results of the strategies $S_1$ and $S_2$ in both the urban and highway scenarios have minor differences when compared with each other or with optimizes solutions produced by the proposed MOGA. Therefore, a broadcasting system can use in real-time either one of the strategies without employing any criteria for detecting the type of VANET environment and vehicle density of the network.

VI. CONCLUSION
In this paper, we have proposed a Multi-Objective Genetic Algorithm (MOGA) consisting of novel fitness function based on the analytic engine to produce optimized relay vehicle selection methodology countering the BSP in VANETs. In addition to this, we designed and developed an analytical model composed of different components to implement optimized RV selection methodology solutions produced by the proposed MOGA. Moreover, a detailed study of the previous research work investigating the BSP is discussed, analyzed and categorized based on the type of solutions proposed RV selection methodology. Moreover, the analytical model is implemented using Python in highway and urban scenarios for different vehicle densities. These results are compared with other latest methodologies, such as SF and AVED, which reveal significant improvements in terms of reducing the number of retransmissions as well as the network coverage time. Overall the proposed model based on MOGA produces a higher number of generations, therefore, increasing the process of evolution and in-turn producing better-optimized results. In addition to this, the results also showed average wait times produced in both highway and urban scenario are applicable to each other producing similar number of retransmissions and network coverage times for various vehicle densities. Consequently, paving the way towards a global solution that can be applied in real time situation without the need of invoking the proposed MOGA. The future work of this study will be extended to multiple source vehicles transmitting various $P_{info}$ in the same time interval.

REFERENCES


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