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MULTI-OBJECTIVE RAINFALL DROP RESOURCE OPTIMIZED CENSOR REGRESSIVE LOAD BALANCING FOR DATA COMMUNICATION IN VANET

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ABSTRACT:
VANETs are mobile wireless networks anywhere nodes are vehicles. It is to permit vehicles to converse with all others. A car must transmit its data to other vehicles which requires enough resources to improve communication. During communication, load balancing is defined as the process of distributing the network traffic across multiple servers. Issue of load blockage frequently happens at minimum bandwidth resulting in increased latency, reduced missing packet rates, and increased battery power consumption. Method Used: A novel technique called a Multi-Objective Rainfall Drop Resource Optimized Censor Regressive Load Balancing (MODEL) technique is developed in VANET. The MORDEL includes two different processes namely multi-objective gradient Elitist rainfall drop optimization and Shapiro–Wilk test censored regression. First, the numbers of vehicle nodes are disseminated in a wireless network. Then optimization process is carried out to select resource efficient node for load balancing. The optimization process starts with an initial population of raindrops. After the initialization, the movement of water drops created through rainfall is identified to optimize the fitness function based on multi-objective functions. It are related to resource of vehicle nodes such as energy as well as bandwidth. Then, vehicle nodes by enhanced residual energy and bandwidth are chosen as optimal vehicle nodes for load-balanced data transmission in the VANET. With the selected optimal vehicle nodes, Shapiro–Wilk test censored regression is applied to find the load of each node. In the regression analysis, the dependent variable (i.e. load of the vehicle node) is censored above or below a certain threshold. As a result, the lesser load and higher load capacity of the vehicle nodes are identified. After that, the heavily loaded vehicle node transmits its load to the nearest lesser-loaded vehicle node for minimizing the delay and loss of data transmission. The Manhattan distance measure is used to find the nearest lesser-loaded vehicle node. Resource-efficient load-balanced data transmission is carried out in VANET Results Achieved: Simulation of the proposed MORDEL technique is implemented through various performance metrics with respect to number of data packets and vehicle nodes. MORDEL technique improved packet delivery by 17%, throughput by 28% and reduces end-to-end delay by 17% ,packet loss ratio by36% when compared to other existing load balanced techniques in VANET. Conclusion: Analyzed outcomes indicate which proposed MORDEL method improves performance of packet delivery ratio and minimum loss rate when compared to conventional works.

KEYWORDS
VANET, Load Balancing, multi-objective gradient Elitist rainfall drop optimization, Shapiro–Wilk test censored regression, Manhattan distance.

1.INTRODUCTION

VANET network is pretended of vehicle nodes communicated with no some framework. Due to mobility of vehicle nodes, restricted energy reserves and so on for efficiently delivering data between vehicles and infrastructure are demands of this kind of VANET network. V2V and V2I data communication is carried out with large number of applications for providing wide range of information to drivers. Different sensors as well as GPS receivers funding vehicles to collect, to procedure and to propagate data regarding itself and their surroundings to other vehicles at close propinquity.

During the data transmission, Load balancing is referred as process of transferring information packets among nodes. Energy-aware load balancing process is carried out to balance the load in VANET with minimum energy consumption. Many researchers carried out their research on energy-efficient load balancing in VANET.Vehicular adhoc networks (VANETs) are sub-part of MANETs. Major limitations of VANET are lost of framework as well as restricted communications assortment. VANET contain different difference in research region. The main challenges of VANET are scalability, vehicle mobility, frequent connection failures, frequent network topology variation, and distributed architecture with heterogeneous devices.

Motivation: Recently with the massive growth in the volume of vehicular traffic, interest in research on Vehicular Ad hoc Networks (VANETs) has grown rapidly. VANETs may serve a wide range of applications, from infotainment to traffic safety. VANETs are basically self-organized distributed networks formed by vehicles moving on the road. The typical architec-ture of VANET, comprises of continuously moving vehicles which communicate with each other and with the stable and fixed Road Side Units (RSUs) along the road. Each and every vehicle on the road is well equipped with in-built radio devices which are known as On-Board Units (OBUs) for vehicle-to-vehicle or vehicle-to-RU communication. Vehicles can serve as nodes with the roadside unit as a gateway [1], [2] to the outer world, such as the Internet or cloud. In many applications, such as patrolling the highways, or mobile surveillance etc., nodes may use various sensors to collect ground data at regular intervals, and the data should be uploaded to the RSU Recently with the massive growth in the volume of vehicular traffic, interest in research on Vehicular Ad hoc

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VANET is a wireless network to provide communication between vehicles. VANETs act a significant role in wireless communication between vehicles to emphasize driver security on the road. Owing to vehicle elevated mobility, VANETs contain elevated topological alter that result at network disconnection. Vehicles functioned as intelligent machines containing sensors, actuators and so on. RSUs are predetermined units used to give uninterrupted service to poignant vehicles.

Objective:

During the data communication in VANET, issue of load congestion happens at minimum bandwidth. The lesser bandwidth causes higher latency. Consequently, it is essential to balance load among vehicles. The major use of load balancing is to distract the information traffic as of high-congestion nodes to low-congestion ones. Load balancing is carried out depend on latency, or in hybrid method. In order to achieve load-balanced data distribution, a novel MORDEL technique is developed. Major aim of the article to perform efficient load balanced data communication in VANET with higher throughput and packet delivery ratio.

Contribution:

- To enhance efficiency of information transmission in VANET, MORDEL technique is developed depend on optimal resource-efficient node selection and load balancing.
- A multi-objective gradient Elitist rainfall drop optimization is applied to a MORDEL technique for selecting the resource-optimal vehicle nodes. The optimization technique includes energy and bandwidth resource parameters. Then the gradient ascent function is applied to a fitness function. Then the Elitist strategy is also applied to selecting the active vehicle nodes based on fitness.
- Then Shapiro–Wilk test censored regression is applied for analyzing the load capacity of the vehicle nodes with a certain threshold. Based on the analysis, the lesser loaded vehicle node receives the data packets from the nearest heavily loaded node by using the Manhattan distance measure. This helps to enhance packet delivery ratio and reduce delay.

Overview of manuscript Organization:

Structure of article is organized as follows. Section 2 provides related works. Section 3 briefly explains MORDEL method with neat diagram. Section 4 provides information on the simulation settings andoutcomes of different metrics. Section 5 describes outcomes with limitations. At last, section 6 summarizes paper.

2.Related works

A Modified Social Spider Optimization (M-SSO) algorithm was designed in [1] to improve data transmission. The designed algorithm increases the throughput but load balancing aware transmission was not performed to further enhance the delivery ratio with lesser delay. A Hybrid Genetic Fire Fly Algorithm-based Routing Protocol (HGFA) was developed in [2] to enhance the communication for both sparse and dense networks. But the efficient optimization technique was not implemented for considering the multiple objective functions to enhance resource-efficient data communication.

Hybrid optimization algorithm called ACO-ABC was developed [3] for energy-aware load balancing of data transmission. But packet delivery was not enhanced. Integration of an ensemble machine learning and hybrid metaheuristic algorithm was introduced in [4] to minimize the latency of data broadcast. However, designed metaheuristic method failed to solve multi-objective problem. RAMO was developed in [5] to improve packet delivery ratio. However higher throughput was not attained.

An Efficient Clustering Routing approach and PSO algorithm were designed [6] to improve routing efficiency. But it failed to accommodate complex traffic models. A reliable routing decision scheme was introduced in [7] for data transmission and routing optimization. But it failed to apply the large and more realistic network environment. It was not also employed machine learning to implement an optimization strategy for VANETs.

Clustering method depend on MFO was developed [8] to improve communication efficiency. However, new evolutionary algorithm failed to obtain the optimal solution. An adaptive jumping multi-objective firefly algorithm was designed in [9] for improving data transmission with lesser delay. But it failed to handle data dissemination in various urgent scenarios. A slow heat-based glowworm swarm optimization and simulated annealing (SA-GSO) algorithm was developed in [10] for VANET. However energy-optimal load-balanced routing was not achieved.

Multi-Objective Harris Hawks Optimization method was developed [11] for selecting efficient forwarding node among the source and destination. But, it failed to minimize computational complexity. A multiobjective firefly algorithm was designed [12] to enhance data delivery. But, execution time was not reduced as the number of nodes increases. A Hybrid Enhanced Glowworm Swarm Optimization (HEGSO) algorithm was developed in [13] for traffic-aware data communication. But it failed to consider more traffic parameters.

Weighted Geographical Routing (W-GeoR) was developed in [14] for VANET's healthcare analysis by selecting the next-hop node to improve data dissemination. But the hop delay was not minimized. Different VANET routing protocols were introduced in [15] to perform data transmission. But the dynamic routing protocol was not employed for solving the issues like mobility models, and network performance metrics.

EE-FMDRP was designed in [16]. But efficient message broadcasting in VANET was a challenging issue. An ANFC and QGSOR was presented [17] to choose finest route for transmission. But network throughput was not improved.

ROAONC method was designed in [18] for reliable information transmission. But it failed to apply the heterogeneous modes of implementation. An Intelligent Harris Hawks Optimization-based clustering was developed in [19] for VANET communication. A decision tree-based classifications algorithm was designed [20] to predict the most appropriate path for information transmission. But the algorithm was not included purely machine learning-based routing to improve information transmission. Efficient data dissemination model was designed [21] for V2I communication without imposing delay tolerance. However, the designed model failed to improve the network throughput.

Effective safety message dissemination system was designed in [22] for urban environments. Designed scheme minimized packet loss through efficient cluster management. Though packet loss was reduced, the time complexity was not minimized by designed scheme. The traffic congestion control algorithm was designed in [23] to address the network utility optimization problem with different network parameters. The designed approach minimized the computational load among the flying nodes. Though computational load was minimized, the cost was not reduced. RSU load-balancing problem was addressed in [24] where whole network partitioned into sub-regions depending on locations. RSU presented Internet access for vehicles in to adopt load migration. But, the computational load was not minimized.

Inter-RSU scheduling method was designed in [25] for load-balancing mechanism based on Smart Requests to enhance network result of VFNs. But, computational complexity was not minimized. Scheduler model was introduced in [26]. The regional security was improved with efficient load balancing. The ground breaking approach was designed in [27] to improve real-time data transmission services in VANETs. But, the transmission delay was not reduced. Vehicle clustering method was designed [28] to improve network scalability and connection reliability that organized vehicle groups in VANET. Though reliability was improved, computational cost was not decreased.

Hybrid optimization method called ACO-ABC was designed [29]. But, the communication overhead was not minimized by ACO-ABC. Dynamic Clustering Mechanism with Load-Balancing was used in [30] to support data packets dissemination in FANETs for increasing the reliability and scalability factor. But, the complexity level was not reduced by designed mechanism.

Vehicular Edge Computing (VEC) Algorithm was designed in [31] with network slicing and load-balancing depending on resources utilization for task offloading from vehicles to edge nodes. However, the delay was not reduced by VEC algorithm. The knowledge defined network was used in [32] to forecast the vehicles topology to identify multiple offloading paths and to minimize costs of identified paths. Though cost was minimized, the communication overhead was not minimized. A batch verification scheme was designed in [33] to improve the messages verification efficiency. An assisted nodes selection algorithm was used to choose the suitable vehicles for parallel verification.

Multi-parameter Fuzzy Logic Resource Management was introduced in [34]. But, the complexity level was not minimized. LB-OPAR was designed in [35] to stability network load as well as to optimize network performance. However, computational cost was not minimized. VANETomo was designed in [36] with statistical Network Tomography (NT) to minimize the transmission delays on link between vehicles from connected nodes. NT joined open and closed loops for efficient congestion control in VANET. But, the computational complexity was not minimized by NT.

Kalman filter prediction scheme was introduced in [37] to determine vehicle next position. Mobile Edge Computing (MEC)-based method was designed in [38] to address the V2V2I

VANET offloading issues. Every vehicle reported information to MEC server periodically depending on centralized computing model. A bandwidth estimation strategy was designed in [39] depending on normalized throughput of link. The interference and packet loss ratio was reduced for hybrid network of VANET. But, the throughput was not increased by designed strategy. SURF channel selection strategy was designed in [40] to recognize appropriate channel as of obtainable options.

STALB routing protocol was designed [41]. It minimized end-to-end latency. But, time complexity was not minimized by STALB protocol. An approximation algorithm was introduced in [42] through tasks offloading in vehicle with maximum load to the vehicle. The adjustment strategy was employed to minimize the load. The hierarchical geography routing protocol was designed in [43] with multiple small grids consistent with geographical location.

Real-time anomaly detection system was introduced in [44] with parallel data processing for data processing. The designed system determined the vehicle density for each section for traffic management. SCRP was designed in [45]. The nodes allocated weights to road sector depending on delay and connectivity. TRADING method was introduced in [46] for big traffic data centric. CRFA to prevent such issues was designed in [47] to determine the traffic depends on traffic condition. However, computational cost was not reduced by CRFA.

A ground breaking approach was designed in [48] for enhancing real-time data transmission services in VANETs. However, computational complexity was not minimized. N-channel MMEE routing method was designed [49] on prognostic energy utilization per packet. A new vehicular architecture was employed in [50] with Software-Defined networks and fog computing. An energy- and QoS-aware routing technique performed excessive dissemination control of data traffic across networks.

The issues identified from the above literature are higher delay, higher packet loss ratio, higher computational complexity, higher computational overhead, higher computational cost, higher traffic congestion, lesser delivery ratio, higher hop cost and so on. In order to address these issues, an efficient technique called MORDEL is introduced for efficient load balancing in VANET.

3.Methodology

The term Vehicular Ad-hoc Networks (VANETs) refers to vehicles in urban surroundings that is associated to every last wirelessly for communication and coordination among each other. VANET is a promising set of wireless networks that offer effective communication among vehicles as well as between vehicles and RSU. It is network of poignant vehicles, in this network moving vehicles can communicate and distribute information between others moving vehicles. Major aspire of VANET is give appropriate communication.

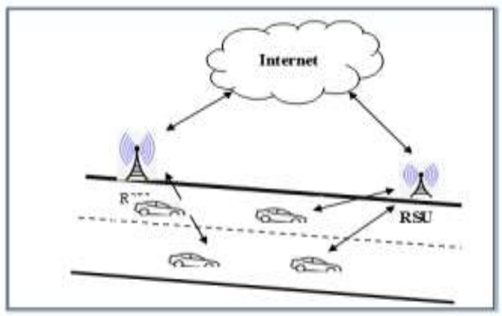

Figure 1. VANETs communication

Figure 1 illustrates that VANET's communication refers to network produced at ad-hoc method anywhere dissimilar moving vehicles as well as last connecting vehicles distribute helpful data to one another. This architecture incorporates wireless network components with roadside units and vehicles to facilitate communication. The VANETs include gathering of sensors installed in every vehicle to collect as well as procedure the information. In VANET, two communications take place for V2V and V2I.

V2V Communication is called inter-vehicle communication. Collection of vehicles connected with one another. V2I Communication: Number of RSU is positioned to provide the ability to upload or download data from or to the vehicles. RSU gathers traffic information as of a fixed sensing region beside road as well as broadcasts information.

System model of MORDEL method is presented. Let us consider the VANET indicated through '$G = (v, e)$' where'v' indicates a number of vehicle nodes $Vn_1, Vn_2, Vn_3, \ldots, Vn_n$ and 'e' represents the edges. Then, vehicle nodes with superior RE as well as higher BW are chosen as best for load-balanced data broadcast in VANET. The source vehicle node (Sn) routes the data packets $DP_i = Dp_1, Dp_2, Dp_2, \ldots, Dp_n$ to the destination node (Dn) through optimal nodes$Nn_i = Nn_1, Nn_2, \ldots, Nn_n$.

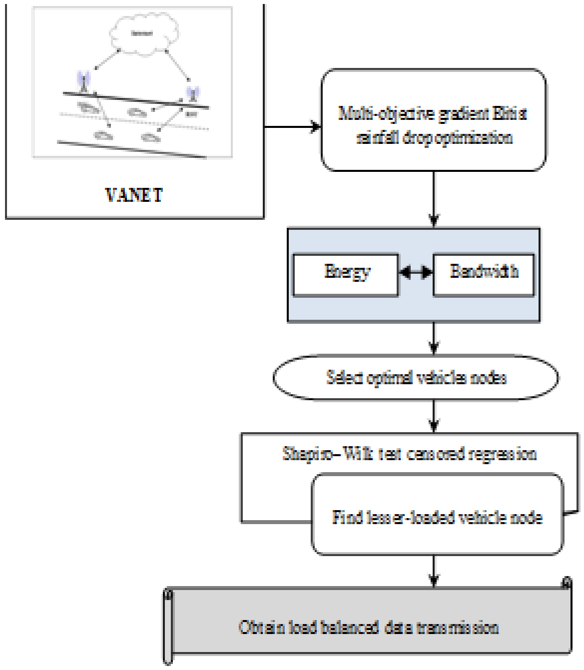

Figure 2 structural design diagram of the MORDEL method

Figure 2 depicts an architecture diagram of MORDEL technique to enhance load-balanced data transmission. Proposed MORDEL technique consists of two major processes to improve the data transmission such as Multi-objective gradient Elitist rainfall drop optimization and Shapiro–Wilk test censored regression. First, the Multi-objective gradient Elitist rainfall drop optimization technique is implemented into the MORDEL technique to select the optimal node depend on resources. Based on resource estimation of the vehicle nodes, an optimal node is determined.

Secondly, the Shapiro–Wilk test censored regression is applied in MORDEL technique for analyzing the load for each optimal vehicle nodes. Censored regression is ML technique employed to measure relationship among dependent variables. In regression analysis, the dependent variable (i.e. load of the vehicle nodes) is censored above or below a certain threshold. The load of vehicle node is calculated based on number of data that the node carries. As a result, the higher load capacity of the vehicle nodes is identified to perform data transmission for minimizing the delay and loss.

These two processes of MORDEL technique is briefly described in the following subsections

3.1 Multi-Objective Gradient Ascent Rainfall Drop optimization

The first process of the MORDEL technique is the Multi-Objective Rainfall Drop optimization for choosing resource-efficient vehicle nodes at network. RFO is a nature-inspired metaheuristic optimization method and it worked on the basis of raindrop behavior. The behavior of raindrops is the falling from a hill or peak and always reaching the lowest land points or valleys into the sea. Here, the raindrops are related to amount of vehicle nodes at network. Proposed optimization technique solves the multi-objective functions through fitness estimation. The multi-objective functions are related to the resource of the vehicle nodes such as energy and bandwidth. The fitness function is estimated for every vehicle node with help of energy and bandwidth value. Then, the vehicle nodes with superior RE as well as higher BW selected as optimal vehicle nodes for load-balanced data transmission in the VANET.

The Multi-Objective Rainfall Drop optimization process starts with an initial population of raindrops. Here, the raindrops are related to number of vehicle nodes at network.

$$Vn_i = Vn_1, Vn_2, Vn_3, \ldots., Vn_n \qquad (1)$$

Where, Vn_i indicates number of vehicle nodes. After the population initialization, progress of water drops created during the rainfall is determined to optimize fitness function. On other hand, the inactive raindrops weaken the searching process and it is removed throughout the iterative process. The active and inactive raindrops are identified through fitness estimation. Fitness is type of objective function which designed for specific issue through including a set of metrics to discover required solution.

Here, the fitness is estimated based on two types of resources such as energy and bandwidth.

$$R_i = E_i^{Res} + Bw_i^{avail} \quad (2)$$

Where, R_i denotes a resources of vehicle node, E_i^{Res} indicates a residual energy, Bw_i^{avail} denotes a bandwidth availability.

Energy is main other characteristic of vehicle nodes to enhance broadcast. Energy plays an important role in performing important operations at VANET. Since node energy reduces, network connection minimizes also resulting it minimizes of the network lifetime.

At first, every nodes contain similar energy levels. Because of data receiving, sending, performing internal operations such as computing, linking, and updating, a certain value of its energy level gets reduced.

Therefore, the consumed energy level of node is computed as below,

$$E_i^{Cons} = E_i^{S} + E_i^{R} + E_i^{com} \quad (3)$$

E_i^{Cons} denotes consumed energy level of ‘i^{th}’vehicle nodes, E_i^{S} denotes a energy for data sending, E_i^{R} indicates a energy for data receiving, E_i^{com} indicates a energy for computing.

RE of vehicle node is computed as dissimilarity among initial energy of vehicle node as well as utilized energy.

$$E_i^{Res} = E_i^{Ini} - E_i^{Cons} \quad (4)$$

Where, E_i^{Res} denotes a residual energy level of ‘i^{th}’vehicle nodes, E_i^{Ini}denotes first energy of vehicle nodes, E_i^{Cons} represents consumed energy of vehicle nodes.

BW is the maximum data transfer rate of a network per unit time. It calculated in bits per second.

$$Bw_i = \left(\frac{Max_{DR}}{time}\right) \quad (5)$$

Where, Bw_i denotes a bandwidth, Max_{DR} indicates a maximum rate of data transfer. The bandwidth capacity is estimated as dissimilarity among total bandwidth and utilized bandwidth.

It is estimated as below,

$$Bw_i^{avail} = Bw_i^{Ini} - Bw_i^{Cons} \quad (6)$$

From (6), Bw_i^{avail} indicates the bandwidth availability, Bw_i^{Ini} signifies an initial bandwidth, Bw_i^{Cons}indicates the consumed bandwidth.

With the above-said resource estimation, the fitness is computed with gradient ascent function. The gradient ascent is a mathematical for finding a local maximum of a function. By applying a gradient ascent function, the estimated resource value of each vehicle node is sorted in descending order.

$$R_i(Vn_1) < R_i(Vn_2) < R_i(Vn_3) \ldots . R_i(Vn_n) \qquad (7)$$

After sorting the resources, maximum value of the resource is determined as given below,

$$f(x) = arg\,max\ \{R_i(Vn_n)\} \quad (8)$$

Where f(x) denotes a fitness function, arg max indicates argument of maximum function, E_i^{Res} denotes a residual energy level, Bw_i^{avail} represents BW availability of the vehicle nodes.

After raindrop falls with ground, it split to little raindrops with the current raindrop as the center.

$$rd_i = D(U_i, L_i) \quad (9)$$

Where, rd_i raindrop, D denotes a uniform distribution function, U_i, L_i denotes a lower and upper limits of raindrop.

After splitting, the positions of these small raindrops or lower limits of raindrop are obtained by formula (10)

$$L_i = x(t) + r(-1,1) * \omega_k \quad (10)$$

$$\omega_k = \omega^{mx} - \frac{k}{k^{mx}} * (\omega^{mx} - \omega^{mn}) \quad (11)$$

Where, L_i denotes location of split small raindrop, $x(t)$ denotes a curret psotion of the raindrop, $r(-1,1)$ denotes group of consistently dispersed D -dimensional random numbers, ω^{mx} and ω^{mn} represent highest and least values of coverage radius of a raindrop.

Partitioned small raindrops are combined into big raindrops, and the positions of current big raindrops 'U_i' are obtained as follows,

$$U_i = \frac{1}{m} \sum_{i=1}^{m} L_i \quad (12)$$

Where positions of current big raindrops 'U_i' is obtained by taking the average value of the small raindrop 'L_i'.

Most of the raindrops run to the lowest position. Rainwater is formed based on the dynamic accumulation of all small raindrops. As the rain falls on land, active raindrops flow as of superior elevation to lesser because of gravity as selecting best path to minimum point on landscape. On other hand, the inactive raindrops weaken the search process and it is removed throughout the iterative process

The active and inactive raindrops are identified through fitness estimation.Inactive raindrops are discarded from the population, and then randomly generated raindrops are reloaded into the population based on the number of active raindrops.

Then theElitist selection strategy is applied to determine the current best solution (i.e. raindrops) based on fitness.

$$Q = \begin{cases} f(x) > f(x)_{th}; & select\ active\ raindrops \\ Otherwise; & inactive\ raindrops \end{cases} \quad (13)$$

Where, Q indicates selection outcomes, $f(x)_{th}$ denotes a threshold, $f(x)$ denotes a fitness. As a result, the raindrop with higher fitness is selected as the active and others inactive raindrops are eradicated. This aids to reduce time utilization and improve performance of optimal selection.

Based on selected number of active raindrops, the position of raindrops are updated as follows,

$$x(t+1) = (1-\delta) * r(-1,1) * \varphi_c * x(t) + \delta * r(-1,1) * \varphi_s * x_{best}(t) \quad (14)$$

Where, δ denotes a weight of raindrop, $r(-1,1)$ random numbers which fulfil to normal allocation, φ_c indicates a contraction factor of present raindrop $x(t)$.After that, the fitness is estimated for modernized location of raindrop. If the fitness of the updated position of raindrop is greater than old location of raindrop, then it replaces present best solution. This procedure is iterated till greatest iteration obtains reached. Finally, optimal solution (i.e. resource optimal vehicle node) is selected.

The flowchart of the multi-objective gradient Elitist rainfall drop optimization is given below,

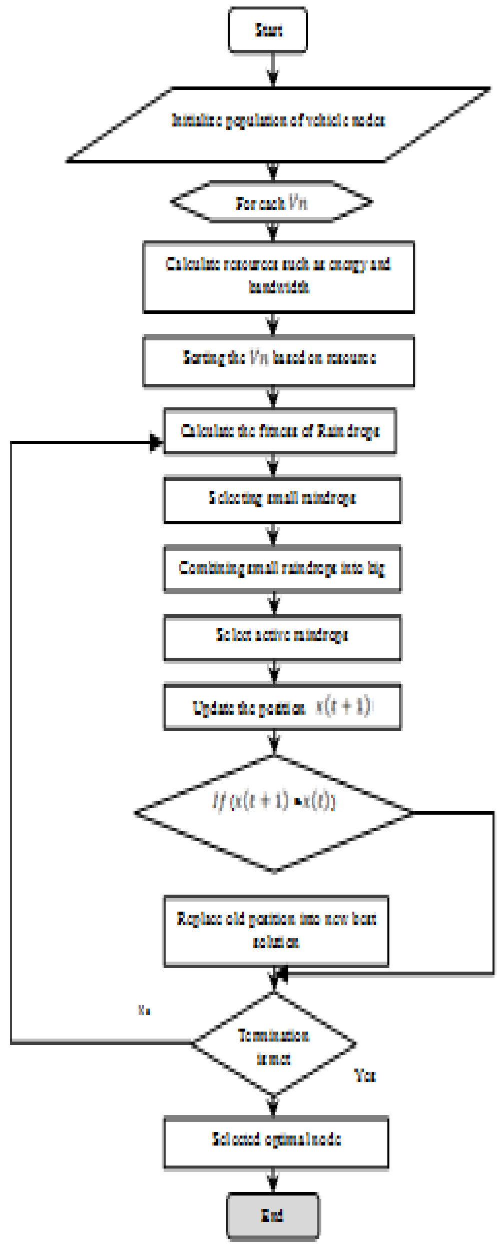

Figure 3 Flow diagram of multi-objective gradient elitist rainfall drop optimization

Figure 3 illustrates an overall flow diagram of multi-objective gradient elitist rainfall drop optimization for selecting an optimal vehicle node.

The algorithmic description of the proposed multi-objective gradient elitist rainfall drop optimization is described as follows,

Algorithm 1: Multi-objective gradient elitist rainfall drop optimization
Input : Number of vehicle nodes $Vn_1, Vn_2, Vn_3, \ldots, Vn_n$,
Output: Select optimal vehicle nodes
Begin
Initialize the population of vehicle nodes $Vn_1, Vn_2, Vn_3, \ldots, Vn_n$
For each Vn_i
Calculate E_i^{Res} and Bw_i^{avail} using (3)(4) (5) (6)
Sorting Vn_i in a descending order using (7)
Compute the fitnessusing (8)
Select current best solution
While ($t < max\_iter$)
For each individual
Splitting into small raindrops by using (9) (10) (11)
Combining into big raindrops by using (12)
Select active raindrops using (13)
$If(x(t+1) > x(t))$ **then**
Update the positions of the raindrops using (14)
Replace current best solution
End if
t= t+1
end for
end while
Return (optimal vehicle nodes)
End

Algorithm 1 illustrates the process of Multi-objective gradient elitist rainfall drop optimization for resource optimal node selection. Initially, populations distributed arbitrarily in search space . For each node, energy as well as bandwidth are estimated. Depend on resources, vehicle nodes are sorted in descending order. Followed by, the fitness computed. After that, the nodes are divided into the upper and lower limit. Due to the movement of the vehicle node, position of lower limit gets updated. After that lower limits raindrops are combined into big raindrops. Then the active and inactive raindrop are identified based on the elitism selection strategy. Then the position of the active raindrop gets updated. This procedure is repeated until the highest iteration gets reached. Finally, current best individual is replaced as the optimal vehicle node.

3.2 Shapiro–Wilk test censored regressive load balancing

After selecting the optimal vehicle nodes, load capacity is estimated for reducing delay and data loss during broadcast. The proposed MORDEL technique uses the Shapiro–Wilk test censored regression to find the load capacity of each node. The censored regression is a ML technique employed to analyze relationship among dependent variable (i.e. load of the vehicle node) is censored above or below a certain threshold. As a result, the lesser load and higher load capacity of the vehicle nodes are identified. After that, the heavily loaded vehicle node transmits its load to the nearest lesser-loaded vehicle node for minimizing the delay and loss of data transmission. The Manhattan distance measure is used to find the nearest lesser-loaded vehicle node

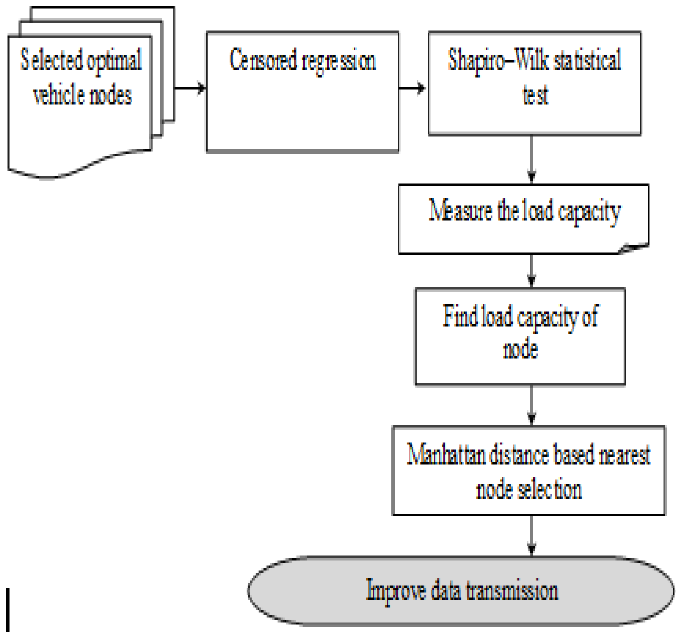

Figure 4 Block diagram of Shapiro–Wilk test censored regressive load balancing

As shown in the above figure 4, let us consider that the optimal vehicle nodes is denoted by '$\{Vn_1, Vn_2, Vn_3 \ldots\ldots Vn_k\}$'. Then, a set of optimal vehicle nodes are given as input to construct a regression model that accurately predicts the less loaded vehicle nodes of each sample. For each optimal vehicle node, load is computed based on number of data packets which the node carries at provided time period that computed as below,

$$L_i^{cap} = \left(\frac{NC_{dp}}{T}\right) \quad (15)$$

Where, L_i^{cap} indicates load of vehicle nodes, NC_{dp} indicates a number of data packets which node carries, T indicates time in seconds (S). Shapiro–Wilk test is a statistical test used to measures a goodness of fit.

$$S = \left(\frac{((\beta L_s^{cap})^2)}{(L_i^{cap} - L_T^{cap})^2}\right) \quad (16)$$

Where, S Shapiro–Wilk test outcome, β denotes a test coefficient, L_s^{cap} denotes a smallest number of data packets that the node carries ,L_i^{cap} denotes a current load of the node, L_T^{cap} threshold value of the load.

$$R = \begin{cases} S = 1 \;, & less\ loaded\ Vn \\ otherwise, & heavy\ loaded\ Vn \end{cases} \quad (17)$$

From (17), R is the output of the regression outcome, if the statistical test outcome is 1 then the node is said to be a less loaded. Or else, node is heavy loaded. The node with weighty loaded causes packet drop as well as it minimizes packet delivery as of source to destination. Consequently, proposed method chose less loaded vehicle node to carry out data broadcast. The least loaded mobile node obtains incoming packets as of nearest heavy loaded vehicle nodes as well as efficiently broadcast data packets to destination with superior delivery ratio.

Manhattan distance measure is used to find the nearest lesser-loaded vehicle node. Let us assume coordinate less loaded vehicle node is (x_1, y_1) as well as heavy loaded vehicle node is (x_2, y_2). Therefore, distance among vehicle nodes is computed as below,

$$D = |x_2 - x_1| + |y_2 - y_1| \quad (18)$$

Where, D indicates a distance among vehicle nodes. After that less loaded vehicle node finds nearest heavy loaded vehicle node as given below,

$$Z = arg\, min\, D \quad (19)$$

Where, Z denotes an outcome,arg min denotes a argument of minimum function, D denotes a distance. Lesser loaded mobile node obtains incoming packets as of the nearest heavy loaded nodes and it effectively broadcast information packets to destination. This helps to enhance data delivery as well as minimize delay.

Algorithm 2 :Shapiro–Wilk test censored regressive load balanced data transmission
Input: number of optimal vehicle nodes $Vn_1, Vn_2, Vn_3 \dots . Vn_k$, number of data packets $\boldsymbol{dp_1}, \boldsymbol{dp_2}, \boldsymbol{dp_3}, \dots \boldsymbol{dp_n}$
Output: Improve data transmission
Begin
1. For each optimal vehicle nodes Vn_i
2. Measure the load capacity 'L_i^{cap}'
3. Measure the test statistics using (16)
4. $If(S = 1)$ **then**
5. Node is classified as lesser loaded
6. **Else**
7. Node is classified as heavy loaded
8. **End if**
9. **For each less loaded** $\boldsymbol{Vn_i}$
10. Find nearest heavy loaded Vn_i using (18) (19)
11. **End for**
12. Less loaded node ($\boldsymbol{Vn_i}$) receive the data from nearest heavy loaded '$\boldsymbol{Vn_i}$'
13. Send data to destination

End

Algorithm 2 describes process of the Shapiro–Wilk test censored regressive load balancing for efficient data transmission. For each optimal node, load of vehicle nodes is estimated. Load of vehicle nodes is analyzed with the application of a statistical test.

Based on the test, the node is said to be less or heavily loaded. Nodes that receive the lesser number of data packets per unit of time are known as less loaded nodes. The less-loaded nodes receive the data packets from the nearest heavy-loaded nodes. Then effective data broadcast is performed by lesser delay.

4.EXPERIMENTAL ANALYSIS AND RESULT DISCUSSION

Proposed MORDELtechnique and conventional techniques M-SSO [1], HGFA [2] implemented in NS2.34 simulator.

Table 1 Simulation parameters settings

Simulation	Values
Network Simulator	NS2.34
Simulation area	1100 m * 1100 m
Number of vehicle	50,100,150,200,250,300,350,400,450,500
Number of data	100,200,300,400,500,600,700,800,900,1000
Mobility model	Random Waypoint model
Nodes speed	0 – 20 m/s
Simulation time	300sec
Routing Protocol	DSR
Number of runs	10

Performance study of MORDELand two existing methods M-SSO[1],HGFA [2] are estimated by various metrics. Performance of dissimilar methods is analyzed through the help of table as well as graphical representation.

4.1 Packet delivery ratio:

It is referred as ratio of number of information packets received at destination to total amount of data packets sent. It expressed as follows

$$RA_{PD} = \sum_{i=1}^{n} \frac{Dp\ received}{DP_i} * 100 \quad (20)$$

Where, ‘RA_{PD}’ symbolizes packet delivery ratio, DP_i denotes number of data packets, ‘Dp received’ denotes data packets received at destination. It is computed in percentage (%).

Table 2 comparison of packet delivery ratio versus number of data packets

Number of data packets	Packet delivery ratio (%)		
	MORDEL	M-SSO	HGFA
100	94	92	90
200	94.5	91.5	90
300	93.33	91.33	89.33
400	94.5	92	90.25
500	93.6	91.6	89
600	93.5	90.83	89.33
700	93.14	90.142	88.85
800	93.5	90.5	88.75
900	93.88	90.55	89.11
1000	92.4	88.6	87.1

Table 2 depicts simulation outcomes of packet delivery ratio involved in data transmission from source to destination using MORDEL method and existing M-SSO [1] and HGFA [2]. In order to calculate RA_{PD}, numbers of data packets are considered from 100 to 1000. For every method, ten different outcomes are performed through dissimilar number of data packets. Overall observed outcomes indicate that MORDEL attains improved results of RA_{PD}than conventional techniques. Number of data packets received at destination is 94 using MORDEL technique and the percentage of $RA_{PD}$is 94%. Therefore, $RA_{PD}$of conventional [1] [2] is found to be 92% and 90% respectively. For each method, ten different outcomes of obtained with different number of data packets. Overall observed outcomes of MORDEL method are compared to conventional results. Then average value is taken for ten comparison results.

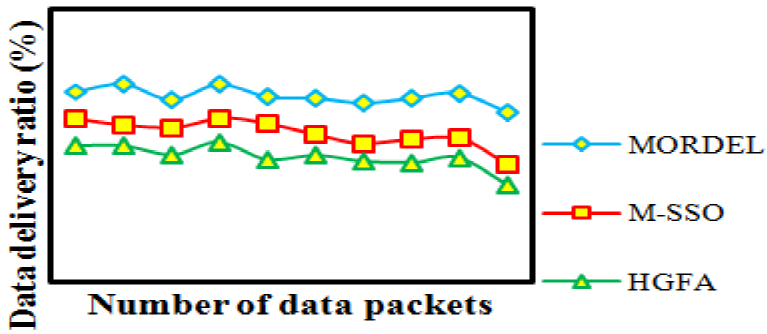

Figure 5 Graphical illustration of packet delivery ratio

As depicted in figure 5, graphical depiction of $RA_{PD}$of MORDEL technique and two conventional methods M-SSO [1] and HGFA [2]. As shown in the above figure, experiments are performed using varying numbers of data packets ranging between 100 and 1000. As exposed in graph, performance $RA_{PD}$is indicated by three dissimilarcolors. The above figure 3 perceives that RA_{PD} of MORDELmethod is improved than the conventional methods. This enhancement is achieved by identifying the optimal vehicle nodes with the help of Multi-objective gradient elitist rainfall drop optimization. The proposed optimization technique finds the resource effective vehicle nodes based on energy as well as bandwidth. With selected nodes, the load balancing among the vehicle nodes are performed. The less loaded vehicle nodes are used for efficient data transmission to achieve higher delivery ratio.

4.2 Packet loss rate:

It is referred as ratio of number of information packets lost to total number of data packets sent. It is estimated as below,

$$RA_{LSS} = \sum_{i=1}^{n} \frac{Dp\ lost}{DP_i} * 100 \quad (20)$$

Where,RA_{LSS}indicatespacket loss rate, Dp lostrepresents number of data packets lost. It is computed in (%).

Table 3 comparison of packet loss rate versus number of data packets

Number of data packets	Packet loss rate (%)		
	MORDEL	M-SSO	HGFA
100	6	8	10

200	5.5	8.5	10
300	6.66	8.66	10.66
400	5.5	8	9.75
500	6.4	8.4	11
600	6.5	9.16	10.66
700	6.85	9.85	11.14
800	6.5	9.5	11.25
900	6.11	9.44	10.88
1000	7.6	11.4	12.9

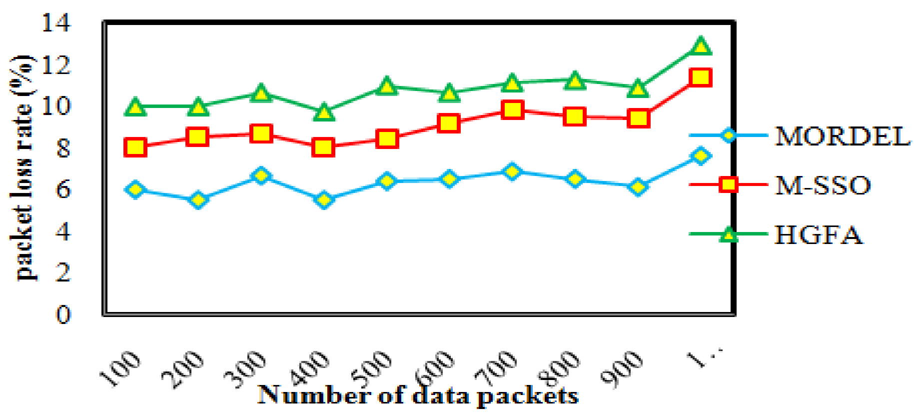

Figure 6 Graphical illustration of packet loss rate

Figure 6 depicts performance outcome ofRA_{LSS}using MORDEL technique and two conventional methods M-SSO [1], HGFA [2]. As illustrated in graph, performance of 'RA_{LSS}' is indicated by three dissimilar colors. The above figure 6 illustrates that RA_{LSS} of the MORDELmethod is reduced than the existing methods. This is owing toMORDEL technique perform load capacity analysis before the data transmission. The Shapiro–Wilk test censored regression method is applied for analyzing the load capacity of the vehicle nodes. The load capacity is calculated depend on number of data packets which node carries at specific time.TheShapiro–Wilk test is carried out to identify less or heavy loaded vehicle node. During the data transmission, the node loses the data packets due to heavy load. In this case, some of the data packets get lost. Therefore, the MORDEL technique finds the nearest vehicle nodes which having less load for distributing the data packets hence it enhance data delivery ,minimize packet loss.

4.3 End-to-End Delay:

It is defined as amount of time utilizedthrough algorithm for delivering packets as of source to destination. Delay is measured in milliseconds (ms).

$$D_{ED} = [DP_{arr}(T) - DP_{sed}(T)] \quad (23)$$

Where, D_{ED} indicates End-to-End Delay, $DP_{arr}(T)$ denotes data packetarrival time, $DP_{sed}(T)$ indicates data packet sending time. It is computed in milliseconds (ms).

Table 4 comparison of End-to-End Delay versus number of data packets

Number of data packets	End-to-End Delay (ms)		
	MORDEL	M-SSO	HGFA
100	16	19.6	22
200	19	22.5	25.7
300	22.6	25.9	28
400	25.9	28	31.9
500	27.4	30.5	35
600	28.4	32	37.4
700	31	35.7	40.5
800	33.9	38	43.7
900	35.7	40.2	45
1000	38.4	42.9	47.6

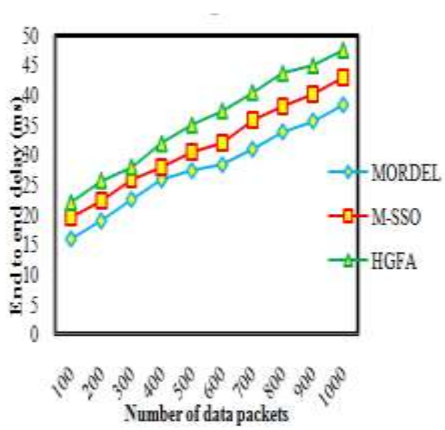

Figure 7 Graphical illustration of End-to-End Delay

Figure 7 illustrates the performance outcomes of D_{ED} of data packet transmission. Overall data transmission $D_{ED}$of three techniques obtains enhanced while increasing number of information packets being sent from source node. However,MORDEL methodutilizes lesser delay of data packet arrival time. Let us assume '100 data packets considered as input for transmission. MORDEL technique utilizes '16ms' of delay at the destination node. Similarly, the performance of delay was observed as 19.6ms' and '22ms' by applying other two existing methods [1] and [2] to deliver data from source to destination node. There are ten performance outcomeswhich are observed for every method. The lesser D_{ED} of MORDEL technique isto select efficient bandwidth availability and higher energy efficient vehicle nodes. These nodes increase the speed of the data transmission from source to destination. Similarly, load balancing among the vehicles nodes also improves the continuous data transmission with minimum delay.

4.4 Impact of throughput:

Throughput is computed assize of packets successfullyreceived at destination in particular time. It is measured in bits/sec

$$T_{put} = \left(\frac{Dp\ received\ (bits)}{t\ (sec)}\right) \tag{24}$$

Where, 'T_{put}' denotes the size of data packets effectively delivered in bits at destinationas well as time (t).

Table 5 Comparison of Throughput

Data packet size (KB)	Throughput (bps)		
	MORDEL	**M-SSO**	**HGFA**
25	212	185	151
50	245	205	185
75	322	265	222
100	412	347	310
125	542	412	384
150	687	563	465
175	736	610	502
200	812	715	631
225	963	810	745
250	1022	914	810

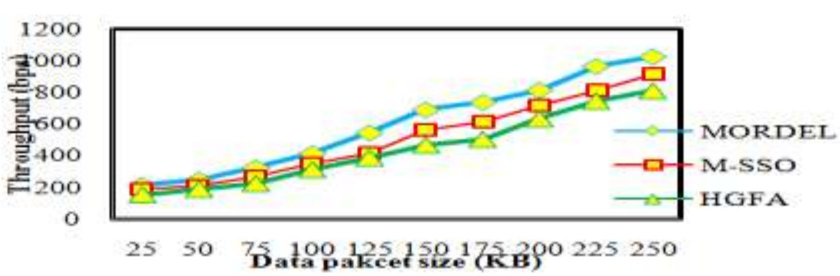

Figure 8 Graphical illustration ofT_{put}

From Table 5 , figure 8 illustrates impact of $T_{put}$with different sizes of data packet considered as input from 25KB to 250 KB. Figure, it is explicatory that overall performance of throughput in enhancing trend asincreasing size of data. In addition, ten different iterations with fair comparison are said carried out for every three methods. Further, to authenticate performance in comparison with MORDEL method other traditional optimization techniques have tested. Similar simulation environment and metrics are taken for proposed as well as existing methods. Graphical outcome shows that performance of throughput using MORDEL technique is found to be increased when compared with M-SSO [1] and HGFA [2]. This important enhancement is attained through choosing energy-efficient and maximum bandwidth capacity of sensor nodes. Moreover, the load balancing among the vehicle nodes are also enhance the performance of the throughput inters of bits per second.

5.DISCUSSIONS AND LIMITATIONS

Vehicular networks vary as of other existing ad hoc wireless networks t hrough occurrence quick alters in wireless link connections and network densities. MORDEL technique is introduced based on optimal resource-efficient node selection and load balancing to enhance effectiveness of data broadcast at VANET. Multi-objective gradient Elitist rainfall drop optimization is used in MORDEL technique for selecting resource-optimal vehicle nodes.

Then Shapiro–Wilk test censored regression is applied for analyzing load capacity of the vehicle nodes with a certain threshold. This helps to improve the RA_{PD} and minimize D_{ED}. Proposed technique is compared with existing methods such as M-SSO [1] and HGFA [2]. Overall outcomes indicate that MORDEL technique model reduces D_{ED} by 12% and 22% than the M-SSO [1] and HGFA [2]. In addition, $RA_{LSS}$of MORDEL method is minimized by 30% and 41% than the M-SSO [1] and HGFA [2] respectively. Subsequently, MORDEL technique model reduces D_{ED} by 12% and 22% more than the M-SSO [1] and HGFA [2]. In addition, the throughput of the MORDEL technique is enhanced by 19% and 37% than M-SSO [1] and HGFA [2] respectively.

In our research work, the proposed MORDEL technique performed load-balanced data communication in VANETs. However, the energy parameter is not considered during data communication in VANET. In addition, security is not achieved during data communication in vehicular networks. Energy Efficient and Secured Data Communication can be carried out in future for vehicular networks.

6.CONCLUSION

In this paper, an optimization algorithm called the MORDEL technique is introduced as new energy-aware load balance management in VANET. Due to high density of vehicles in an urban scenario, efficient data transmission is a major challenge. The proposed MORDEL technique first, performs the optimization process by using multi-objective gradient Elitist rainfall drop optimization. Then, the vehicle nodes with enhanced residual energy, BW availability is selected as best vehicle for enhancing the data broadcast. With the selected optimal vehicle nodes, Shapiro–Wilk test censored regression is developed to find the load capacity of the node. In this way, resource-efficient load-balanced data broadcast is carried out between source as well as destination in VANET. Simulation is conducted to calculate the performance of MORDEL technique over two existing methods and various metrics. The numerically analyzed results have indicated that the MORDEL technique improved packet delivery by 17%, throughput by 28% and reduces $D_{ED}$by 17% as well as RA_{LSS}by36% when compared to other existing load-balanced techniques in VANET.

7. REFERENCES

[1]Achyut Shankar, RajaguruDayalan, ChinmayChakraborty, ChandramohanDhasarathan& Manish Kumar, “A modified social spider algorithm for an efficient data dissemination in VANET”, Environment, Development and Sustainability , Springer, 2022, Pages 1-44.https://doi.org/10.1007/s10668-021-01994-w

[2]Gagan Deep Singh, Manish Prateek , Sunil Kumar, MadhushiVerma, Dilbag Singh and Heung-No Lee, “Hybrid Genetic Firefly Algorithm-Based Routing Protocol for VANETs”, IEEE Access, Volume 10, 2022, Pages 9142 – 9151. DOI: 10.1109/ACCESS.2022.3142811

[3]RenQun and Seyedeh Maryam Arefzadeh, “A new energy-aware method for load balance managing in the fog-based vehicular ad hoc networks (VANET) using a hybrid optimization algorithm”, IET Communications, Wiley Publications, Volume 15, 2021, Pages 1665-16768. https://doi.org/10.1049/cmu2.12179

[4] GaganPreetKourMarwah&Anuj Jain, “A hybrid optimization with ensemble learning to ensure VANET network stability based on performance analysis”, Scientific Reports, Volume 12, 2022, Pages 1-20. https://doi.org/10.1038/s41598-022-14255-1

[5] Sami Abduljabbar Rashid, Mohammed Alhartomi, LukmanAudah, Mustafa MaadHamdi, “Reliability-Aware Multi-Objective Optimization-Based Routing Protocol for VANETs Using Enhanced Gaussian Mutation Harmony Searching”, IEEE Access , Volume 10, 2022, Pages 26613 – 26627. DOI: 10.1109/ACCESS.2022.3155632

[6]Khalid Kandali, LamyaeBennis, Omar El Bannay, Hamid Bennis, “An Intelligent Machine Learning Based Routing Scheme for VANET”, IEEE Access , Volume 10,Pages 74318 – 74333. DOI: 10.1109/ACCESS.2022.3190964

[7] HonghaoGao, Can Liu, Youhuizi Li, Xiaoxian Yang, “V2VR: Reliable Hybrid-Network-Oriented V2V Data Transmission and Routing Considering RSUs and Connectivity Probability”, IEEE Transactions on Intelligent Transportation Systems , Volume 22, Issue 6, 2021, Pages 3533 – 3546. DOI: 10.1109/TITS.2020.2983835

[8] Yaser Ali Shah, FarhanAadil, Amaad Khalil, Muhammad Assam, Ibrahim Abunadi, AlaSalehAlluhaidan, And Fahd N. Al-Wesab, “An Evolutionary Algorithm-Based Vehicular Clustering Technique for VANETs”, IEEE Access, Volume 10, Pages 14368 – 14385.DOI: 10.1109/ACCESS.2022.3145905

[9]Mustafa MaadHamdi, LukmanAudah, Sami Abduljabbar Rashid, “Data Dissemination in VANETs Using Clustering and Probabilistic Forwarding Based on Adaptive Jumping Multi-Objective Firefly Optimization”, IEEE Access, Volume 10, Pages 14624 – 14642. DOI: 10.1109/ACCESS.2022.3147498

[10]Pavan Kumar Pagadala, P. Lalitha Surya Kumari, Deepak Thakur, VivekBhardwaj, Mohammad Shahid, AbdulrajakBuradi, Abdul Razak, and AbiotKetema, “Slow Heat-Based Hybrid Simulated Annealing Algorithm in Vehicular Ad Hoc Network”, Computational Intelligence and Neuroscience, Hindawi, Volume 2023, February 2023, Pages 1-10. https://doi.org/10.1155/2023/9918748

[11]Mohammad AsifHossain, RafidahMd Noor , Kok-Lim Alvin Yau , SaaidalRazalliAzzuhri, Muhammad Reza Z’abar, Ismail Ahmedy, And Mohammad Reza Jabbarpour, “Multi-Objective Harris Hawks Optimization Algorithm Based 2-Hop Routing Algorithm for CR-VANET”, IEEE Access , Volume 9, Pages 58230 – 58242. DOI: 10.1109/ACCESS.2021.3072922

[12]Christy Jackson Joshua &VijayakumarVaradarajan, “An optimization framework for routing protocols in VANETs: a multi-objective firefly algorithm approach”, Wireless Networks, Springer, Volume 27, 2022, Pages 5567–5576. https://doi.org/10.1007/s11276-019-02072-w

[13] Dr. R. Naveen Kumar1,Ms. Moumita Sarkar2, Bandwidth Optimization Techniques For Faster Data Transfer Avoiding Traffic Congestion Using Distributed Bandwidth Network European Chemical Bulletin (ISSN 2063-5346)10 (12(10),), 12501-1250

[14] Pawan Singh, Ram Shringar Raw, Suhel Ahmad Khan, Mazin Abed Mohammed, Ayman A. Aly, And Dac-Nhuong Le, "W-GeoR: Weighted Geographical Routing for VANET's Health Monitoring Applications in Urban Traffic Networks", IEEE Access ,Volume 10, Pages 38850 – 38869. DOI: 10.1109/ACCESS.2021.3092426

[15] Ishtiaq Wahid, SadafTanvir , Masood Ahmad, FaseeUllah, Ahmed S. AlGhamdi , Murad Khan and Sultan S. Alshamrani, "Vehicular Ad Hoc Networks Routing Strategies for Intelligent Transportation System", Electronic, Volume 11, Issue 15, Pages 1-36. https://doi.org/10.3390/electronics11152298

[16]K. Satheshkumar and S. Mangai, "EE-FMDRP: energy efficient-fast message distribution routing protocol for vehicular ad-hoc networks", Journal of Ambient Intelligence and Humanized Computing, Springer, Volume 12, 2021, Pages 3877–3888. https://doi.org/10.1007/s12652-020-01730-8

[17]KoppisettiGiridhar, C. Anbuananth, N. Krishnaraj, "Energy efficient clustering with Heuristic optimization based Routing protocol for VANETs", Measurement: Sensors, Elsevier, 2023, Pages 1-15.https://doi.org/10.1016/j.measen.2023.100745

[18]SwathiKonduru and M. Sathya, "Remora optimization algorithm-based optimized node clustering technique for reliable data delivery in VANETs", International Journal of Intelligent Networks, Elsevier, Volume 3, 2022, Pages 74-79.https://doi.org/10.1016/j.ijin.2022.07.002

[19]GhassanHusnain , Shahzad Anwar , FahimShahzad, GulbadanSikander, Rehan Tariq, MaheenBakhtyar, and Sangsoon Lim, "An Intelligent Harris Hawks Optimization Based Cluster Optimization Scheme for VANETs", Journal of Sensors, Hindawi, Volume 2022, October 2022, Pages 1-15.https://doi.org/10.1155/2022/6790082

[20] PratimaUpadhyay, VenkatadriMarriboina, Shiv Kumar, Sunil Kumar, MohdAsif Shah, "An Enhanced Hybrid Glowworm Swarm Optimization Algorithm for Traffic-Aware Vehicular Networks", IEEE Access, Volume 10, Pages 110136 – 110148.DOI: 10.1109/ACCESS.2022.3211653

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